TESE DE DOUTORADO

WELD BEAD GEOMETRY MODELING IN GMAW PROCESS BY MACHINE LEARNING TECHNIQUES AND DATA MINING PROCESS

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UNIVERSIDADE DE BRASÍLIA

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A Iná, mi nueva fuente de energía y vida ...

A mis abuelos, no presentes físicamente pero sé que me acompañan ...

A mis padres ...

ABSTRACT

Weld Bead Geometry Model in GMAW process by Machine Learning Techniques and Data Mining Process

The GMAW process has a non-linear behavior and has led many researchers to develop several studies on it. One of the main interests has been to optimize the process to develop better performance in industrial processes. Thus, current advances in image processing, predictive model, and intelligent modeling can help to optimize processes. These techniques can obtain good results in welding analysis. These techniques can be grouped into, techniques of machine learning, deep learning, and reinforcement learning, and data mining processes. They are responsible for the current advances in prediction, real-time image classification, and intelligent control. Its application in the welding area has the potential for a better study and analysis of processes, optimization of welding technologies, and better process controls. This research focuses on the objective of developing a weld bead geometry model in GMAW process by applying machine learning techniques and data mining process. As a result of the research, a deep learning model was obtained for the analysis of the arc, a predictive model of the process behavior, and a mode to optimize it. The methodologies developed with these models demonstrate a valid efficiency to be applied in real GMAW processes.

RESUMO

Modelamento da Geometria do Cordão da Solda no Processo GMAW Mediante Técnicas de Aprendizado de Máquina e Processo de Mineração de Dados

O processo GMAW possui um comportamento não linear, e tem levado muitos pesquisadores a desenvolverem diversos estudos sobre ele. Um dos principais interesses tem sido otimizar o processo para desenvolver melhor desempenho nos processos industriais. Dessa forma, os avanços atuais em processamento de imagem, modelo preditivo e modelagem inteligente podem ajudar a otimizar processos. Essas técnicas podem obter bons resultados na análise de soldagem. As técnicas se podem agrupar em: técnicas de aprendizado de máquina, aprendizado profundo, aprendizado por reforço e processos de mineração de dados. Eles são responsáveis pelos avanços atuais em predições, classificação de imagens em tempo real e controle inteligente. Sua aplicação na área de soldagem tem como potencial um melhor estudo e análise de processos, otimização de tecnologias de soldagem e melhores controles de processo. Esta pesquisa tem como objetivo desenvolver um modelo de geometria do cordão de solda no processo GMAW através da aplicação das técnicas de machine learning e do processo de mineração de dados. Como resultado da pesquisa, foi obtido um modelo de deep learning para a análise do arco, um modelo preditivo do comportamento do processo e um modo com o objetivo de otimizá-lo. As metodologias desenvolvidas com esses modelos demonstram uma eficiência válida para serem aplicadas em processos reais de GMAW.

SUMMARY

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1 INTRODUCTION

Welding is considered one of the most important processes of joining metals used in industries. It is used in the fabrication of simple structures, as well as components of a high degree of responsibility in chemical, petroleum, and nuclear industries. One of the welding techniques is Gas Metal Arc Welding (GMAW). This is a welding process in which heat is generated by an electric arc incorporating a continuous-feed consumable electrode that is shielded by an externally supplied gas. In addition, this welding technique can be applied in ferrous and non-ferrous materials. This is due to its versatility, relatively high productivity, reliability, and automation. GMAW is a stochastic process, and the interrelation between its inputs and outputs parameters have a non-linear behavior. Then, this is one of the main problems that researchers find when modeling a GMAW process. The balance between the initial parameters and metal transference modes defines the shape of the weld bead geometry. However the difficulty to control the relationship between these parameters has led to many studies that focus on making an analysis based on only one metal transfer mode. Another problem is that many investigations do not get a real-time analysis. Due to the slowness of the classic image processing techniques. Which, on many experiments, does not guarantee a generalization of the analyzes.

In practical welding production, welding conditions are often changing, such as the errors of pre-machining and fitting work-piece would result in differences of gap size and position, the change of work-piece heat conduction and dispersion during welding process would bring on weld distortion and penetration odds. The arc welding process contains complicated, stochastic and uncertain information. Monitoring the state of arc welding process is very important for predictive and controlling the welding process. Many sensing methods for welding process have been used in consideration of the disturbance from arc, high temperature, vibration, electromagnetic fields and the features of the process. Thus, in order to obtain the effectual features of arc welding process for real-time control of weld quality, various signal processing methods have been applied for information of welding process, such as processing algorithms for arc voltage, current, visual, optical, mechanical information.

It is apparent that machine learning techniques help to analyze and find solutions to many modeling problems. Machine learning uses the theory of statistics in building mathematical models, making inferences from larges samples of data. Deep learning techniques obtain excellent results in the classification of complex images. Further, other machine learning techniques, such as reinforcement learning are being used in intelligent control processes. These techniques have excellent performance in deployment environment after a hard model training. They, together, can accomplish a weld bead geometry model of GMAW process in real-time.

Furthermore, small computers with graphic cards can execute the weld bead geometry model in real-time. In addition to allowing the process to be faster than in a conventional computer, it will also make the equipment cheaper and lower energy consumption.

1.1 GENERAL OBJECTIVE

The aim of this work is to develop a weld bead geometry model of GMAW process by applying techniques of machine learning, deep learning, and reinforcement learning.

1.2 SPECIFICS OBJECTIVES

- To develop a real-time detection model of short circuit and droplet detachment in GMAW process using deep learning techniques.
- To develop a predictive model of the weld bead geometry of a GMAW process using machine learning techniques.
- To develop the weld bead geometry model of a GMAW process in real-time by applying reinforcement learning techniques.

1.3 SUMMARY OF CONTRIBUTIONS

This research contribute:

- In the proposal of two methodologies for weld bead geometry modeling of the GMAW process.
- In a new GMAW arc images analysis with deep learning technique in real-time.
- In the integration of transfer modes in one computational model for GMAW process.
- In a comparison of predictive GMAW model.
- In a new intelligent modeling process with reinforcement learning for GMAW process.

1.4 POTENTIAL APPLICATIONS

The research developed shows a series of models that both individually and together can be used for other studies of GMAW process. Also, the image processing techniques used can be useful for monitoring short circuits and drop detachment in a GMAW process. The predictive model represents a low-cost technique to identify the behavior of weld bead geometry of GMAW process. That way, this quality allows its use in teaching processes and simulation tests in the production industry. Indeed, the real-time modeling of the weld bead geometry to having the same potentialities of a predictive model is a precedent to define an intelligent control of GMAW process.

1.5 PUBLICATIONS RESULTS

Papers presented in conferences and published in conference proceedings.

- Thompson, R.; Absi Alfaro, S. C. A. and Martin, A. "Dynamic drop volume function and deep learning to obtain drop and molten volume in GMAW process", in *IV Conferencia Internacional de Soldadura y Unión de Materiales - ICONWELD 2018*. Lima, Perú. ISBN: 978-612-47965-0-0, pp. 136.
- Thompson, R.; Martin, A and Absi Alfaro, S. C. "Obtaining of drop and molten volume in GMAW process with a dynamic drop volume function and Deep Learning technique", in *XLIV CONSOLDA – Congresso Nacional de Soldagem, 2018*. Uberlândia, Brazil.
- Thompson, R. and Absi Alfaro, S. C. "Intelligent control proposition on GMAW process with machine learning techniques", in *COB2019 Conference, 2019*. DOI: 10.26678/ABCM.COBEM2019.COB2019-0263.
- Thompson Martínez, R.; Alvarez Bestard, G. ; Martins Almeida Silva, A.; and Absi Alfaro, S. C.; "Analysis of GMAW process with deep learning and machine learning techniques," J. Manuf. Process., vol. 62, pp. 695–703, Feb. 2021. https://doi.org/10.1016/j.jmapro.2020.12.052.
- Thompson Martinez, R., Alvarez Bestard, G., Absi Alfaro, S. C. (2021). Two Gas Metal Arc Welding process dataset of arc parameters and input parameters. Data in Brief, 35, 106790. https://doi.org/10.1016/j.dib.2021.106790.

Chapter of book.

- Thompson R. and Absi, S. C. (March 10th, 2020). "Data Analysis and Modeling Techniques of Welding Processes: The State-of-the-Art", Welding - Modern Topics, ISBN: 978-1-83881-896-8. DOI: 10.5772/intechopen.91184.

1.6 DOCUMENT STRUCTURE

This work is organized in six chapters, the bibliography references, and annexes.
Chapter 1 explained the research problem, as well as the objectives and their possible contribution.
Chapter 2 presents a conceptual analysis of the GMAW process, data analysis techniques, models process, and the interdisciplinary that they may possess.
Chapter 3 presents a bibliographic review of data analysis techniques in welding.
Chapter 4 presents the equipment and materials used, as well as the experimental design.
Chapter 5 presents the methodology developed in research based on the stages of data mining

processes. In each stage, the obtained results are explained.

Chapter 6 develops a proposal for the design of components necessary to apply the models obtained in an experimental lab.

Conclusions and future works present the general results of research and potential researches that can be developed from this one.

2 GMAW PROCESS, DATA ANALYSIS AND MODELING CONCEPTUALIZATIONS

This chapter describes the GMAW process, its characteristics, and fundamental parameters that will be analyzed in this research. Also, it presents a conceptual analysis and potentialities of an interdisciplinary area between welding processes, specifically the GMAW process, machine learning, and data mining process techniques. Moreover, the chapter explains the possible contributions of the computer science area in the welding process.

2.1 GAS METAL ARC WELDING (GMAW)

Welding is considered one of the most important processes of joining metals used in industries as shown in (Villani, Modenesi and Bracarense 2016). Because, it is used in the fabrication of simple structures, as well as components of a high degree of responsibility in chemical, petroleum, and nuclear industries. In other words, one of the welding techniques that contribute to the mentioned utilities is the Gas Metal Arc Welding (GMAW). It is a consumable electrode welding process that produces an electric arc between a weld pool and supplied electrode wire. The electric arc is its energy source to join metal pieces. The process can be performed either as an automated, as a manual hand-held process, or semi-automatic (Thomsen 2005). Furthermore, It can be applied to ferrous and non-ferrous materials. It is mainly due to its versatility, relatively high productivity, reliability, and ease of use and automation (ASM 1994, Scotti, A; Ponomarev, V 2008, Cary and Helzer 2005). This welding process is considered a highly non-linear, multi-parameters and time-varying system (Yan 2011).
The basics equipment used for a typical GMAW semiautomatic setup is shown in Figure 2.1.

(1) Welding torch: It contains wire electrode and shielding gas supplied (Figure 2.2). The electrode extension is the amount the end of the electrode wire sticks out beyond the end of the contact tube.

(2) Workpieces: they are the metals to welding.

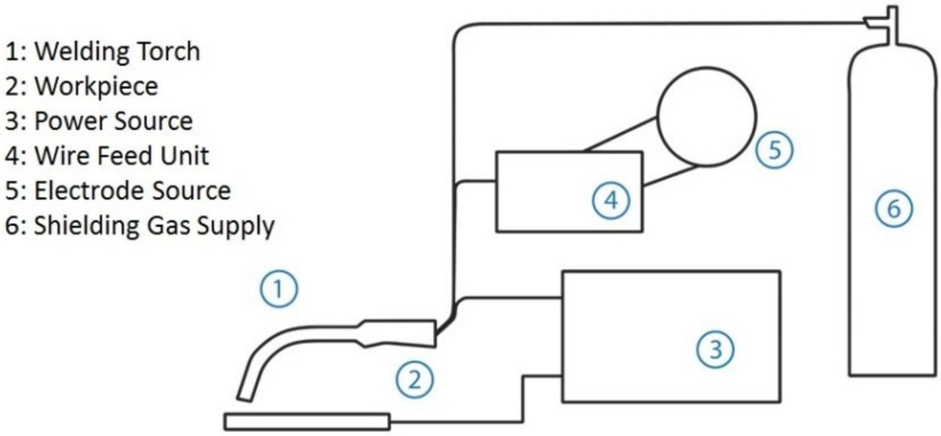
(3) Welding Source: It is a constant voltage power source whose one terminal is connected with the welding torch and the other is connected to the workpiece through a clamping device.

(4) Wire feed unit: it is the control to wire supply.

(5) Electrode source: It is the metal wire which is used as the metal electrode in the GMAW welding.

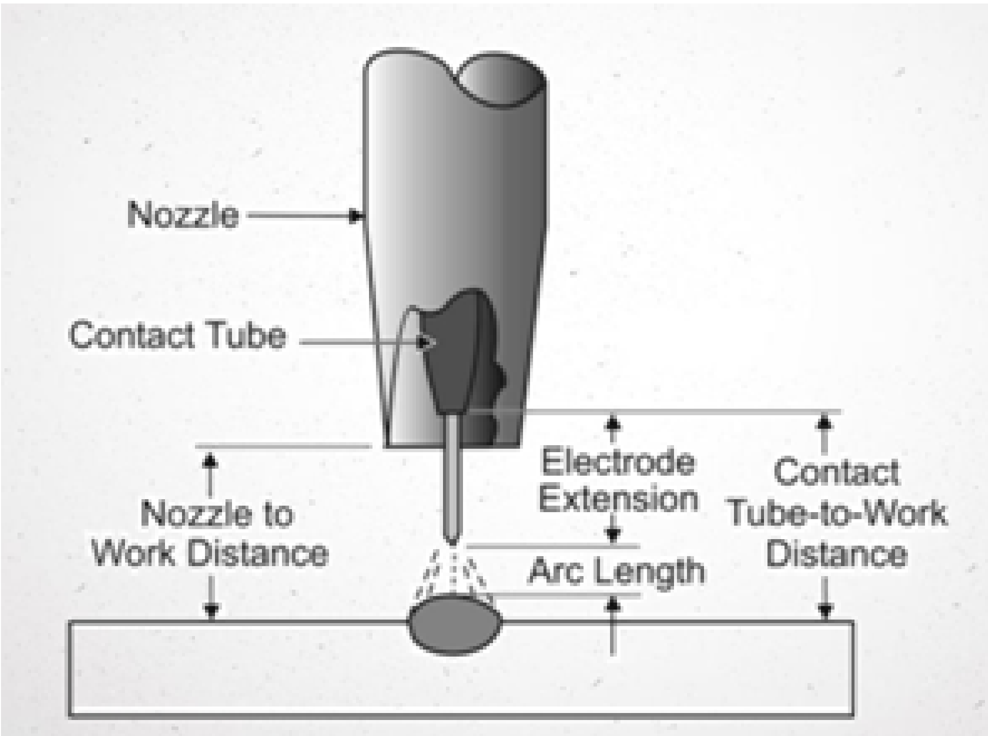
(6) Shielding gas supply: it provides a supply of shielding gas to the arc area.

Figure 2.1: GMAW Circuit



Source: (The Welding Master 2017)

Figure 2.2: Welding torch

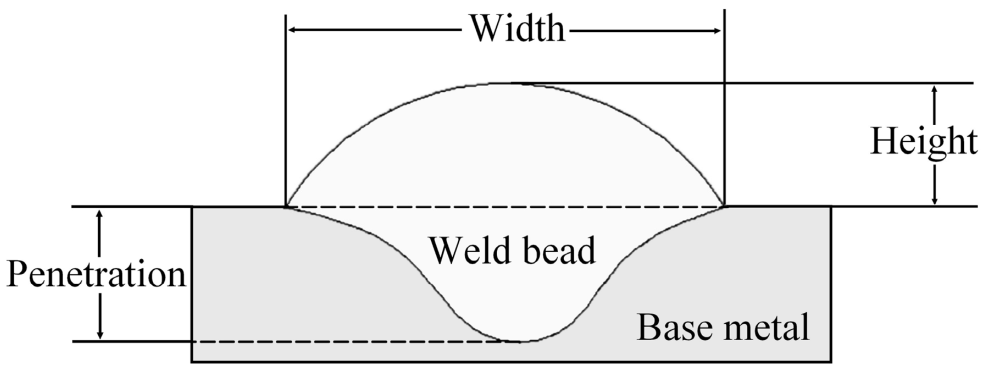


Source: (EuroTech 2019)

2.1.1 GMAW parameters

GMAW parameters are the parameters involved in the welding process, whose changes have influences on the characteristics of heat, metal transfer and welding bead geometry (Cayo 2013). GMAW process offers some difficulty correcting welding parameters, this is mainly due to the relatively high number of parameters and above all, a strong interrelation between them (Scotti, A; Ponomarev, V 2008, Bingul and Cook 2006). In this research, some parameters are selected for GMAW process analysis. It is valuable to note the parameters are those that can be adjusted during the process, they are wire feed speed, welding velocity, and voltage. The adjustable parameters are those that make it possible to control some of them in the process. They are also known as input parameters. Add to this the arc parameters are constituted by those phenomena produced by the electric arc. Some experiments are analyzed as output parameters. These parameters were selected because they are those that can be estimated through arc-image processing. Some arc parameters are unmelted wire length, drop volume, melted wire volume, short circuit frequency, and drop frequency. Weld-bead parameters are weld-bead depth, weld-bead width, and weld-bead height. The bead parameters consist of geometric characteristics as shown in the Figure 2.3.

Figure 2.3: Welding bead



Source: (Pinto-Lopera et al. 2016)

GMAW process, being a process that uses consumable wire, is mainly characterized by metal transfer modes. Thus the metal transfer modes are influenced by GMAW input parameters, characteristics of materials, and components used. Metal transfer in the GMAW process can be grouped into three modes:

(1) **Short-circuiting metal transfer** is a mode of metal transfer whereby a continuously fed solid or metal-cored wire electrode is deposited during a repeated electrical short-circuiting. The short-circuiting metal transfer mode is the low heat input mode of metal transfer for GMAW. Then, the metal transfer occurs when the electrode is electrically shorted with the base material or molten puddle. Central to the successful operation of short-circuiting transfer is the diameter of electrode, the shielding gas type, and the welding procedure employed (The Lincoln Eletric Company 2014).

(2) **Globular metal transfer** is a GMAW mode of metal transfer whereby a continuously fed solid or metal-cored wire electrode is deposited in a combination of short-circuits and gravity-assisted large droplets. The larger droplets are irregularly shaped. During the use of all metal-cored or solid wire electrodes for GMAW, there is a transition between short-circuiting transfer ends and globular transfer begins. Globular transfer characteristically gives the appearance of large irregularly shaped molten droplets that are larger than the diameter of the electrode. The process at this current level is difficult to control and spatter is severe. Gravity is instrumental in the transfer of the large molten droplets with occasional short-circuits (The Lincoln Eletric Company 2014).

(3) **Spray metal transfer** is the higher energy mode of metal transfer whereby a continuously fed solid or metal-cored wire electrode is deposited at a higher energy level, resulting in a stream of small molten droplets. The droplets are propelled axially across the arc. For most of the diameters of filler metal alloys, the change to spray transfer takes place at the globular to spray transition current (The Lincoln Eletric Company 2014).

Indeed the variability of these modes and the inaccuracy of the values under which they occur are important elements that define the complexity of GMAW process. This makes the analysis of the arc a very important element that determines what can happen at the end of the process.

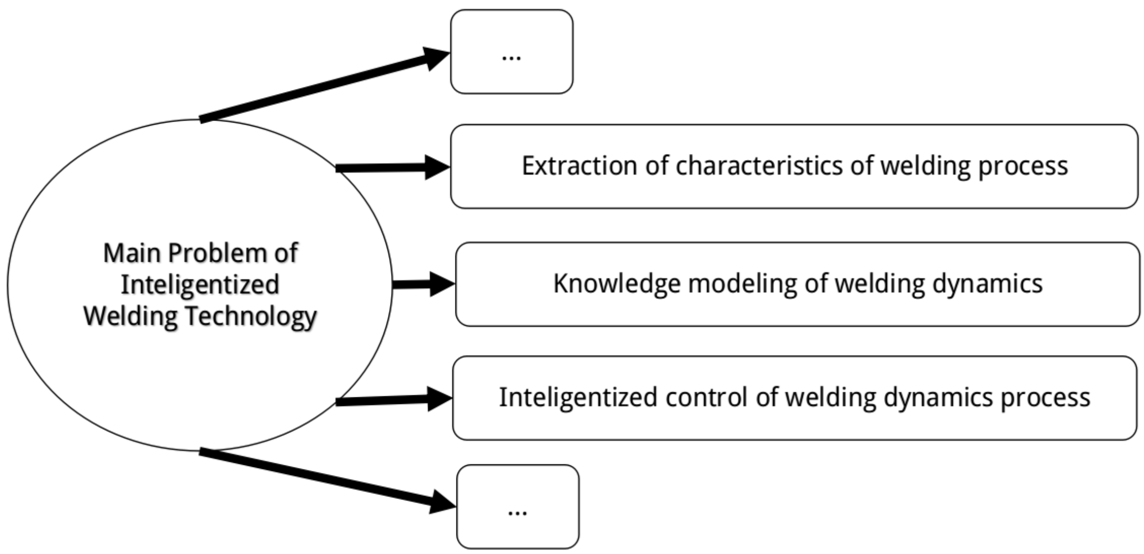
2.1.2 GMAW process as a complex system

Despite the great advantages of the GMAW process. It requires a careful setting of process parameters to avoid fusion defects, especially on thicker base metals. Careful configurations are ideal for a wide range of industrial welding requirements. Most common welding problems fall into the category of improper weld bead profile, As was shown in diversifying investigations such as (Moncayo Torres 2013, Giron Cruz 2014, Alvarez Bestard and Absi Alfaro 2018) exposed. In certain industrial applications, it is required to obtain specific dimensions from the weld bead geometry. Meeting these objectives requires an excellent understanding and enough experience, which few specialists have, as (Scotti, A; Ponomarev, V 2008) said.

Welding defect is defined as any flaw compromises the usefulness of any products, the irregularities in the weld metal produced due to incorrect welding parameters or wrong welding procedures or wrong combination of metal and non-metal plates. In the welding process there are many wear or defects occur. These wear factor may include oversize work piece, casting blow holes in the work piece, thermal and mechanical properties, and variation of different metal work piece hardness. The weld defects occur during welding due to the complexities of the welding processes, moisture in the air and the unpredictable factors (Mathers 2002, Rajeev Kumar and Dr. Vandana Somkuva 2015).

The welding process in general can be viewed as a complex system that has multiple inputs, multiple outputs, and multiple disturbances. This kind of system adds difficulty in determining the correct set of input values to achieve the desired outputs. The history of inputs to outputs can help to optimize the adjustment of input values to improve the speed taken to converge at the desired levels of outputs. A non-linear model may be obtained to correlate outputs and inputs values as was showed by (Zhang YuMing 2008). Hence, (Chen and Lv 2014) suggested a modern welding manufacturing technology. The intelligentized welding manufacturing technology (IWMT) is mainly related to key intelligent technical elements. The studies establish the foundation work of intending researches and applications on intelligentized technologies for modern welding manufacturing. IWNT promotes systematization research for forming an effective combination of modern welding manufacturing, computer science, and artificial intelligence technology. In addition, the development of modern welding technology is changing from traditional handicraft to modern science manufacturing. They also show some key scientific and technical problems in IWMT. Figure 2.4 shows three of them that will be analyzed in this research.

Figure 2.4: The key scientific and technical problems in IWMT.

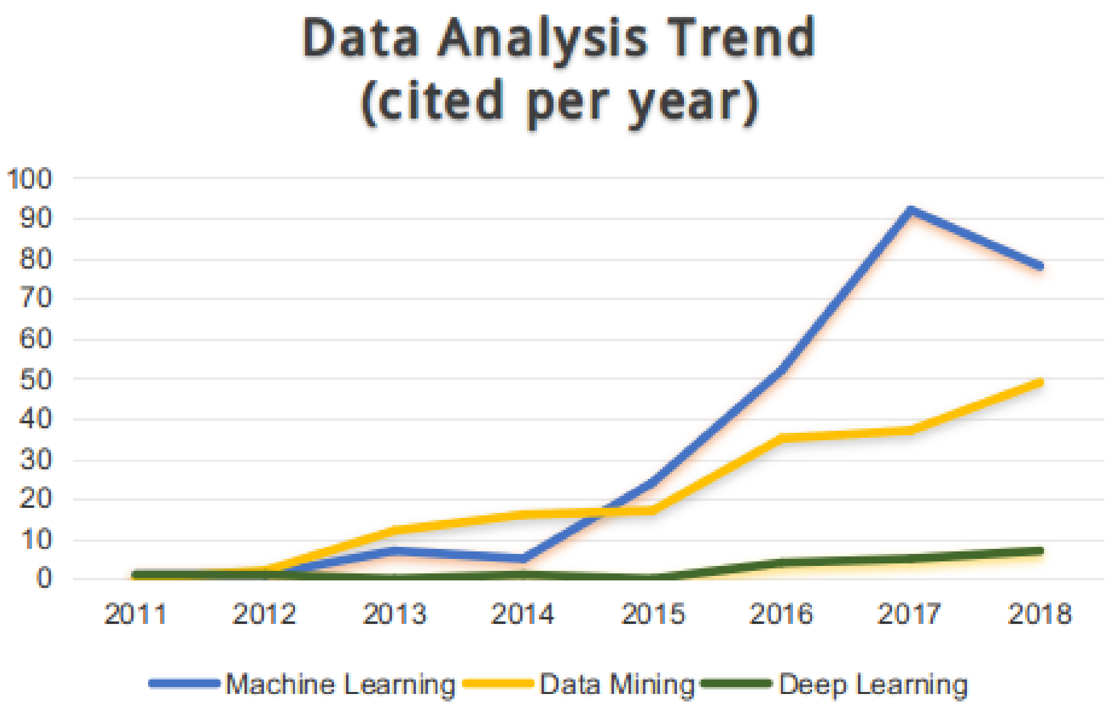


Source: (Chen and Lv 2014)

As of present, computer science has the potentials to solve these three problems. Computer science field had great results with the new technique applications of data analysis, learning models, and intelligent control. Data analysis objectives indicate non-trivial features on amount large data. Due to the increase and complexity data has been developed for more efficient data analysis techniques. Welding process can be analyzed from this point of view. As a result, welding process analysis with new techniques is nothing more than continuity in the development of welding analysis processes. This interdisciplinarity is one of the necessary contributions proclaimed by called industry 4.0, like (Haffner et al. 2017, Jiang, Zhang and Wang 2017, Chong, Ramakrishna and Singh 2018) shown. The industrial 4.0 refers to the next manufacturing generation, where automation technology will be improved by self-optimization and intelligent feedback (Tuominen 2016). For this reason, the application of the most recent data analysis techniques and processes can contribute to better modeling and monitoring of welding processes. This new data analysis technique can be groups in Data Mining process and machine Learning techniques.

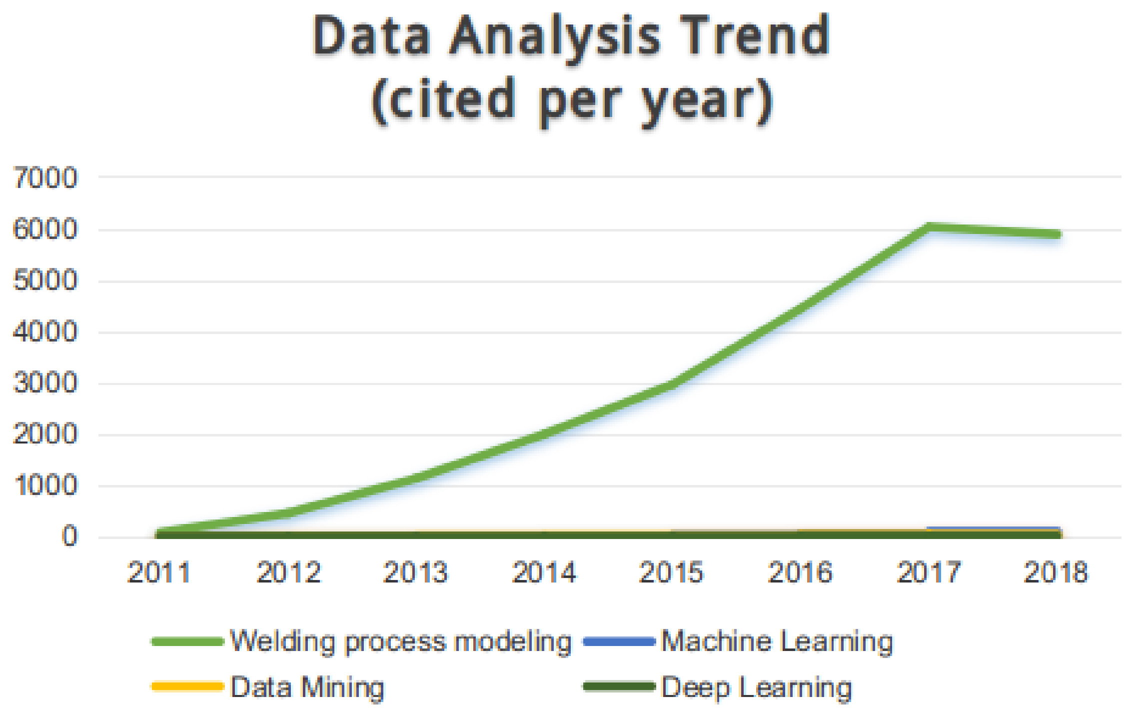
An inquiry conducted in the Web of Science from 2011 to October, 3rd 2018 shows that there is a growing trend of these new data analysis techniques in welding process researches, Figure 2.5 shows this trend. Whereas when comparing with the investigations on the models welding process, the growth is still very small, as appear in Figure 2.6. This confirmed a need to encourage research among these areas and greater socialization of results.

Figure 2.5: Cited per year on welding (Web of Science (Analytics 2018))



Source: Produced by author

Figure 2.6: Cited per year on welding (Web of Science (Analytics 2018))

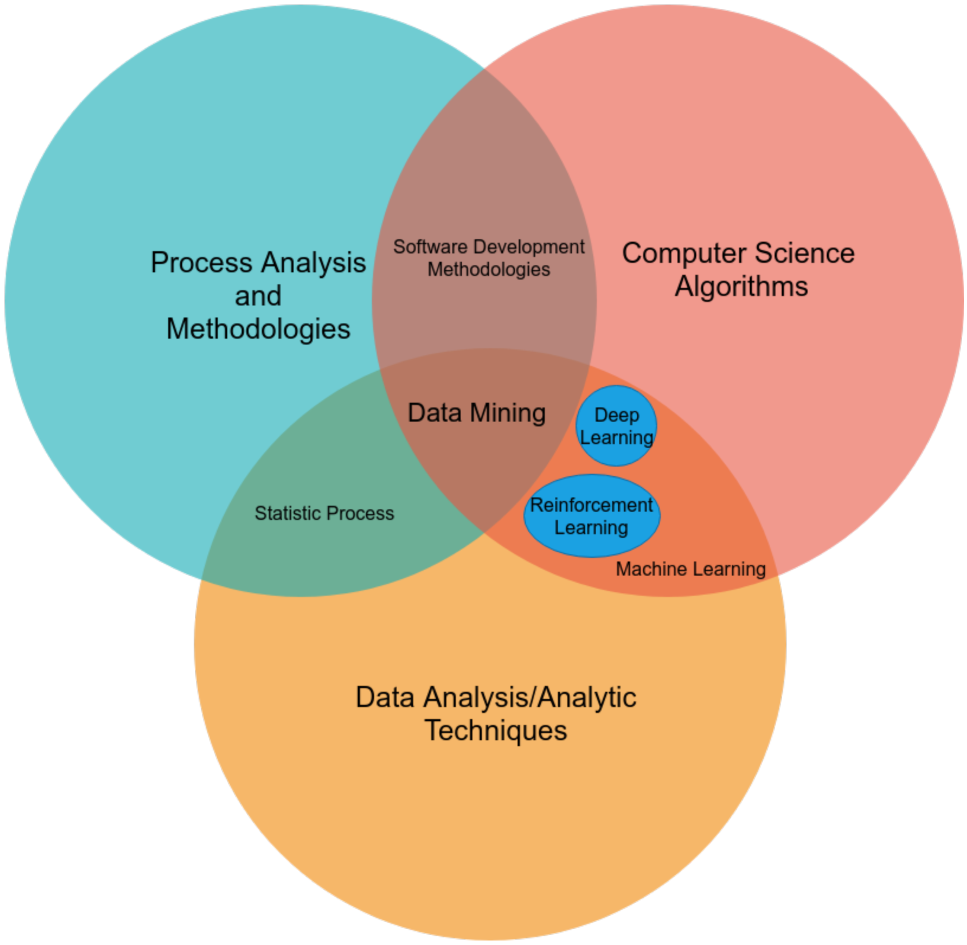


Source: Produced by author

2.2 DATA ANALYSIS

From Shannon's contributions to information theory (Weaver 1949), data analysis had increasing importance for technological, social, and scientific processes. Information theory is a branch of applied mathematics that involves the quantification of information as expressed (Liu et al. 2012). Entropy and information-theory principles are still widely used in data analysis in several areas as shows (Qi and Guo 2014, Varadan and Anastassiou 2006, Wollstadt et al. 2014, Dishion et al. 2004, Rhea et al. 2011, Seyyed and Mohammad 2011). An important objective of data analysis is to reveal and to indicate diverse, non-trivial features in data. For this reason, welding process can be analyzed from this point of view.
The contemporary techniques of data analysis can join in machine learning techniques as shown (Hernandez Orallo, Ramirez Quintana and Ferri Ramirez 2004, Yu and Deng 2011, Marsland 2015, Bell 2015, Casalino 2018), in data mining process as shown (Hirji 1999, Norton 1999, Olson and Delen 2008, Piatetsky 2014, Chambers, Doig and Stokes-Rees 2017) and in intelligent control process by machine learning and reinforcement learning techniques exemplified by (Chi et al. 2019, Huang et al. 2019, Woods and La 2019). The interrelation of these areas and their origins are presented in Figure 2.7.

Figure 2.7: Origin diagram of the new data analysis techniques



Source: Produced by author

2.3 MACHINE LEARNING TECHNIQUES

In 1959, Arthur Samuel defined machine learning as, field of study that gives computers the ability to learn without being explicitly programmed (Bell 2015). Machine learning is one of the fast-growing areas of computer science, with far-reaching applications for data analysis. The term machine learning refers to the automated detection of meaningful patterns in data (Shalev-Shwartz and Ben-David 2014). Machine learning helps to find solutions to many problems in vision, speech recognition, and robotics. Thus, this uses the statistics theory in building mathematical models making inferences from a data sample. The role of computer science is twofold by (Alpaydin 2010). First, in training, we need efficient algorithms to solve the optimization problems, to store and process the massive amount of data we generally have. Second, once a model is learned, its representation and algorithmic solution for inference need to be efficient as well. The model may be predictive to make predictions in the future, or descriptive to gain knowledge from data or both. As an interdisciplinary field, machine learning shares common threads with the mathematical area of statistics, information theory, game theory, and optimization. It is naturally a subfield of computer science. Its goal is to program machines to learn. In this sense, machine learning can be view as a branch of artificial intelligence (AI) since the ability to turn the experience into expertise or to detect meaningful patterns in complex sensory data is a cornerstone of human (and animal) intelligence (Shalev-Shwartz and Ben-David 2014). Two classification of machine learning algorithms are supervised learning and reinforcement learning. Supervised learning use a training set of examples with the target responses is provided. Based on this training set, the algorithm develops a model to respond correctly to all possible inputs. Reinforcement learning is used to solve interacting problems where the info observed up to time t is taken into account to decide which action to require at time t + 1. The algorithms that are categorized in this group can be used in optimization and intelligent control tasks (Marsland 2015). Some famous and best-used supervised machine learning techniques are:

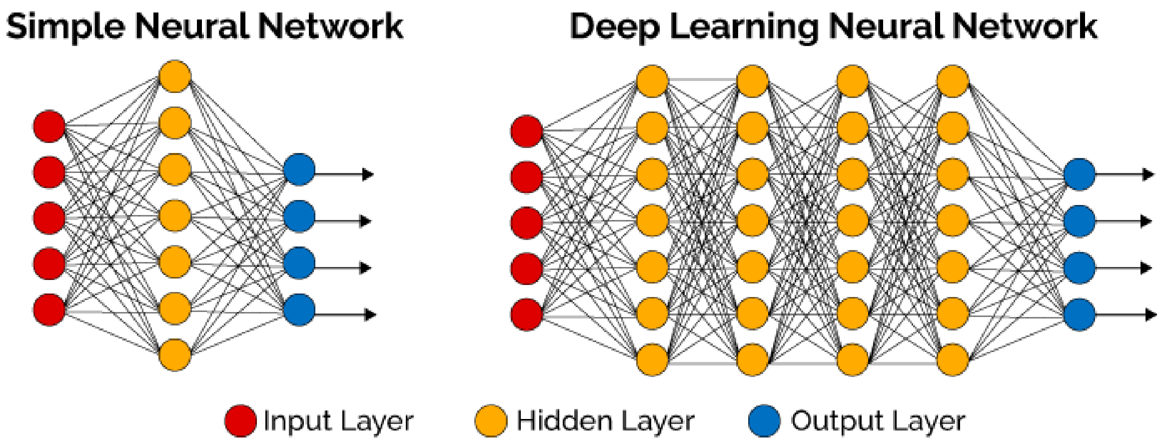
- Linear discrimination: is a common statistical tool for modeling the relationship between some explanatory variables and some real-valued outcome. It is a discriminant based approach that estimates the parameters of the linear discriminant directly from a given labeled sample. A example of this technique is Linear Regression (LR) (Alpaydin 2010, Shalev-Shwartz and Ben-David 2014).
- Support vector machine (SVM): is one of the most popular algorithms in modern machine learning. It was introduced by Vapnik in 1992. It provides a very impressive classification performance on reasonably sized data sets. It consists of a vector representation of records, with a real component for each attribute (Marsland 2015).
- Nearest neighbor algorithms: are among the simplest of all machine learning algorithms. The idea is to memorize the training set and then to predict the label of any new instance on the basis of the labels of its closest neighbors in the training set (Shalev-Shwartz and Ben-David 2014).
- Bayesian networks: based on a set of variables or parameters, it is possible to predict outcomes based on probabilities. These variables are connected to each other that the resulting value of one variable will influence the output probability of another, hence the use of networked nodes. A Bayesian Network manages to combine probability theory with graph theory and provides a handy method for dealing with complexity and uncertainty (Bell 2015).
- Artificial neural network: is a computation model inspired by the structure of neural networks in the brain. In simplified models of the brain, it consists of a large number of basic computing devices (neurons) that are connected to each other in a complex communication network, through which the brain is able to carry out highly complex computations. Artificial neural networks are formal computation constructs that are modeled after this computation paradigm (Shalev-Shwartz and Ben-David 2014). Artificial neural networks (ANN) are the most popular artificial learning tool in computer science and other research disciplines (Casalino 2018).

These techniques have great applicability in the development of predictive models. They can be used in the development of a predictive model of the weld bead geometry of GMAW process. Consequently, for a good analysis of welding arc images, other techniques with better results in the image processing area would be necessary.

2.3.1 Deep Learning

Machine learning technicians are instrumental in signal processing investigations, although in 2006 a new area has emerged in automatic learning called *deep learning* (Yu and Deng 2011). Deep learning allows computer models to be composed of multiple-layers processing to represent the learning of these data with several layers of abstraction like it is shown in Figure 2.8. These methods are essential part of the research on speech recognition in states-of-the-arts (Mesnil et al. 2013), image recognition (Zhu et al. 2014, Pachitariu et al. 2013), object detection (Pachauri et al. 2014) and other domains as the human genome (LeCun, Bengio and Hinton 2015).

Figure 2.8: Deep learning vs Neural network architecture

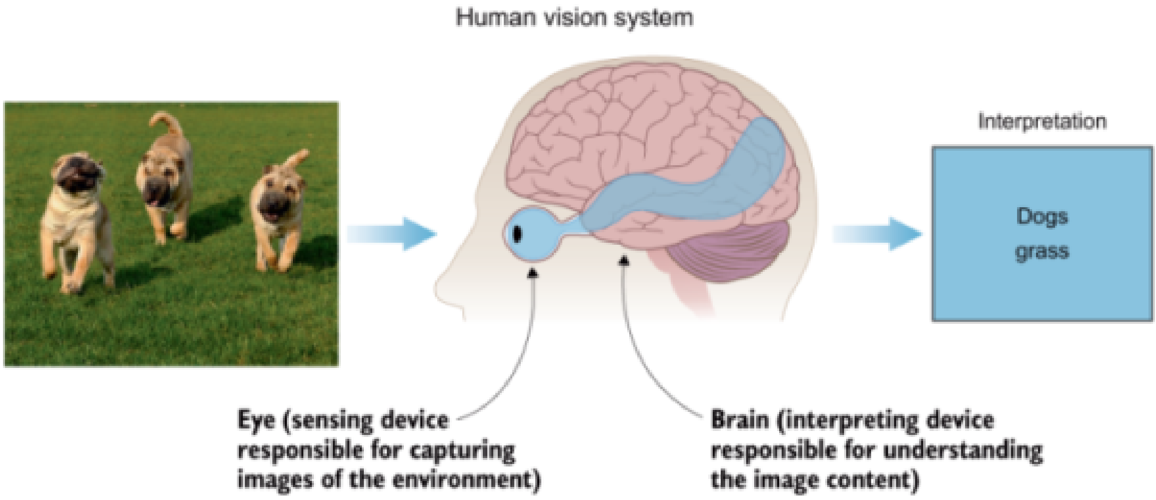


Source: (Gill 2018).

2.3.1.1 Deep Learning in vision system

In past decades, traditional image-processing techniques were considered computer vision systems, but that is not accurate. A machine processing an image is completely different from that machine understanding what's happening within the image, which is not a trivial task. At the highest level, vision systems are pretty much the same for humans, animals, insects, and most living organisms. In the same way, they consist of a sensor or an eye to capture the image and a brain to process and interpret the image (Elgendy 2020), like is shown in Figure 2.9. Scientists were inspired by the human visual system and in recent years have done amazing research on visual ability with machines. Its works were initialized by Yann LeCun's paper in 1998 (Lecun et al. 1998). This paper reviews various methods applied to handwritten character recognition and compares them on a standard handwritten digit recognition task.

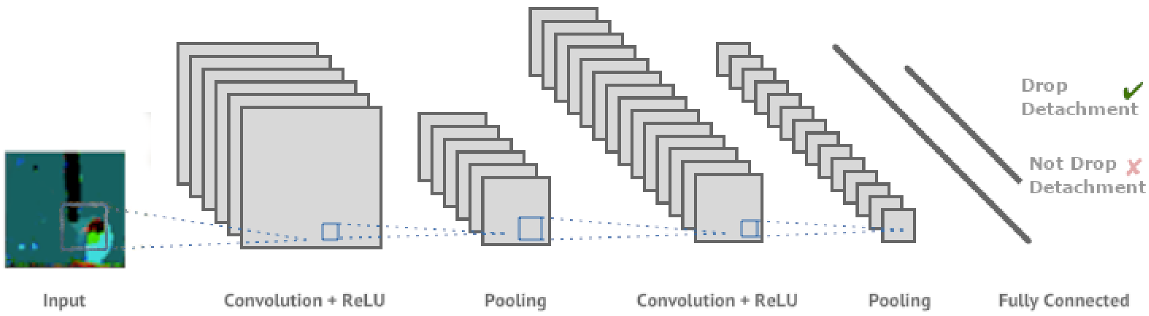
Figure 2.9: The human vision system uses the eye and brain to sense and interpret an image



Source: (Elgendy 2020).

This new architecture is shown to outperform all other techniques. Convolutional neural networks (CNN), as is called, are specifically designed to deal with the variability of 2D shapes, like show the Figure 2.10. The convolutional and pooling layers have the objective of extracting the patterns that identify a group of images concerning others. The objective of the full connected layers is to transform these patterns to the corresponding classification, like it was expressed in (Krizhevsky, Sutskever and Hinton 2017).

Figure 2.10: Architecture of Convolutional neural networks

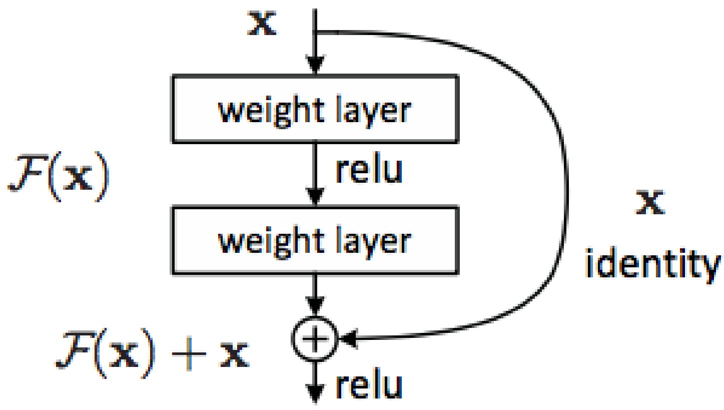


Source: Produced by author.

2.3.1.2 Residual Neural Network (ResNet)

Deeper neural networks are more difficult to train. Residual Neural Network (ResNet) is to ease the training of networks that are substantially deeper than those used previously (He et al. 2015). ResNet is based on deep residual learning. It explicitly reformulates the layers as learning residual functions concerning the layer inputs, instead of learning unreferenced functions (He et al. 2015). The idea behind the above block is, instead of hoping every few stacked layers directly fit a desired underlying mapping say $H(x)$, It explicitly lets these layers fit a residual mapping $F(x) = H(x) - x$. Thus original mapping $H(x)$ becomes $F(x) + x$, like it shows in Figure 2.11.

Figure 2.11: Building block of residual learning



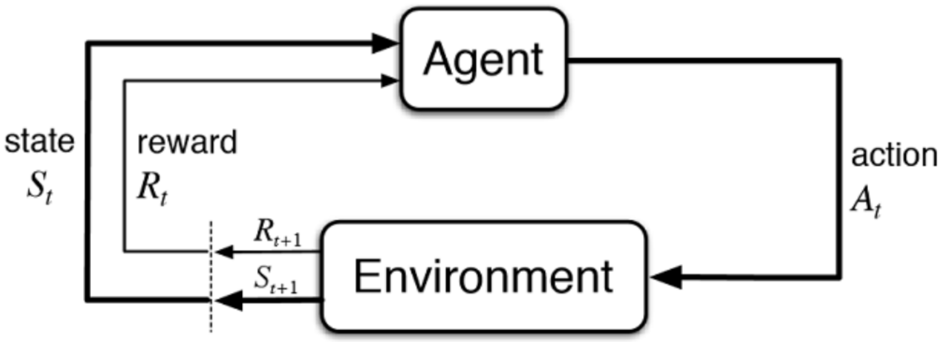
Source: (He et al. 2015).

The advantage of adding this type of skip connection is because if any layer hurt the performance of architecture then it will be skipped by regularization. So, this results in training very deep neural network without the problems caused by vanishing/exploding gradient. In fact, the ResNet models were extremely successful. It won 1st place in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) 2015 classification competition with a error rate of 3.57% (Sik-Ho Tsang 2018). These advantages could be exploited in a model to detect short circuit and droplet detachment, which can help in obtaining arc parameters, like droplet frequency, short-circuit frequency, and an estimate of the molten-wire volume of GMAW process. Furthermore, these parameters can be input parameter for the predictive model of weld bead geometry.

2.3.2 Intelligent Modeling

The definition of intelligent modeling is very associated with reinforcement learning. Intelligent Modeling is a heuristic, autonomous, non-linear, and adaptive (with learning) controller. Intelligent Modeling is born with the intention of applying a control technique in information theory, computer science, artificial intelligence, in order to obtain good results in complex systems modeling and consolidated as a discipline (Santos 2011). Likewise, an application advantage of this control strategy, the mathematical model can be obtained with the techniques mentioned in the previous sections. As an optimization-based method, the q-learning algorithm can be applied. It can be used to solve optimal control problems (Li et al. 2018). Q-learning has shown a good control performance when exposed to time-varying external disturbances (Yin, Yu and Zhou 2018). Q-learning is an effective scheme for unknown dynamical systems because it does not require any knowledge of the system dynamics to solve optimal control problems (Chun, Park and Choi 2018, Li et al. 2018). The q-learning algorithms are important pieces for reinforcement learning (RL) techniques. RL is a machine learning paradigms concerned with how software agents ought to take actions in an environment, so as to maximize some notion of cumulative reward (Sutton and Barto 2017). The decision-maker is an agent that interacts with the environment it's placed in, as shown in Figure 2.12. This process of selecting an action from a given state, transitioning to a new state, and receiving a reward happens sequentially over and over again, which creates something called a trajectory that shows the sequence of states, actions, and rewards (Deeplizard 2019).

Figure 2.12: Reinforcement Learning diagram



Source: (Sutton and Barto 2017)

- **State**: The states are the values that must be controlled. These are the processes results that occur in the environment.
- **Action**: The actions are the agent executions to reach the control objective. the actions are the control variables.
- **Reward**: The reward is the prize value to reach the control objective.

The q-learning algorithm goal is to learn a policy, which tells an agent what action to take and under which circumstances(present state). Then, this algorithm can be used to model the weld bead geometry, using like environment the model predictive of weld bead geometry.
With only a good machine learning algorithm, you do not get a good learning model. Some analytic functions are often automated, but human setup prior to implementing procedures is required. Proper selection of data to include in searches is critical. Similarly, data transformation is often required. Too many variables produce too much output, while too few can overlook key relationships in the data (Olson and Delen 2008). Therefore, to obtain a good learning model, it is necessary to use a good data analysis process. Data mining is one of them. Data mining is defined as the process of discovering patterns in data (Witten and Frank 2005). Machine learning provides algorithmic techniques for data mining process.

2.4 DATA MINING PROCESS

Data mining is an interdisciplinary field that brings together techniques from machine learning, pattern recognition, statistics, databases, and visualization to address the issue of information extraction from large dataset (Hirji 1999). Data mining is a field of the intersection of computer science and statistics, used to discover patterns, prediction, and classification in the information bank. The main aim of the data mining process is to extract useful information from the dossier of data and mold it into an understandable structure for future use (Agarwal 2013). It has proven to be extremely effective in improving research in many areas. These articles (Pan and Yang 2010, Felzenszwalb et al. 2010, Shaw, Sicree and Zimmet 2010, Tamura et al. 2011), are the most cited articles in the area, with more than 2000 time citations from Web of Science. This demonstrates that the potentialities of data mining techniques can be applied in any area since its raw materials are given. Data mining requires a problem identification, along with a collection of data that can lead to better understanding, and computer modeling to provide statistical or other means of analysis (Olson and Delen 2008). All these requirements are defined in many similar processes and methodologies like:

- Knowledge Discovery in Databases: refers to the broad process of finding knowledge in data, and emphasizes the "high-level" application of particular data mining methods. It is of interest to researchers in machine learning, pattern recognition, databases, statistics, artificial intelligence, knowledge acquisition for expert systems, and data visualization (Piateski and Frawley 1991, Fayyad et al. 1996, Norton 1999).
- SEMMA Methodology: The SEMMA process was developed by the SAS Institute. The acronym SEMMA stands for Sample, Explore, Modify, Model, Assess, and refers to the process of conducting a data mining project (Olson and Delen 2008).
- CRISP-DM Methodology: which stands for Cross-Industry Standard Process for Data Mining, is an industry-proven way to guide your data mining efforts. As a methodology, it includes descriptions of the typical phases of a project, the tasks involved with each phase, and an explanation of the relationships between these tasks (Larose 2014, Piatetsky 2014).
- Data Science Process: is an agile, iterative data science methodology to deliver predictive analytics solutions and intelligent applications efficiently (Stanton 2012, Chambers, Doig and Stokes-Rees 2017).

Essentially, these processes and methodologies define some stages as shown in (Marbán, Mariscal and Segovia 2009). These stages can resume to:

- Research understanding, it shows the research objective.
- Data acquisition. It starts with an initial data collection and proceeds with activities to get familiar with the data.

- Data preparation. It covers all the activities required to construct the final dataset from the initial raw data for the model to develop.
- Modeling. Various modeling techniques are selected and applied. Their parameters are calibrated to optimal values.
- Evaluation. It evaluates the different models obtaining to select the best from this objective.
- Deployment. The objective is to deploy and use the Discovered Knowledge.

Each of the stages contains a series of good practices that help us to obtain a better final result (Chapman et al. 2000, Chambers, Doig and Stokes-Rees 2017). Interesting patterns come out from data mining practice. That is, besides some common properties, different perspectives of data mining put strong emphases on different aspects, like efficiency, effectiveness, and validity of process (Zhou 2003). Data mining process in GMAW process analysis should help to validate efficiency or effectiveness on data acquisitions, data preparations, and modeling. The methodology proposed in this research must be closely related to the steps of the referenced methodologies and processes. This will guarantee the tools for a better evaluation of each of the defined methodological stages.

2.5 CHAPTER CONSIDERATIONS

The transversality of data analysis techniques allows its use in various areas. The use of these analyses in welding processes is still new. Although, there are applications of these techniques as this chapter demonstrates. This chapter presented how deep learning techniques, machine learning, and reinforcement learning can solve technical problems of welding processes. The stages developed by data mining processes can contribute in other areas to carry out an efficient investigation of welding processes.

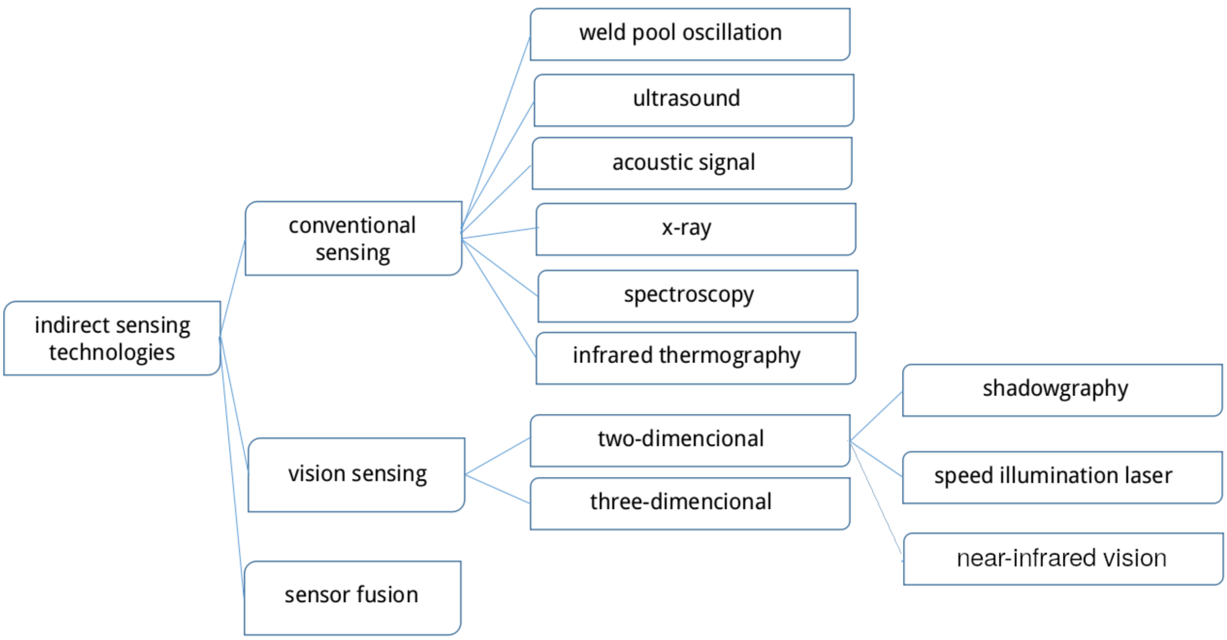
3 DATA ANALYSIS AND MODELING TECHNIQUES OF WELDING PROCESSES: THE STATES-OF-ARTS AND METHODOLOGICAL PROPOSALS

The analysis of the State-of-the-art of welding processes will be developed according to some stages mentioned in the section of Data Mining Processes (see chapter 2). This allows a better understanding of possible applications of the new techniques and the most utilized at each stage of welding investigations.

3.1 SENSORS

Several sensors have been applied in welding processes to obtain information as can be seen in Figure 3.1. The utilization of infrared vision techniques has been applied in researches on welding processes as shown in (Fidali and Jamrozik 2013, Sreedhar et al. 2012, Bagavathiappan et al. 2013, Coniglio et al. 2016). Thus, one of the problems of this technique is that the environment where it is applied can interfere with the precision of the data obtained from the process. This may be due to the own heat emission of the technologies been utilized. Another type of sensor with great potential in welding processes is the sound sensor.

Figure 3.1: Diagram of sensors



Source: (Bestard 2017)

3.1.1 Vision sensor

Vision sensor is largely utilized in welding process to analyze welding pool (Xu et al. 2012, Liu, Huang and Zhang 2015), welding arc (Fei Gao and Qinglan Chen 2015, Ogawa 2011) and weld bead geometry (Günther et al. 2014, Günther et al. 2016). The high light generates by arc becomes hard the images obtentions. In this case, some techniques are utilized. One of them is utilized by (Chen and Farson 2010). This author made effective monitoring and control of the hybrid laser/gas metal arc welding process quality with an economical sensor system. A coaxial vision system for the hybrid process monitoring was integrated from a relatively inexpensive industrial vision system and a personal computer (PC). Other visualization technique is *Shadowgraphy*, applied in (Ramos, Carvalho and Absi Alfaro 2013) and (Siewert et al. 2014). This is based on obtaining the shadow of the process through the utilization of a laser source. With high-speed illumination laser, (Ma, Li and Chen 2017) obtained great quality images. This technique is new but it needs a laser with more potential than the traditional Shadowgraphy technique.

3.2 IMAGES PROCESSING

Some papers defined their structured light image processing technology into pipeline welding automation projects. It develops a vision-based pipeline too, as shown in (Yue et al. 2009). Here, Weld image processing adopts the base theory, including the Laplacian of a Gaussian filter, the neighborhood mean filter, the largest variance threshold segmentation, and morphologic. Other works like (Xu et al. 2014) applies the main characteristics of the gray gradient. A new improved Canny edge detection algorithm was proposed to detect the weld-image edges and extract the seam and pool characteristic parameters. (Wu et al. 2014) drove to find out the optimal noise filtering algorithm. It made a comparison of three noise filters: Gaussian filter, Median filter, and Wiener filter with welding seam image captured from the CCD camera. As a result, this paper considers the Median filter to have a better enhancement effect than the other two filters. In classic image processing, it difficult to generalize a filter or algorithm because it depends on the conditions and characteristics of camera parameters and light. According (Redmon et al. 2016), deep learning techniques have efficient result in real-time executions, while (Zhu et al. 2014) and (Pachitariu et al. 2013) affirm that the classification is better. One example applied in welding process is (Günther et al. 2014, Günther et al. 2016). It utilizes the autoencoder deep learning technique to extract features of images process in laser welding. Hence, the deep autoencoder features yielded a lower classification error when utilized as input for two Support Vector Machine (SVM) classifiers. Not only focusing on welding arc analysis but with good results, (Hou et al. 2018) propose an automatic detection for weld defects in x-ray images. It is constructed based on a deep neural network and classification model which was trained and tested by the patches cropped from x-ray images. Consequently, the proposed model obtains a maximum classification accuracy rate of 91.84%. This was one more example of the potential of these techniques in welding area.

3.3 MODELING A WELDING PROCESS

Demand for quality products has led to the rapid advancement of today's manufacturing environments. Many techniques and methods are applied to correlate between process parameters and bead geometry. One of them was the Response Surface Methodology (RSM). It was applied by (Sen 2015), where he evaluated the correlations that occurred between double pulsed gas metal arc welding (DP-GMAW) process parameters and weld bead geometry. (Santhana Babu et al. 2016) have acquired good results with the same technique to predict and control the weld bead quality in GTAW process. The problem of this method is that researchers should find the equation called response surface by test and error which can be hard. Many theoretical models have been defined to determine the process that occurs in the welding arc including (Boutaghane et al. 2011). The main problem of these models was that they lose precision because it was tricky to obtain a formula that contains all the complexity of the processes as affirmed by (Dong et al. 2016).

Mathematical models based on machine learning techniques have better results in problems as complex as this one. In the same paper, (Dong et al. 2016) expresses the potential of these models. One of the well-known and utilized regression algorithms is the least-squares method. It was utilized in (Gao et al. 2011) to predict the seam position directly under strong disturbing influence from the arc light. (Li and Gao 2014) utilized a linear regression model between pool image centroid deviation and the weld based for visual weld deviation measurement in GTAW process. Another technique was Gaussian Process Regression(GP) utilized in (Dong et al. 2016) to predict the characteristic performance of an arc welding process in GTAW.

One interesting method utilized in (Feng et al. 2012), is Mahalanobis Distance Measurement. It was illustrated and employed to determine whether welding faults have occurred or not. The same method was utilized in 2017 by Khairul Muzaka in his work (Muzaka et al. 2017) on GMAW process to optimize welding current for A vertical-position welding. The worst thing with this method is that it only correlates in the function of one input. (Bai and Lubecki 2016) proposed an on-line analysis method based on Localized Minimum and Maximum (LMM) of the welding process stability, for a welding monitoring system. The problem of LMM is to show a simple function to quality measures, then not define the complexity of the system. And that is why this work is limited only to the short circuit transfer mode.

(Park and Kim 2017) proposed an SVM with bootstrap aggregating to improve the prediction accuracy on the noisy RSW data with computational efficiency. In this framework join other technique as Generalized Regressive Neural Networks (GRNN) and Genetic algorithms for optimization. This article demonstrates an increase in more complex computer science techniques for better analysis of welding processes. Even though the only way to know if all this is the best solution is by comparing with other techniques.

3.3.1 Artificial Neural network models (ANN)

Some researchers already had references to these algorithm's advantages. Like Bo Chen that utilized ANN and Dempster-Shafer evidence theory, in (Chen, Wang and Chen 2010), to predict the penetration status in GTAW process.
They have also been utilized for different purposes and in different welding processes like:

- In SAW process, to predicting weld bead geometry (Sarkar et al. 2016).
- In GMAW Cold Metal Transfer (CMT) process, to predicting weld bead geometry (Pavan Kumar et al. 2017).
- In GTAW process, it is predicted the angular distortion considering the weld bead geometry (Rong et al. 2016).
- In Girth Welded Pipes process, to predicting of residual stresses (Mathew et al. 2017).
- In Underwater Wet Welding Process, to predicting the weld seam's geometric parameters (Chen and Feng 2014).

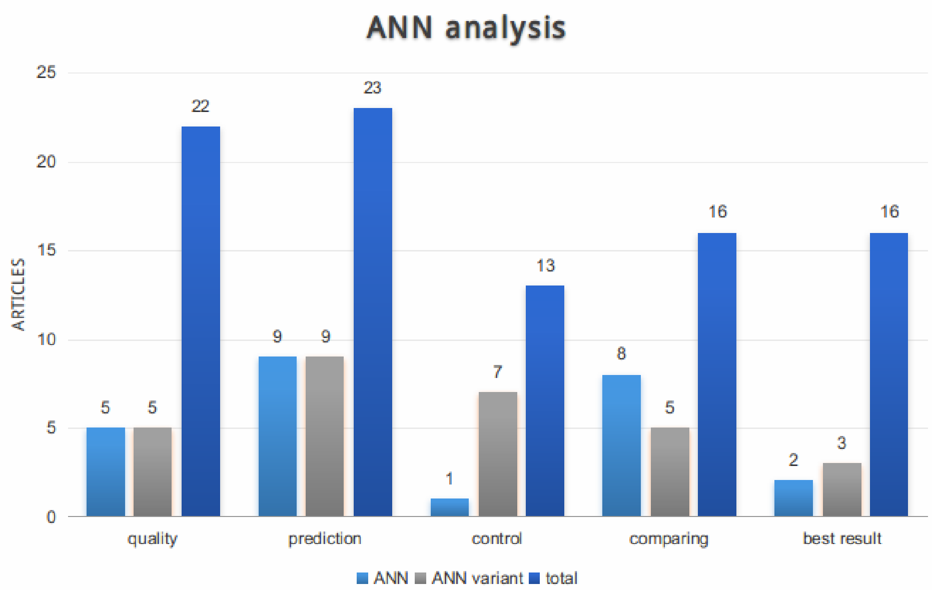
ANNs have been mixed with other techniques to obtain better results. One example of this is shown in (You, Gao and Katayama 2015), where it utilizes ANN and Support Vector Machine (SVM) for monitoring a welding defect in a laser welding process. (Chen and Chen 2010) predict the penetration in GTAW process, but used different ANNs to process information from different sensors, and finally predictive fuzzy integral method. Another example is in (Rios-Cabrera et al. 2016), where ANN Fuzzy ARTMAP was utilized to predict bead width and height in GMAW process like monitoring task.
The increase in computational resources has allowed an increase in the complexity of ANN architectures. These are called Deep Neural Networks (DNN). Bit by bit, they begin to be applied in the welding process. One of them was utilized in (Keshmiri et al. 2015). The model is based on a four-hidden-layer neural network architecture to make a study of the estimation of weld bead parameters. This article mixed data from different welding processes. This is a risk for results analysis since different processes can have different outcomes with the same input parameters. (Rao, Srinivasa Rao and Deepak 2017) utilized the Generalized Regressive Neural Networks (GRNN) technique, for estimating and optimizing the vibratory assisted welding parameters, to produce quality welded joints. But in this case, it does not have a comparison with other algorithms. (Wu et al. 2017) wrote a paper addressing "t-stochastic neighbor embedding" and deep belief network (DBN), other DNN variant, to perform variable polarity plasma arc welding (VPPAW) process monitoring and penetration status identification. Thus experimental verification and comparisons show that the classification performance of DBN can reach 97.62%, which indicates DBN outperforms ANN and support vector machine (SVM) models. This reaffirms the good results offered by the learning models developed with these algorithms. This work did not have as an objective the use of DNN algorithms to analyze images and sound in real-time, which could have been very interesting in the research.

Despite being the most used technique in welding processes analysis, Figure 3.2 presents that the best results are not always obtained. This figure was created with the articles studied in this review, and it proves that, with a comparative analysis, better models can be identified with a lower computational cost.

3.3.2 Why is it necessary to test and compare different models?

As it has been expressed in the previous sections, there are new techniques to analyze complex systems. But they require expensive computational resources for their construction and sometimes for their execution. A comparison between models will allow knowing which model has better results and which model can be the most effective to be utilized. This effectivity is measured in function of problem necessity like it is shown in data mining (DM) methodologies and processes (Piatetsky 2014, Chambers, Doig and Stokes-Rees 2017).

Figure 3.2: comparison between ANNs and ANN variations



Source: Produced by author

The best result, for weld deviation extraction and weld groove state in Rotating Arc Narrow Gap MAG welding (RANGMW), was obtained by a comparison between Support Vector Machine (SVM) and ANN model (Li et al. 2014). This showed that the SVM model's predictive ability was better than the ANN model because it adapts to the little sample problem and can avoid the local extreme. One comparison with a focus on time optimized was (Kumar et al. 2014). Here, it utilized an ANN and ANN with differential evolutionary algorithm (DEA) separately. The results obtained were closer to ANN, but the computational time of ANN using DEA was shorter than the other algorithm. In the article, (Escribano-García et al. 2014) Response Surface Methodology (RSM) was compared with regression models based on DM (linear regression (LR), isotonic regression (IR), GP, ANN, SVM and regression trees (RT)) to evaluate mechanical properties in GMAW process. The results showed that the regression models obtained with DM generally have poorer generalization capacity than the regression model obtained with RSM. Because DM techniques require a relatively large amount of data to obtain acceptable results. The article (Sumesh et al. 2015) compared decision trees (DT), ANN, fuzzy logic, SVM, and random forest techniques for weld quality monitoring in SMAW. It knows the importance of comparing data mining techniques. The most efficient technique was the random forest. This shows that not always the most complex techniques offer the best results. One of the few comparative analyses algorithms was shown in (Kumar et al. 2016). This paper explores the self-organizing maps(SOM) algorithm as a mechanism for performing unsupervised learning. It compared the performance, characteristics of various welding parameters. The SOM result was compared with the Probability Density Distributions (PDDs) obtained during statistical analysis. Finally, it is shown that, in addition to PDD, analysis of voltage and current data using the SOM technique can also be utilized to evaluate arc welding process. These studies demonstrate that there are other potential algorithms for step analysis in welding process. And it is necessary to evaluate and compare several of them to select the best upon in a real-time process.

Another comparison was done by (Wu et al. 2016). The article compared a prediction model of Plasma Arc Welding based on the Extreme Learning Machine (ELM) technique with ANN and SVN. This proposed model is faster and has better generalization performance. This potentiality is established by (Nandhitha 2016). In this case, he utilized Radial Basis Networks (RBN) and Generalized Regressive Neural Networks (GRNN) to torch current prediction in GTAW process. GRNN outperforms RBN in predicting the torch current deviation with 98.95 % accuracy. (Kim, Park and Sohmshetty 2017) discusses the Resistance Spot Welding (RSW) process. He examines the prediction performance of k-nearest neighbor (kNN) and GRNN. The results indicate that using a smaller k on properly-inconsistent data increases the prediction performance measured by mean acceptable error (MACE).

Another quality welding article was (Wan et al. 2017). A different neural network model was proposed for weld quality prediction in large scale RSW process. In the research, a simple ANN was more proper in failure load estimation. The probabilistic neural network model was more appropriate to be applied in quality level classification. One of the few articles with DM techniques mention in welding process was (Huang et al. 2017). This is an investigation of porosity in pulsed Gas tungsten arc welding (P-GTAW) of aluminum alloys based on spectral and x-ray image analyses. This made spectral analyses based on DM and empirical mode decomposition (EMD) were proposed to detect porosity. (Petković 2017) predicted a laser welding quality by training data for the computational intelligence methodologies and support vector regression(SVR). Support Vector Regression is a novel variant of Support Vector Machine usually for regression tasks. This article made a comparison between SVR, ANN, and GP. It is another example that, in specific problems, less complex algorithms can offer better results. It defines which of the techniques is most effective for solving the problem. Moreover, it helps in the effectiveness of a future process of intelligent control.

Table 3.1 presents some articles that were based on quality monitoring of welding processes. The preparation column defines the processing technique of data obtained by the sensors. The classic value represents welding processes that do not use the newest techniques of image processing and

DL for those who use them. The modeling column defines the algorithms used in the specific article. The online column defines whether the proposed model was executed in real-time. The compare column defines whether this paper made a comparison between several algorithms. When there is a comparison, the first model before the comma is of the best quality result. As all tables show (Table 3.1, Table 3.2 and Table 3.3), the best algorithm does not always be the same.

Table 3.1: Table articles with quality objective

author	year	welding process	sensors	Preparation	Modeling	Online	compare
(Saini 1998)	1998	GMAW	sound	classic	no	yes	no
(Yue et al. 2009)	2009	no speak	visual	classic	theorical model	no	no
(Chen and Farson 2010)	2010	LBW/GMAW	visual	classic	no	yes	no
(Horvat et al. 2011)	2011	GMAW	sound	classic	no	yes	no
(Gao et al. 2011)	2011	GTAW	visual	classic	LR-ANN	no	no
(Feng et al. 2012)	2012	GMAW	standard	classic	MDM	yes	no
(Kalaichelvi, Karthikeyan and Sivakumar 2013)	2013	GMAW	standard	classic	GA-Fuzzy	yes	no
(Fidali and Jamrozik 2013)	2013	GMAW	infrared	classic	statistical analysis	yes	no
(Sreedhar et al. 2012)	2013	GTAW	infrared	classic	statistical analysis	yes	no
(Kumar, Anand and Srivastava 2014)	2014	no speak	visual	classic	ANN	no	no
(Kumar et al. 2014)	2014	GMAW	visual	classic	ANN, ANN-DEA	yes	yes
(You, Gao and Katayama 2015)	2015	Laser welding	Spectrometer	classic	FFANN-SVM	yes	no
(Sumesh et al. 2015)	2015	SMAW	sound	classic	some DM (RF)	yes	yes
(Baraka, Panoutsos and Cater 2015)	2015	FSW	standard	classic	ANN-Fuzzy, ANN	yes	yes
(Kumar et al. 2016)	2016	SMAW	standard	classic	PDDs, SOM	no	yes
(Muzaka et al. 2017)	2016	GMAW	standard	classic	MDM	yes	no
(Bai and Lubecki 2016)	2016	GMAW	standard	classic	LMM	yes	no
(Park and Kim 2017)	2017	RSW	standard	classic	GRNN-SVM	yes	no
(Wan et al. 2017)	2017	LSRSW	standard	classic	ANN(BP), ANN(Prob)	yes	yes
(Huang et al. 2017)	2017	P-GTAW	visual	classic	DM, EMD	no	yes
(Petković 2017)	2017	Laser welding	multiples	classic	SVM, ANN, GP	yes	yes
(Muniategui et al. 2017)	2017	RSW	visual	DL, classic	fuzzy	yes	yes

Table 3.2: Table articles with prediction objective

author	year	welding process	sensors	Preparation	Modeling	Online	compare
(Chen, Wang and Chen 2010)	2009	GTAW	multiples	classic	ANN-DS	no	no
(Chen and Chen 2010)	2010	GTAW	multiples	classic	ANN-Fuzzy	no	no
(Seyyedian Choobi, Haghpanahi and Sedighi 2012)	2012	Butt welding	standard	classic	ANN	yes	no
(Chiumenti et al. 2013)	2013	FSW	standard	classic	math model	no	no
(Li and Gao 2014)	2014	GTAW	visual	classic	LR	no	no
(Chen and Feng 2014)	2014	UWW	visual	classic	ANN	yes	no
(Escribano-García et al. 2014)	2014	GMAW	standard	classic	RSM, some DM	yes	yes
(Li et al. 2014)	2014	RANGMW	visual	classic	SVM, ANN	yes	yes
(Sen 2015)	2015	DP-GMAW	standard	classic	Taguchi-RSM	no	no
(Keshmiri et al. 2015)	2015	GMAW, GTAW	standard	classic	DNN	yes	no
(Nandhitha 2016)	2016	GTAW	thermografy	classic	ELM, RBN, GRNN	yes	yes
(Wu et al. 2016)	2016	VPPAW	sound	classic	ELM, ANN, SVM	yes	yes
(Lv et al. 2016)	2016	GTAW	sound	classic	BP-Adaboost	yes	yes
(Dong et al. 2016)	2016	GTAW	standard	classic	GPR	yes	no
(Kim, Park and Sohmshetty 2017)	2016	RSW	standard	classic	kNN, GRNN	yes	yes
(Sarkar et al. 2016)	2016	SAW	standard	classic	MRA, ANN	yes	yes
(Rong et al. 2016)	2016	GTAW	standard	classic	ANN	yes	no
(Rios-Cabrera et al. 2016)	2016	GMAW	visual	classic	ANN-Fuzzy-ARTMAP	yes	no
(Aviles-Viñas, Rios-Cabrera and Lopez-Juarez 2016)	2016	GMAW	visual	classic	ANN-Fuzzy	yes	no
(Pavan Kumar et al. 2017)	2017	GMAW CMT	standard	classic	ANN	yes	no
(Mathew et al. 2017)	2017	Butt welding	standard	classic	ANN	yes	no
(Wu et al. 2017)	2017	VPPAW	visual, sound	classic	t-SNE and DBN	no	no
(Wan et al. 2017)	2017	RSW	standard	classic	ANN, LR	no	yes

Table 3.1 and Table 3.2 also show a scarcity of comparative analysis, and little application of these machine learning techniques, especially in the GMAW process. Most of these papers do not take advantage of deep learning techniques in image processing. This highlights the innovative potential of applying these techniques in welding processes.

3.4 INTELLIGENT CONTROL

The intelligent control approach offers interesting perspectives since it can provide methodologies that allow performing some of the tasks typically performed by humans automatically (Santos 2011). This combines with data mining models.
One intelligent control tendency is to utilize fuzzy methods with an ANN model. An example of this is shown in (Chen, Wang and Ma 2010). It predicted dynamical characteristics of the weld pool during robotic welding in GTAW process. In (Hailin et al. 2012), GMAW pipe-line welding is shown to improve the welding quality. (Cruz, Torres and Alfaro 2015) is another example of modeling and control in GMAW process. Other fuzzy methods examples but a different technique was shown in (Sharma, Maheshwari and Rathee 2016). This article proposes a response to a fuzzy logic approach with surface methodology (RSM), demonstrating that, any model obtained from a welding process can be integrated into a control system as long as it meets time demands.
An emerging control system was used by (Günther et al. 2016) for Laser welding Control. This technique is called reinforcement learning (RL) and it is a branch of machine learning and artificial intelligence. It is focused on goal-directed learning and decision making (Sutton and Barto 2017). Integral to RL approach are methods for learning expectations of future observations from samples of experience (prediction learning), and using samples of experience to affect policy change (control learning) (Günther et al. 2016). Control learning can be an optimization-based method like a q-learning algorithm. Also, it can be used to solve optimal control problems (Li et al. 2018). (Günther et al. 2016) used reinforcement learning to acquire generalized predictions for use as inputs to a laser welding system. This makes this work an important contribution to welding process engineering. Likewise, RL is a new technique open now in welding process with noble success in other areas like it shows (Chincoli and Liotta 2018, Ramanathan, Mangla and Satpathy 2018, Yin, Yu and Zhou 2018).
Table 3.3 presents a summary of some welding area articles that apply intelligent control techniques. In addition to showing the same pattern as the previous Table 3.1 and Table 3.2, it exhibits a high application of fuzzy algorithms for process control. For this reason, the application of reinforcement learning in a GMAW process can be considered innovative in this research.

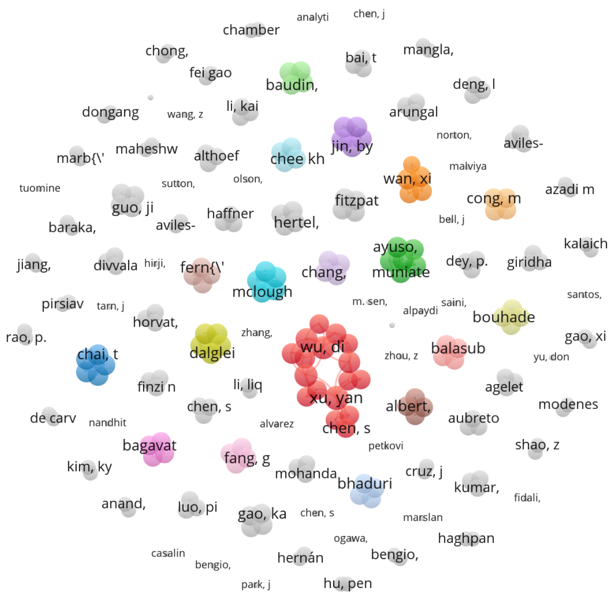
Table 3.3: Table articles with control objective

author	year	welding process	sensors	Preparation	Modeling	Online	compare
(Chen et al. 2000)	2000	P-GTAW	doble-visual	classic	ANN-learning Control	yes	yes
(Chen, Wang and Ma 2010)	2009	GTAW	visual	classic	ANN-Fuzzy	yes	no
(Malviya and Pratihar 2011)	2011	GMAW	standard	classic	ANN-PSO	yes	no
(Hailin et al. 2012)	2012	GMAW	visual	classic	ANN-Fuzzy	yes	no
(Wang 2014)	2014	GMAW	visual	classic	ANN-Fuzzy	yes	no
(Cruz, Torres and Alfaro 2015)	2015	GMAW	visual	classic	ANN-Fuzzy	yes	no
(Santhana Babu et al. 2016)	2016	GTAW	standard	classic	RSM	yes	no
(Günther et al. 2016)	2016	Laser welding	visual	DL	DL-RL	yes	no
(Santhana Babu et al. 2016)	2016	GTAW	standard	classic	RSM	yes	no
(Sharma, Maheshwari and Rathee 2016)	2016	SAW	standard	classic	RSM-Fuzzy	yes	no
(Azadi Moghaddam, Golmezergi and Kolahan 2016)	2016	GMAW	visual	classic	ANN-PSO	yes	no
(Lv et al. 2017)	2017	GTAW	sound	classic	ANN	yes	no
(Rao, Srinivasa Rao and Deepak 2017)	2017	Vibratory Welding	standard	classic	GRNN	yes	no
(Hu, Huang and Zeng 2017)	2017	GMAW	standard	classic	math-model-Fuzzy	yes	no

3.5 FUTURE PERSPECTIVE

These data analysis techniques based on learning, as appear in this article, are not yet widespread in welding process area. A bibliometric analysis among the authors studied in this research presents a very little relationship between them. Figure 3.3 exposes this affirmation.

Figure 3.3: Bibliometric analysis: Authors interrelationship



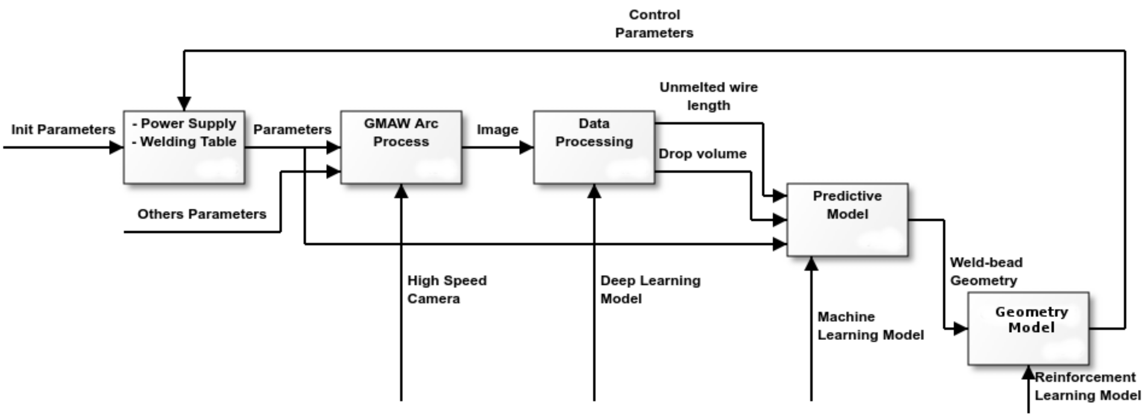
Source: Produced by author

In this study, all the articles referenced in this research were analyzed. Through the interrelationship between authors is validated with their participation in the same publication. Consequently, in the articles analyzed, this interrelation did not go beyond level 2 (the authors only participated jointly in 2 publications). In addition, this level 2 tends to be among the same researchers. All these affirm, the small dimensions of the authors' clouds (articles with welding process and new data analysis techniques) and their small relationships (Author interaction by publication), show little maturity in the interrelation of these areas. The cases that show a greater cloud of relationship, is due to the participation of many authors in the same publication.
Some of the works demonstrate a small approximation between areas, fulfilling the interdisciplinarity that industry 4.0 advocates. Achieving this interdisciplinarity implies new study processes. For this reason, it defines new methodologies that unify the potential of these two areas. The needs of the modern world are going to make this happen in a short time. The new data analysis conception in welding processes area will be an acceleration in obtaining new and better models more efficient predictions and controls.

3.6 METHODOLOGIC DIAGRAMS

After the previous analysis on algorithms and techniques used for information acquisition, prediction, and control in welding process. It can be observed that there are computer science techniques little experienced in welding processes, and even more in GMAW process. This research proposes the development of two methodologic diagrams with these techniques. Diagram 1 (Drop-Volume Methodology), Figure 3.4, will be analyzed with some GMAW arc parameters like unmelted wire length, drop volume, and melted wire volume. Diagram 2 (Drop-Frequency Methodology), Figure 3.5, will be analyzed with by GMAW arc parameters of drop frequency and short circuit frequency.

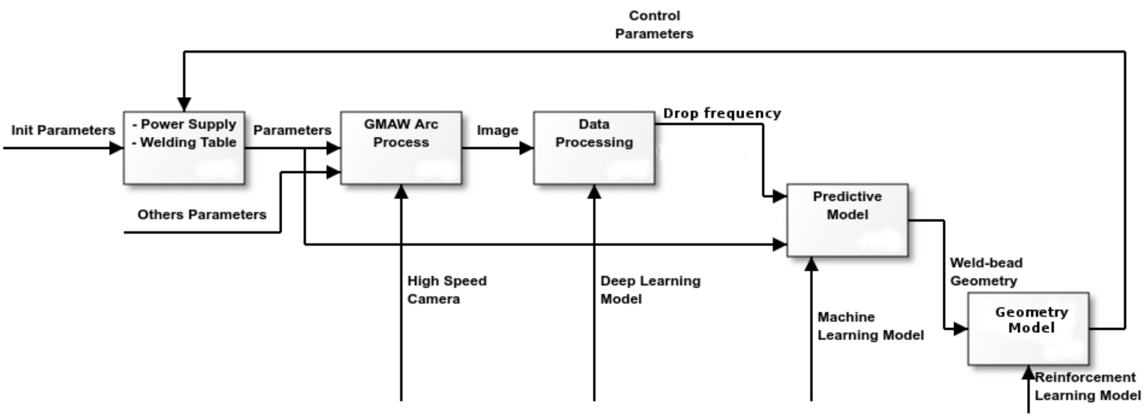
Figure 3.4: Drop Volume Methodologic Diagram



Source: Produced by author

Drop Volume Methodologic will be analyzed with some GMAW arc parameters like unmelted wire length, drop volume, and melted wire volume. This process has more parameters, which can allow you more precision in the results, like show in (Thompson Martínez et al. 2021).

Figure 3.5: Drop Frequency Methodologic Diagram



Source: Produced by author

The drop frequency methodology accumulates the data processing values for a time interval and then applies the predictive model. It will allow better computational performance than the drop volume methodology. Thereby, both methodologic diagram will be developed in next chapters. All stages will be compared and evaluated to define better process. Both have the same experiments and process, they only differ in the parameters obtained in the image processing. The diagrams were developed with Integration Definition for Function Modeling (IDEF0) (United States Air Force commissioned). Each box represents the processes that were developed. Horizontal arrows mean inputs or outputs parameters. While, vertical bottom arrows mean the mechanism needed to executed the function. Vertical top arrows mean the control system.

- The first step is focused on the parameters acquisition of experimental from the GMAW process with the help of power supply and welding table. This require the develop of experimental plan.
- The second step aims to capture images of what is happening in the GMAW welding arc, based on the parameters provided by initial step. The mechanism used to develop this objective was a high speed camera.
- The third step aims to develop a deep learning model to detect the droplet detachment and the occurrence of short circuit. This model will allow the calculation of unmelted wire length and melted wire volume for drop volume methodology, short circuit and droplet frequency for the drop frequency methodology.
- The fourth step aims to develop a predictive model, using machine learning techniques, based on the parameters generated in the previous step and the input parameters of the GMAW process. Predictive model will output parameters of the weld bead geometry.
- The fifth step aims to develop intelligent control, using a reinforcement learning model. This model would have the ability to generate which are the most acceptable control parameters to meet a requirement of weld bead geometry in GMAW process.

The developed diagrams can also be analyzed as the process flow of the system prototype, once the models are satisfactorily validated. For these validations, the strategies and propositions of the data mining process will be taken into account. As a consequence, the results will allow an analysis and comparison of the two proposed methodologies.

3.7 CHAPTER CONSIDERATIONS

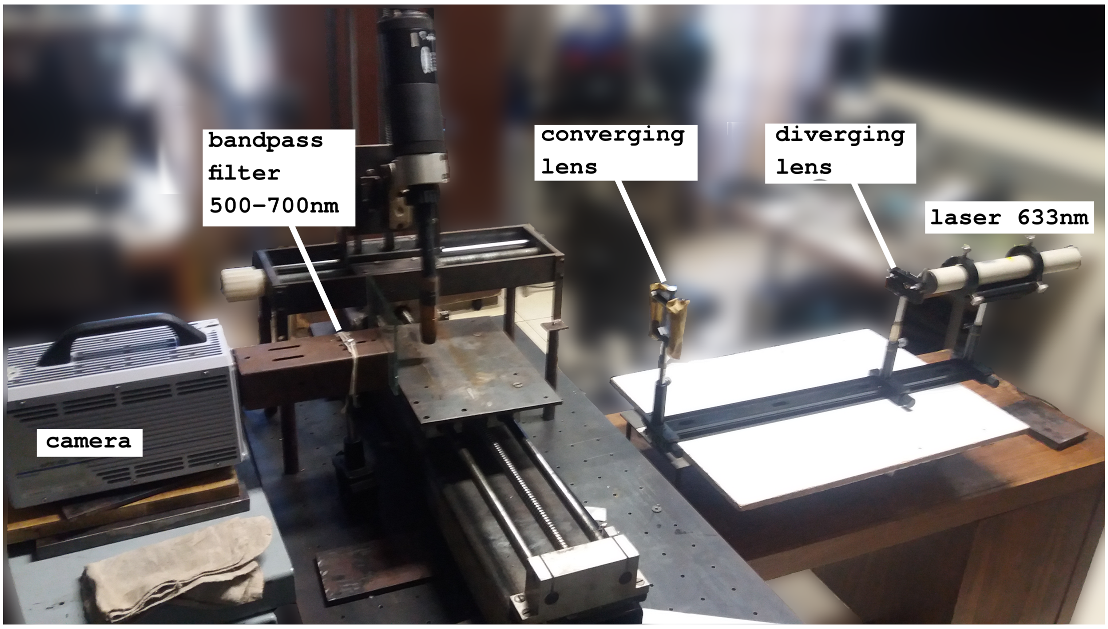
In this chapter, we carried out an analysis of several articles about the welding process. It allowed determining for each data mining stage how it is possible to optimize the results to obtain a good result of process analysis. Several analysis algorithms of the welding process were shown, and it was demonstrated that the comparison between them can make the process analysis more efficient and less expensive. The potential of learning-based techniques is described because computational resources are becoming cheaper and welding information can be obtained more and more quality information. All these premises aligned with the so-called industry 4.0 where a set of technologies that allow a fusion of the physical and digital world, to create more intelligent systems.

4 EQUIPMENT, MATERIALS AND DATA ACQUISITION OF THE EXPERIMENTS

This chapter explains the equipment and materials used during the research development. The strategy developed for data-acquisition through the experiments is also shown. The location of these pieces of equipment is in the Automation and Control Group laboratory (GRACO) of the University of Brasilia (UnB). They are:

- **Welding supply:** is a fully digitized microprocessor controlled inverter power sources. The modular design and potential for system add-ons ensure a high degree of flexibility. The device can be adapted to any specific situation (Fronius 2012).
- **Welding Supplied Interface:** A communication system was used between the welding supply and the computer, which was developed by (Moncayo Torres 2013, Giron Cruz 2014) in GRACO. It was developed to control the welding supply parameters (voltage and wire-rate).
- **Welding Table:** The welding table used was developed by the research work (Díaz Franco 2008) in GRACO, it is a linear table with one-dimensional movement. it has a control system translation speed (welding speed) as shown in Figure 4.1.
- **High-speed camera:** the camera provides full mega pixel resolution, images at frame rates up to 3,000 frames per second (fps), 512 x 512 pixels. This camera has e Gigabit Ethernet and Optical interfaces available, as it is shown in figure 4.1. In these experiments, a frame rate of 1000 fps and resolution of 1024 px were used.

Figure 4.1: Welding table, camera and laser



Source: Produced by author

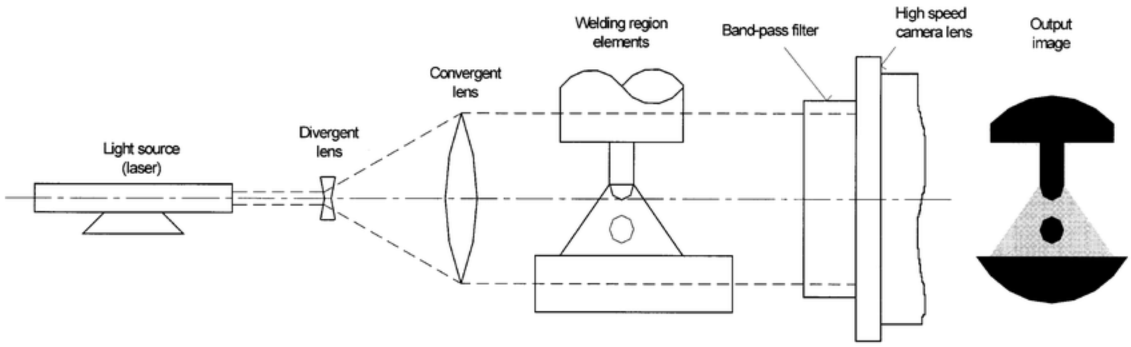
4.0.1 Materials

The materials used in this study are electrode wire copper with 1,2 mm of diameter.The base material is a 1020 steel in flat sheet format, dimensions 6,35 mm thick, and 300 mm x 40 mm long and width respectively. Shielding gas used 96% argon and 4% carbon dioxide.

4.0.2 Visualization technique

The technique used to visualize the welding arc is Shadowgraphy, it was also used in (Mota et al. 2013, Ramos, Carvalho and Absi Alfaro 2013, Siewert et al. 2014). The term Shadowgraphy has been used to refer to a projected shadow of several elements in the welding region (torch, electrode, droplets, weld bead and plate) over a flat surface, technique also known as Back-lighting (Figure 4.2). As the arc light is too intensive and it irradiates to all directions, its use is not possible to obtain the shadow (Balsamo et al. 2000). This is achieved with laser of 633 nm, diverging lens, converging lens and bandpass filter of 500 nm - 700 nm as it is shown in figure 4.1. To obtain the images, it was necessary to align the laser with a high-speed camera.

Figure 4.2: The principle of Shadowgraphy Back-lighting applied to welding



Source: (Balsamo et al. 2000)

4.1 PLANNING OF EXPERIMENTS

The application used to configure the parameters of the welding supply and welding table. It was developed by the investigations (Moncayo Torres 2013, Giron Cruz 2014) and modifications of the doctoral student Jairo Muñoz Chavez. For this investigation, 3 data-acquisition experiments are developed.

4.1.1 Experiments 1 and 2

Data experiments 1 and 2 were obtained with factorial design of Central Composite Design (NIST), this is because it generates a reasonable data distribution with long possible distribution in the data set. The objective here is to obtain the greatest possible variety of data for the predictive model creation. In Table 4.1 and Table 4.2, it is shown, the experimental input parameters by time.

Table 4.1: Experiment 1: input parameters by time

time(s)	wire rate(m/min)	voltage(v)	welding speed(mm/s)
0	5.5	20	8
3	5.5	20	8
5	7.5	20	8
7	5.5	29	8
9	7.5	29	8
11	5.5	20	12
13	7.5	20	12
15	5.5	29	12
17	7.5	29	12

4.1.1.1 Results of experiments 1 and 2

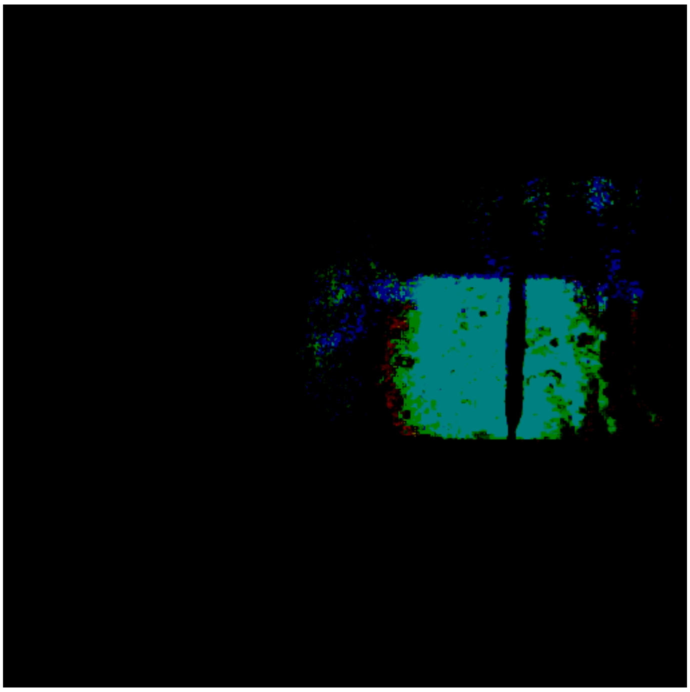
As a result of the aforementioned experiments, the following were obtained: 24 578 and 24 577 welding arc images of the experiment 1 and experiment 2 respectively. Figure 4.5

Table 4.2: Experiment 2: input parameters by time

time(s)	wire rate(m/min)	voltage(v)	welding speed(mm/s)
0	4.8	24.5	10
3	4.8	24.5	10
5	8.2	24.5	10
7	6.5	17	10
9	6.5	32	10
11	6.5	24.5	6.6
13	6.5	24.5	13.4
15	6.5	24.5	10
17	6.5	24.5	10

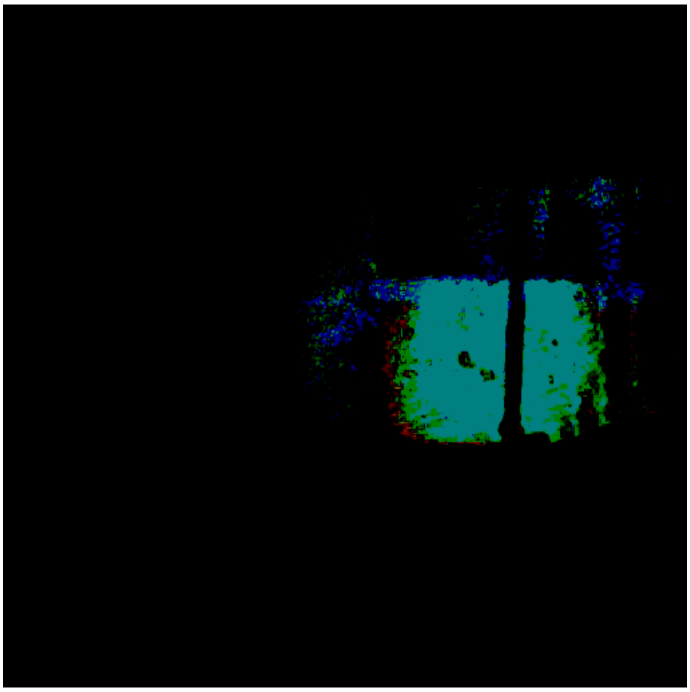
and Figure 4.6 are two examples of welding arc images obtain by high-speed camera and shadowgraphy technique.

Figure 4.3: Experiment 1: Example of Welding arc images No. 9608



Source: Produced by author

Figure 4.4: Experiment 2: Example of Welding arc image No. 16458

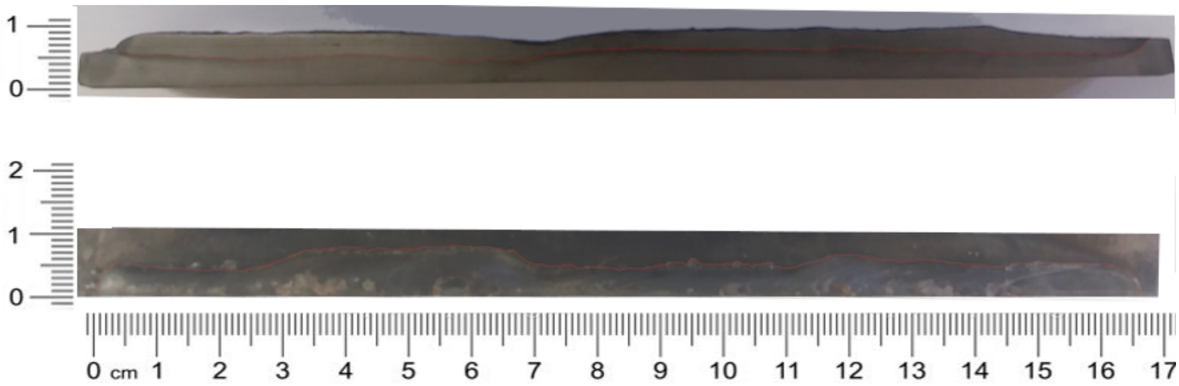


Source: Produced by author

4.1.1.2 Parameters of weld bead geometry

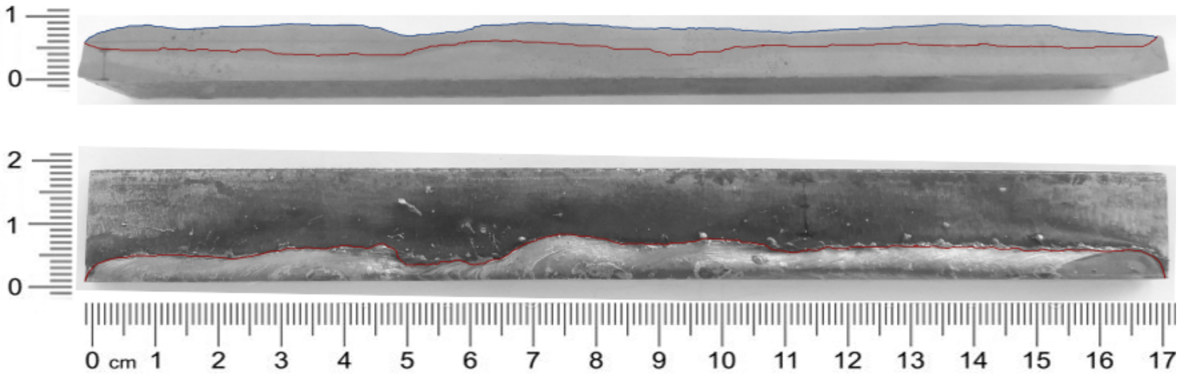
The weld bead geometries ((width, depth, and height)) were obtained from the macrographic analysis. The macrographic analysis was made in a longitudinal direction, this is in the direction of the torch movement. In these cases, it is taken the maximum value in each measurement point, as expressed in (Bestard 2017, Alvarez Bestard and Absi Alfaro 2018, Bestard et al. 2018). To obtain weld bead geometry data was necessary polished and etched using 2.5% nital solution to display the weld bead penetration. Figure 4.5 and Figure 4.6 show an example of the resulting pieces. Thus, the dimensions were obtained using an image processing algorithm. This calculates the geometric parameters from the horizontal line to find the parameters color by the vertical line. The values were transformed to the corresponding scale.

Figure 4.5: Experiment 1: Weld bead geometry



Source: Produced by author

Figure 4.6: Experiment 2: Weld bead geometry

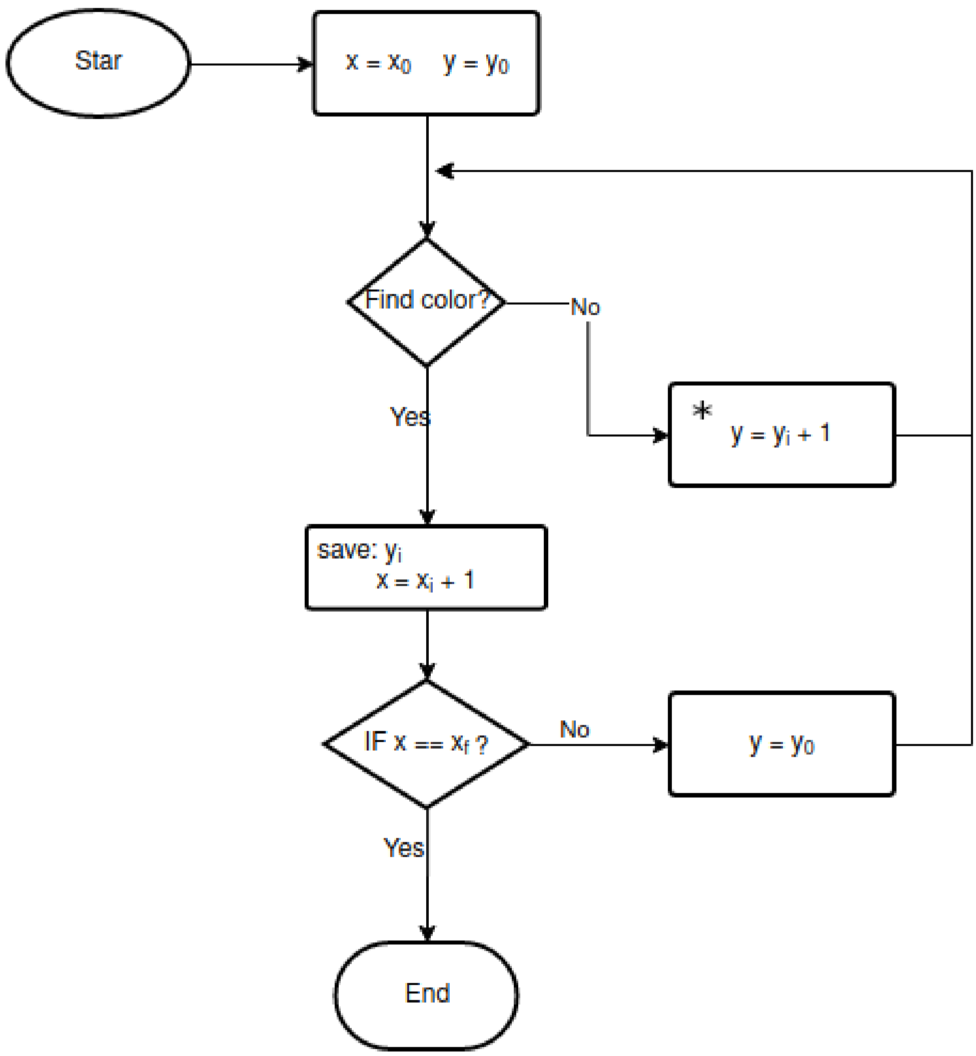


Source: Produced by author

4.1.1.3 Output parameters

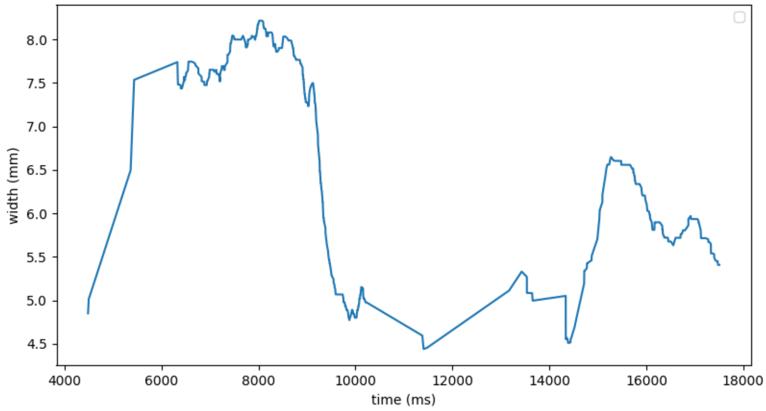
The dimensions of the weld bead geometry were obtained using an image processing algorithm. They were painted on the image, the dimensions corresponding to weld bead geometry like shown in Figure 4.5 and Figure 4.6. The algorithm is shown in annex A and diagram flow in Figure 4.7. It was applied to convert the values in respective millimeters dimensions. Similarly, for this algorithm is necessary to know the pixel relationships with millimeters dimensions, the coordinates of the beginning and the end of the process, and the colors with which they were drawn. Figure 4.8, Figure 4.9, and Figure 4.10 are the weld bead geometries dimension of experiment 1. In addition, Figure 4.11, Figure 4.12, and Figure 4.13 are the weld bead geometries dimension of experiment 2.

Figure 4.7: Sequence diagram of weld bead geometry calc



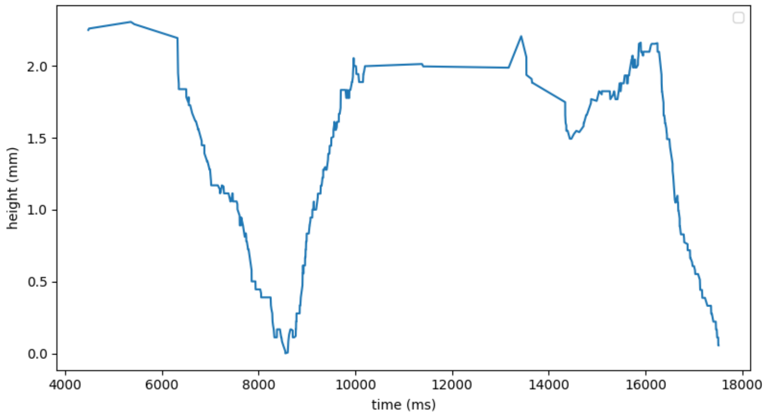
(*) The equation for depth changes to $y = y_i - 1$
Source: Produced by author

Figure 4.8: Experiment 1: Width geometry vs time



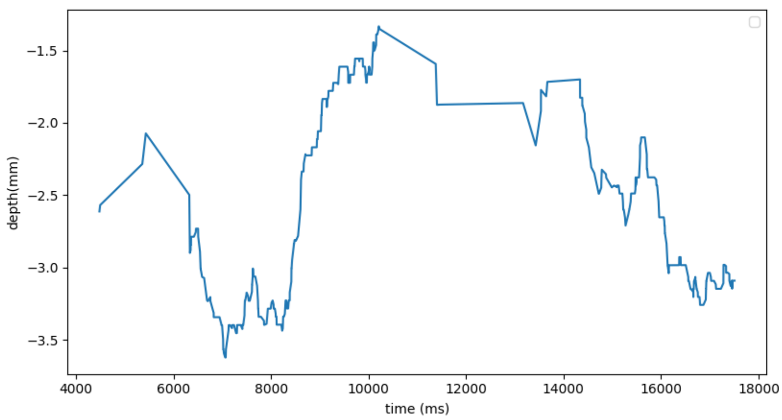
Source: Produced by author

Figure 4.9: Experiment 1: Height geometry vs time



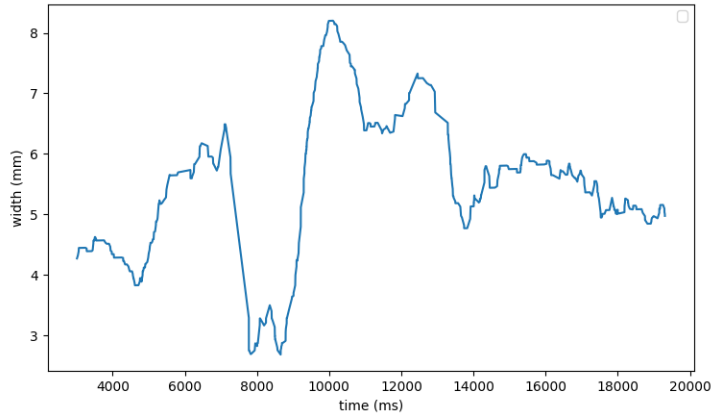
Source: Produced by author

Figure 4.10: Experiment 1: Depth geometry vs time



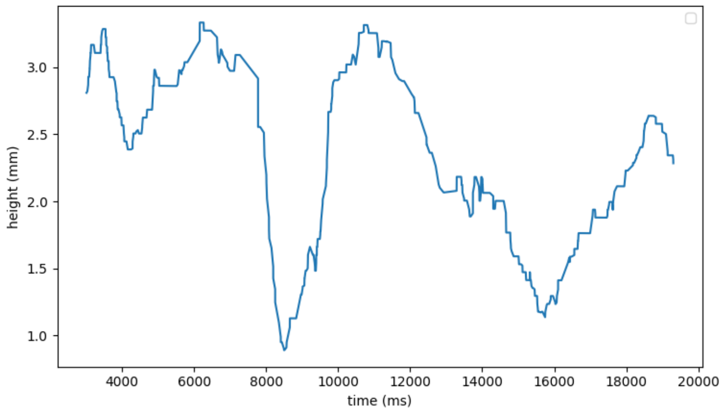
Source: Produced by author

Figure 4.11: Experiment 2: Width geometry vs time



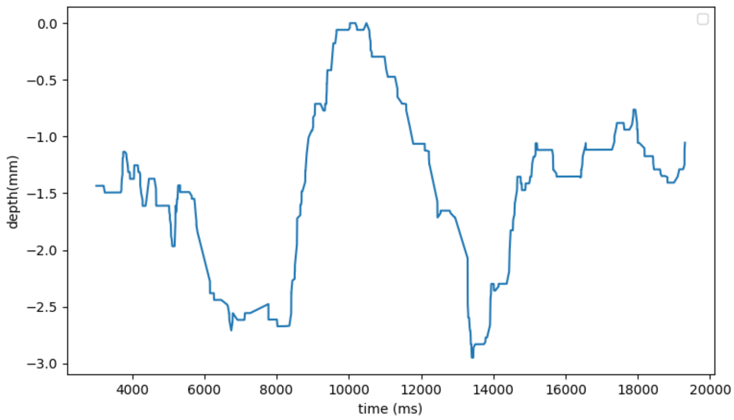
Source: Produced by author

Figure 4.12: Experiment 2: Height geometry vs time



Source: Produced by author

Figure 4.13: Experiment 2: Depth geometry vs time



Source: Produced by author

4.1.2 Experiments 3

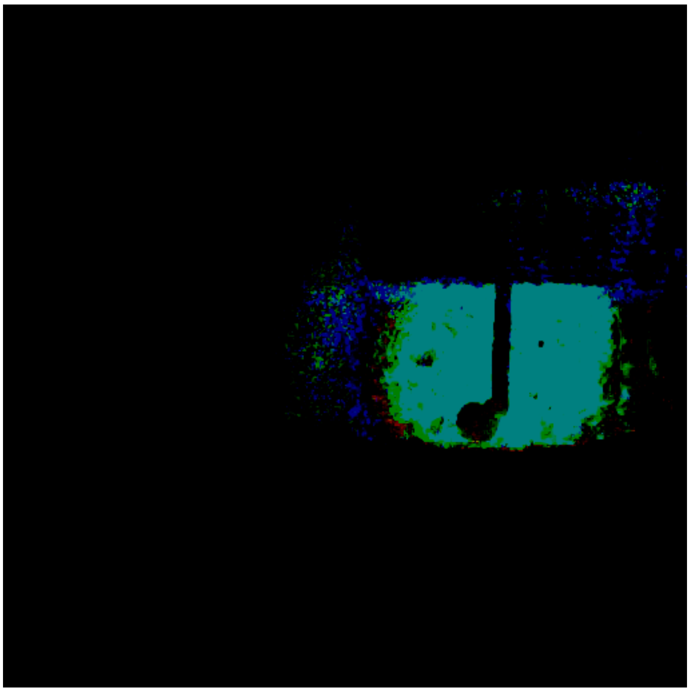
In the experiment, wire-rate speed and welding speed were constants. Voltage value is increased 1,5 v every 2 s as shown in weld bead Table 4.3. The objective of this experiment was to gather images of the three main transfer modes and to test the deep learning model proposal.

Table 4.3: Experiment 3: input parameters by time

time(s)	wire rate(m/min)	voltage(v)	welding speed(mm/s)
0	6.8	19	9
2.5	6.8	19	9
4.5	6.8	20.5	9
6.5	6.8	22	9
8.5	6.8	23.5	9
10.5	6.8	25	9
12.5	6.8	26.5	9
14.5	6.8	28	9
16.5	6.8	29.5	9

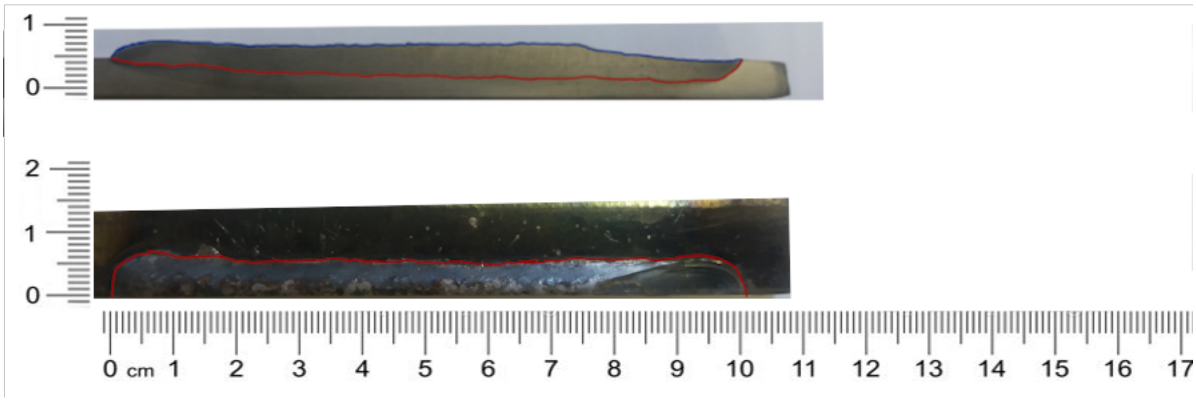
4.1.2.1 Results of experiments 3

Figure 4.14: Experiment 3: Example of Welding arc image No. 20117



Source: Produced by author

Figure 4.15: Experiment 3: Weld bead geometry



Source: Produced by author

4.2 CHAPTER CONSIDERATIONS

The planned experiments allowed compiling the necessary data in the analyses developed in the following chapters. Therefore, images of the arc from the three experiments, as well as the input, and output parameters, were collected. The final dataset preparation was carried out using time as a reference and considering the response time of the equipment used and the process.

5 RESULTS OF THE TWO METHODOLOGIES PROPOSALS FOR WELD BEAD GEOMETRY MODELING IN GMAW PROCESS

In this chapter, the two methodological diagrams proposed in Chapter 3 will be developed. The objective of this chapter is to validate the results of the two methodological diagrams and to carry out a comparative analysis between them. The data collected were those gathered through the experimental designs shown in the previous chapter (Chapter 4). Thus, these data are conformed by input parameters (wire-rate speed, voltage, welding speed, and process time) of the process and by arc images obtained. The Welding arc image token contains information like unmelted wire length and drops detachment. Others parameters can be taken into the analysis of welding arc image are short circuit frequency and drop frequency. These data were correlated with the parameters of the weld bead geometry for the development of the models.

5.1 DATA PREPARATION

The data preparation phase covers all the activities required to construct the final dataset from the initial raw data. Data Preparation tasks are likely to be performed repeatedly and not in any prescribed order (Chapman et al. 2000, Marbán, Mariscal and Segovia 2009).

5.1.1 Short circuit and drop detection

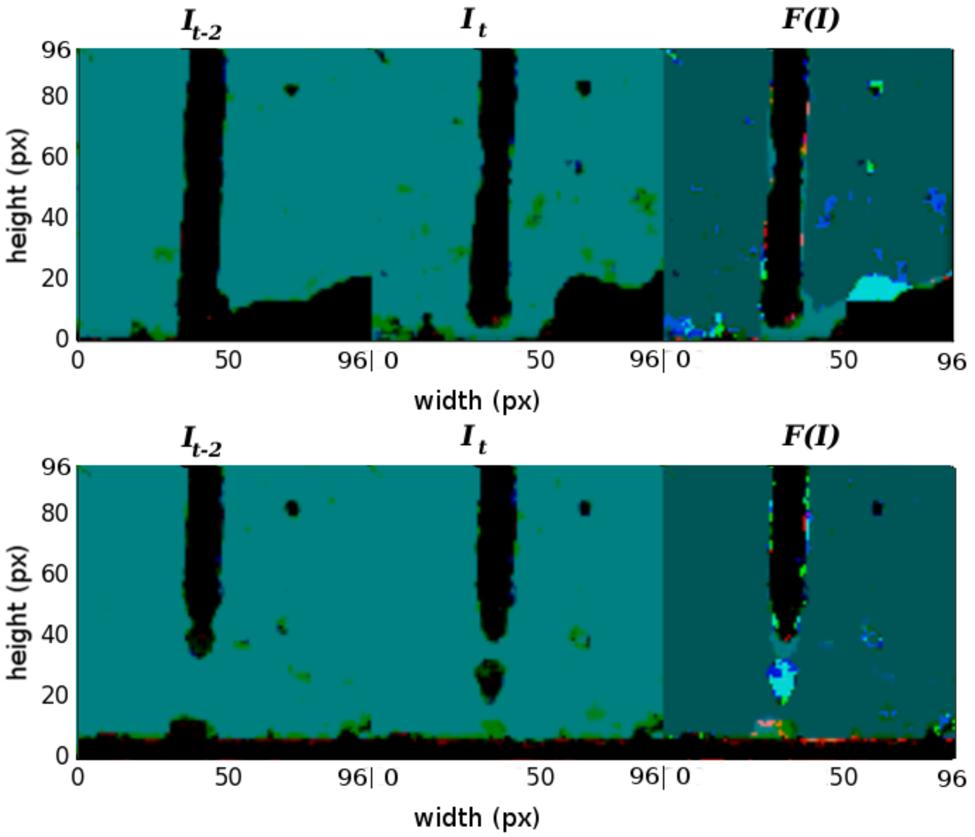
For application molten or drop volume equation shown by (Choi et al. 2001). It is necessary to detect drop detachment or short circuit in a GMAW process by image sequence. In this process, the background subtraction techniques help.
Background subtraction is a widely used approach for detecting moving objects in videos from a static camera (Bouwmans et al. 2014). Frame differencing is the simple way to detect movement like is showed by (Bouwmans et al. 2014, Bouwmans, Aybat and ZAHZAH 2016).
The frame differencing equation used in this work is:

$$F(t) = I_{t-2} - \frac{I_t}{3} \tag{5.1}$$

Where I_t is the image on same time t.

The division by 3 aims to keep visible image elements because the spatial patterns conformed by the common elements and the movement produced allows a better classification analysis and error reduction. The final pattern is showed in figures 5.1 and 5.2.

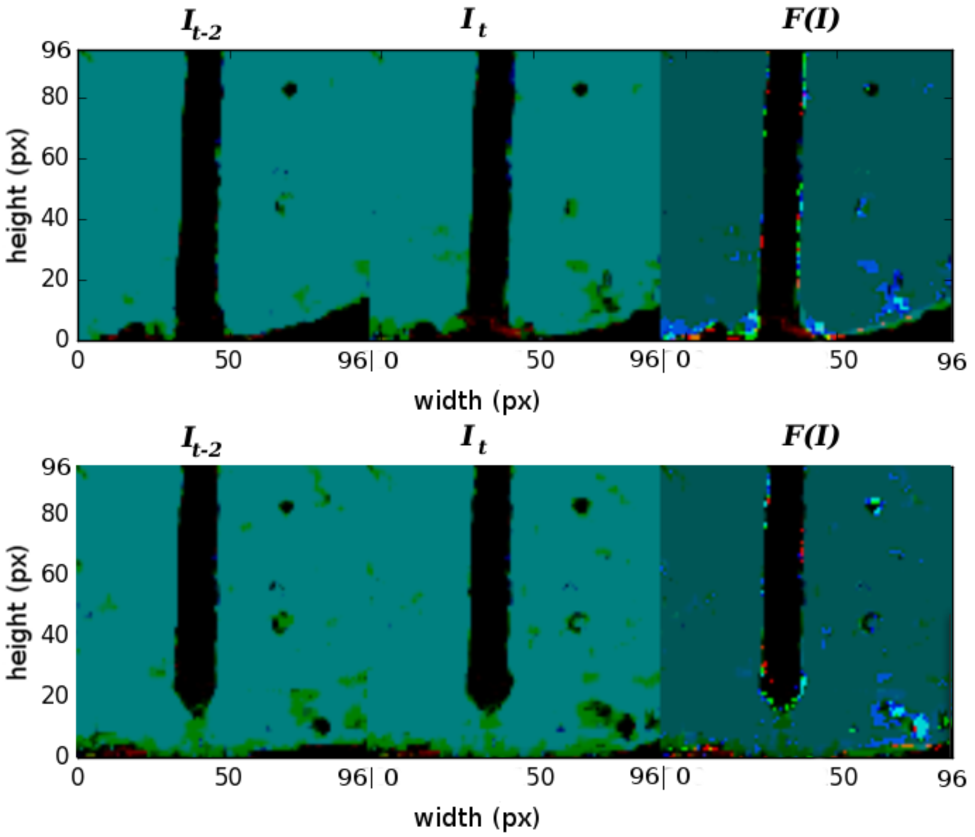
Figure 5.1: Images example: short circuit(top) and drop detachment(bottom)



Source: Produced by author

As shown in Figures 5.1 and 5.2, $F(I)$ is the result of applying the equation 5.1. As a result of this, different patterns can be observed in short circuit and drop detachment, figure 5.1 compares $F(I)$ result with figure 5.2. This pattern differences can be detected with deep learning technique of Convolutional Neural Network.

Figure 5.2: Images example: both no short circuit and no drop detachment



Source: Produced by author

5.1.1.1 Convolutional neural network model

The best result in image classification is a convolutional neural network (CNN). CNN is a deep learning technique designed to work with two dimension patterns. It was the first successful hierarchical learning algorithm. It is a topology trainer that balances the spatial relationship to reduce the number of parameters that must be learned. Thus, virtually all feed-forward back propagation formation better (Arel, Rose and Karnowski 2010). The CNN architecture selection is ResNet (He et al. 2015, Szegedy et al. 2016).The code used is shown in annex B.

The architecture was defined with 18 hidden layers and adam optimization. Adam is an adaptive learning rate optimization algorithm that is been designed specifically for training deep neural networks (Kingma and Ba 2015). Deep learning models are model by learning. For this reason, they need groups of train images, test images, and validation images. In this process, it is necessary, a manual division of images into classes. These classes are the categories for the model. In this research the classes are:

- Short circuit and drop-detachment images (SCDD), $F(t)$ of figure 5.1.
- No short circuit and no drop-detachment images (no SCDD), $F(t)$ of figure 5.2.

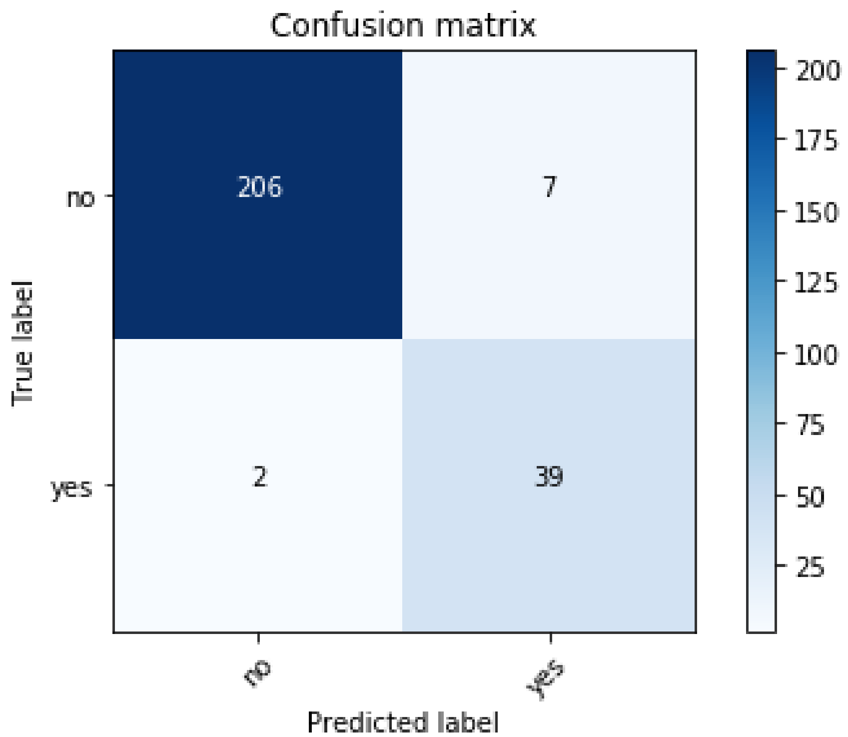
This Table 5.1 show images distribution.

Table 5.1: Images distribution by class and process

	SCDD	no SCDD
Train	618	2783
Test	100	408
Validation	42	212

The model obtained shows 97,24% of correct test images group classification and loss value of 0,10.Figure 5.3 show the ResNet-model confusion matrix analyzed with validation values. It is a performance measurement for a machine learning classification problem where output can be in two or more classes. In this case, it means that 206 no SCDD and 39 SCDD were detected correctly. Only 7 no SCDD and 2 SCDD were incorrectly classified, which shows an excellent proportion in the classification process and excellent detection of the short circuit, drop detachment, and the contrary cases.

Figure 5.3: RestNet-model confusion matrix



Source: Produced by author

Up to this step, functionalities common to the two methodologies shown in the research have been developed. The following stages develop topics that can be specific to some of the defined methodologies.

5.1.2 Drop Volume Methodology: calculate volume

Based on the obtained parameters, an analysis was made in which were used the volume calculation methods. Due to the wide usage of GMAW in the industry, numerous models have been presented to study the droplet transition process. Typical approaches include:

- Static Force Balance Model: it predicts drop detachment by comparing the surface tension of the drop with the external forces exerted on the drop (Version 2004).
- Pinch Instability Theory(PIT): is a detachment criterion can be derived, that does not rely on the balance of axial forces, but rather relies on radial forces (Version 2004, Wang, Lü and Jing 2016).
- Mass-Spring Model: this has lead to simple calculation as well as reflected oscillation during droplet growth as it is shown in (Wang, Lü and Jing 2016).
- Volume-of-Fluid (VOF) method: VOF method is based on the magnetohydrodynamic analysis (Zhao and Chung 2018, Murphy 2013, Wang, Huang and Zhang 2004).

All these methods use equations in which they involve a spherical analysis of drop. But in (Choi et al. 2001), based on VOF and PIT. It showed a good analysis that when the drop detaches. The entire drop volume is assumed to be ejected from the wire tip. A drop detachment detection by image processing would allow the use of simple equations that are proposed in this article. The equations 5.2 and 5.3 was token of him.

$$\frac{dl_{es}}{dt} = v_f - v_m \tag{5.2}$$

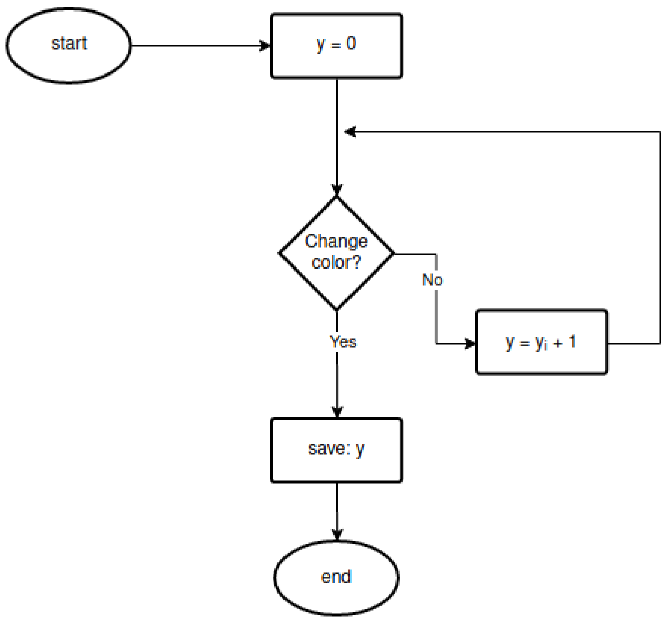
$$\frac{dV_d}{dt} = (\frac{\pi * D_e^2}{4}) * v_m \tag{5.3}$$

Where l_{es} represents unmelted wire extension, v_f the wire-feed rate, v_m the wire-melting rate. Where V_d the attached drop volume, and D_e the wire diameter. Uniting the two equations is obtain as a result the equation 5.4

$$V_d = (\frac{\pi * D_e^2}{4}) \int (v_f dt - l_{es}) \tag{5.4}$$

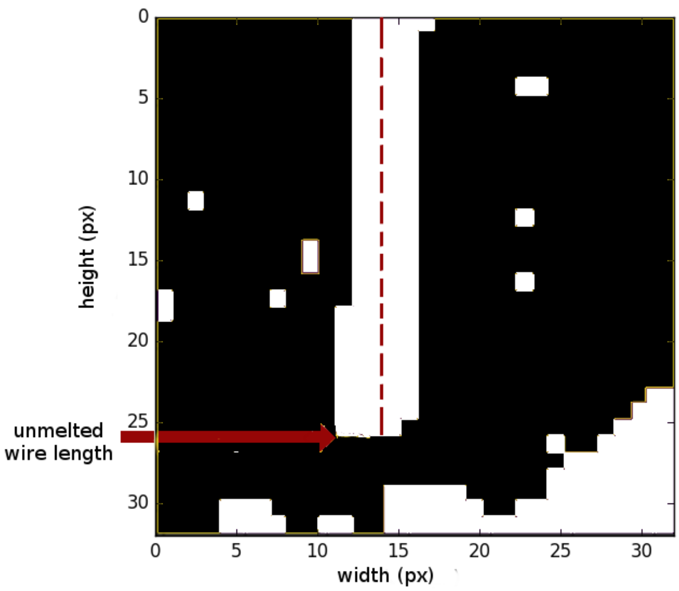
The unmelted wire length (l_{es}) necessary for volume calculation is obtained with classical images processing. The method used is shown in annex C, and the algorithm has the flow shows in Figure 5.4. The arc image is binarized and a pixel count is made vertically from the center of the wire until a change in pixel colors occurs. This process is showed in figure 5.5.

Figure 5.4: Algorithm for unmelted wire length calc



Source: Produced by author

Figure 5.5: Diagram of unmelted wire length calculation

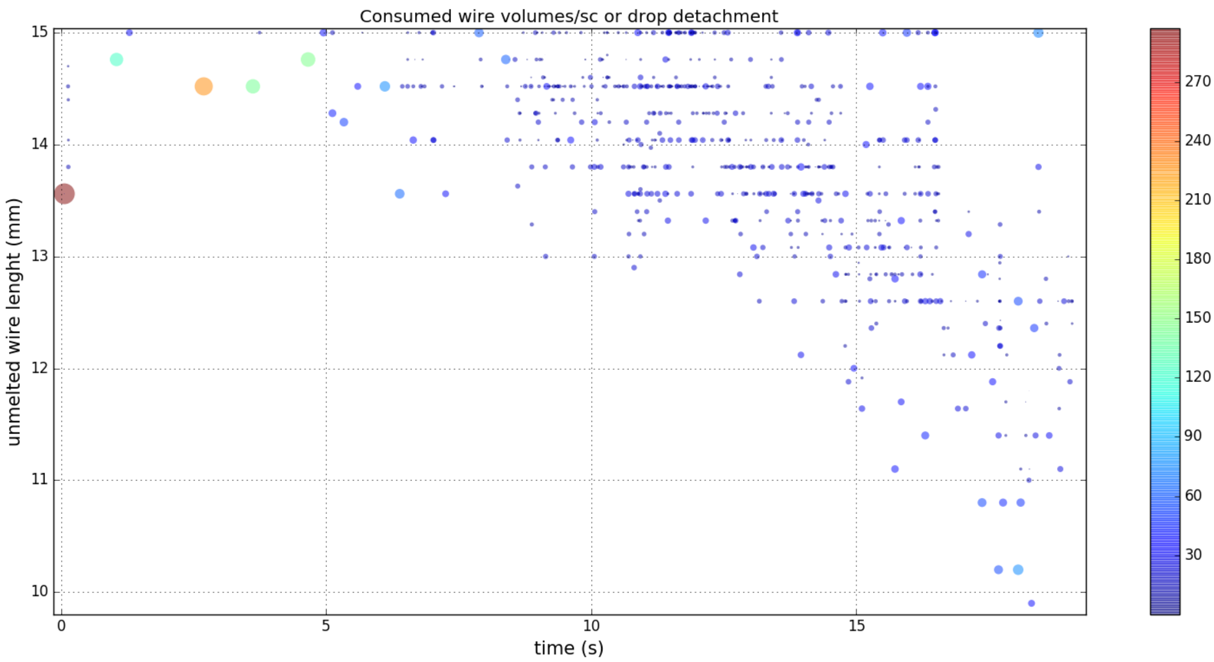


Source: Produced by author

5.1.2.1 Result of volume calculation

Figure 5.6 belonging to experiment number 3 shows a distribution of the largest volumes and lower volume frequencies in the firsts seconds of GMAW process. In the middle, it shows a decrease in the unmelted wire size, a greater frequency, and a decrease in the molten wire volume. It characterizes the globular metal transfer mode in this process. In the last seconds, it shows the spray transfer mode through the reduction of the unmelted wire length and increases in drops frequency. This demonstrates a valid characterization of the process with these techniques.

Figure 5.6: Volume distribution on unmelted wire length vs time



Source: Produced by author

5.1.2.2 Volume dataset characteristics

After calculation of the molten volume(or drop volume) and unmelted wire length. It was started the correlation of all data on one dataset. This generated a dataset of 2170 records, taking experiments 1 and 2 into account, figure 5.2 shows a summary of dataset formed. The column $main$ represents average values, column min and max are minimum and maximum values of each parameters. Column std is standard deviation over requested parameters. The values of standard deviation validate that there is a great diversity of values in the range of maximum and minimum specified.

Table 5.2: Volume dataset

	main	std	min	max
$wire_v(m/min)$	6.38	1.06	4.80	8.20
$voltage_(volt)$	26.09	3.63	17.00	32.00
$weld_v(mm/s)$	9.99	1.90	6.20	13.40
$wire_l(mm)$	13.78	1.12	9.00	15.00
$volume_(mm^3)$	0.74	0.98	$5.6 * 10^{-5}$	10.54
$depth_(mm)$	1.95	0.89	0.00	3.62
$height_(mm)$	1.77	0.86	0.00	3.33
$width_(mm)$	5.94	1.28	2.67	8.21

5.1.3 Frequency dataset characteristics

With the parameter dataset generated in the previous section, the frequency dataset was generated removing some fields, like volume and unmelted wire length. Table 5.3 shows a summary of dataset formed. The row $dropfreq$ represent short circuit and drop frequency detected on 50ms. It has 585 records.

Table 5.3: Frequency dataset

	main	std	min	max
$dropfreq(unit)$	3.68	3.82	1.00	24.00
$wire_v(m/min)$	6.42	1.05	4.80	8.20
$voltage_(volt)$	25.17	4.09	17.00	32.00
$weld_v(mm/s)$	10.06	1.90	6.20	13.40
$depth_(mm)$	1.97	0.86	0.00	3.62
$height_(mm)$	1.97	0.74	0.00	3.33
$width_(mm)$	5.91	1.29	2.67	8.21

The common parameters have similar behavior, which allows these two methodologies to be compared. The differences in the drop frequency dataset are related to the sampling frequency. This decreases the parameters for analysis.

5.2 PREDICTIVE MODEL FOR GMAW PROCESS

In the construction of this model, the scikit-learn library was used (INRIA). This library contains several machine learning algorithms that allow making a comparison between them. The selection of algorithms is based on those with good results in prediction tasks. They were:

- **Lasso regression**: is a type of linear regression that uses shrinkage. Shrinkage is where data values are shrunk towards a central point, like the mean. The lasso procedure encourages simple, sparse models (i.e. models with fewer parameters). (Tibshirani 1996, Friedman, Hastie and Tibshirani 2010).
  Meta-parameters selected: $alpha = 1.802e - 01, fit_intercept = True, normalize =$

$False, precompute = False, copy_X = True, max_iter = 1000, tol = 0.0001, warm_start = False, positive = False, random_state = None, selection =' cyclic'$.

- **Ridge regression**: is a technique for analyzing multiple regression data that suffer from multicollinearity (Fearn 2013, Breheny 2016). Ridge regression is like least squares but shrinks the estimated coefficients towards zero (Tibshirani 2013).
  Meta-parameters selected: $alpha = 1.802e - 01, fit_intercept = True, normalize = False, copy_X = True, max_iter = None, tol = 0.001, solver =' auto', random_state = None$.

- **Bayesian regression**: Bayesian regression is one of the techniques widely used since 1960s as shown in (Zellner and Chetty 1965, Currin et al. 1991, Sahu, Dey and Branco 2003, Chan and Vasconcelos 2012). It is based on probabilistic Bayes' Theorem with excellent results in classification and prediction task as demonstrated by (Pawlak 2002, Rudner and Liang 2002, McNamara, Green and Olsson 2006).
  Meta-parameters selected: $n_iter = 300, tol = 0.001, alpha_1 = 1e - 06, alpha_2 = 1e - 06, lambda_1 = 1e - 06, lambda_2 = 1e - 06, alpha_init = None, lambda_init = None, compute_score = False, fit_intercept = True, normalize = False, copy_X = True, verbose = False$.

- **Support vector machines (SVMs)**: are a set of supervised learning methods used for classification, regression, and anomaly detection. They are effective in high dimensional spaces and still effective in cases where a number of dimensions are greater than the number of samples. Different Kernel functions can be specified for the decision function. Common kernels are provided, but it is also possible to specify custom kernels (Cortes and Vapnik 1995, Smola, Smola and Schölkopf 2004).
  Meta-parameters selected: $gamma =' scale', coef0 = 0.0, tol = 0.001, C = 1.0, epsilon = 0.1, shrinking = True, cache_size = 200, verbose = False, max_iter = -1$.

These algorithms, compared with ANN are less expensive in computational training process. They need less time for the development and definition of the learning hyperparameters. All these allow a reduction in research time, whether any of them offers a satisfactory result. Then it possibly discarded the use of neural networks based on the previous arguments. All this allows a reduction in research time if any of them show good results like it shows in table 5.4. The technique column is some machine learning techniques used in this research, RMSE is root mean square error. The grade represents the function grade for algorithms with polynomial functions.

5.2.1 Result of volume dataset

The best performance was obtained by SVM with radial basis function (RBF) kernel as can be seen in table 5.4. The RMSE of this algorithm was 0.27. The code used is shown in annex D.

Table 5.4: Minimus error calculation of each models(Volume dataset)

technique	RMSE	grade
Lasso regression	0.30	5
Ridge regression	0.36	3
Bayesian regression	0.31	4
SVM polinomial	0.67	1
SVM-RBF	0.27	-

5.2.2 Result of frequency dataset

The best performance was obtained by SVM with Radial Basis Function (RBF) kernel too, like it shows in table 5.5.

Table 5.5: Minimum error calculation of each models(Frequency dataset)

technique	RMSE	grade
Lasso regression	0.61	3
Ridge regression	0.39	3
Bayesian regression	0.40	3
SVM polinomial	0.89	1
SVM-RBF	0.33	-

The margin error with the volume dataset is not very large. Therefore, based on better performance, the SVM-RBF model of frequency dataset could be applied.

5.3 SIMULATION OF WELD BEAD GEOMETRY FOR GMAW PROCESS

The mathematical model was obtained in the previous section which characterizes the relation of the selected input parameters and the weld bead geometry on GMAW process. As defined in the section on intelligent modeling (chapter 2), the modeling can be defined as a reinforcement learning technique with a q-learning algorithm. This technique was analyzed in chapter 3. In the q-learning algorithm, it is necessary to define the states, actions, and rewards as is shown in figure 2.12 of chapter 2.
In this experiment, the state are going to be the vector of *'height', 'width', 'depth'* values. This is because these are the parameters to be controlled and the interrelation between them makes it impossible to control one without modified the others. The actions can be increased, decrease or maintain the same for each value of vector *'voltage', 'wire-rate', 'welding velocity'*. Based on the experience and the experiments carried out, the increases or decreases have different values for the vector. The **reward** is defined like distance-based in the manhattan distance between state to reach and actual state vectors, because manhattan distance will allow simple and efficient distance calculation between state vectors.
The ranges of minimum and maximum action values were also defined based on the experiments carried out in the research presented in Table 5.2. As an optimization policy,

the Bellman optimality equation was used for the learned value as in equation 5.5 cited by (Sutton and Barto 2017).

$$q(s,a) = R_{t+1} + \gamma * maxq(s', a') \tag{5.5}$$

Where q is the function of any state-action pair (s, a) at time t. R_{t+1} is the expected reward we get from taking action a in state s plus the maximum expected discounted return that can be achieved from any possible next state-action pair (s', a'). γ is the discount rate constant and $maxq$ is the function of maximum value for action a' in state s' and with the value 0.99 in this research. It makes it possible to take into account the previous states, which will allow the algorithm to select the path with the least loss. At that time, for a new $q^{new}(s, a)$ is equal to a weighted sum of the last value and the learned value as it is shown in equation 5.6.

$$q^{new}(s,a) = (1-\alpha) * q^{old}(s,a) + \alpha[R_{t+1} + \gamma * maxq(s', a')] \tag{5.6}$$

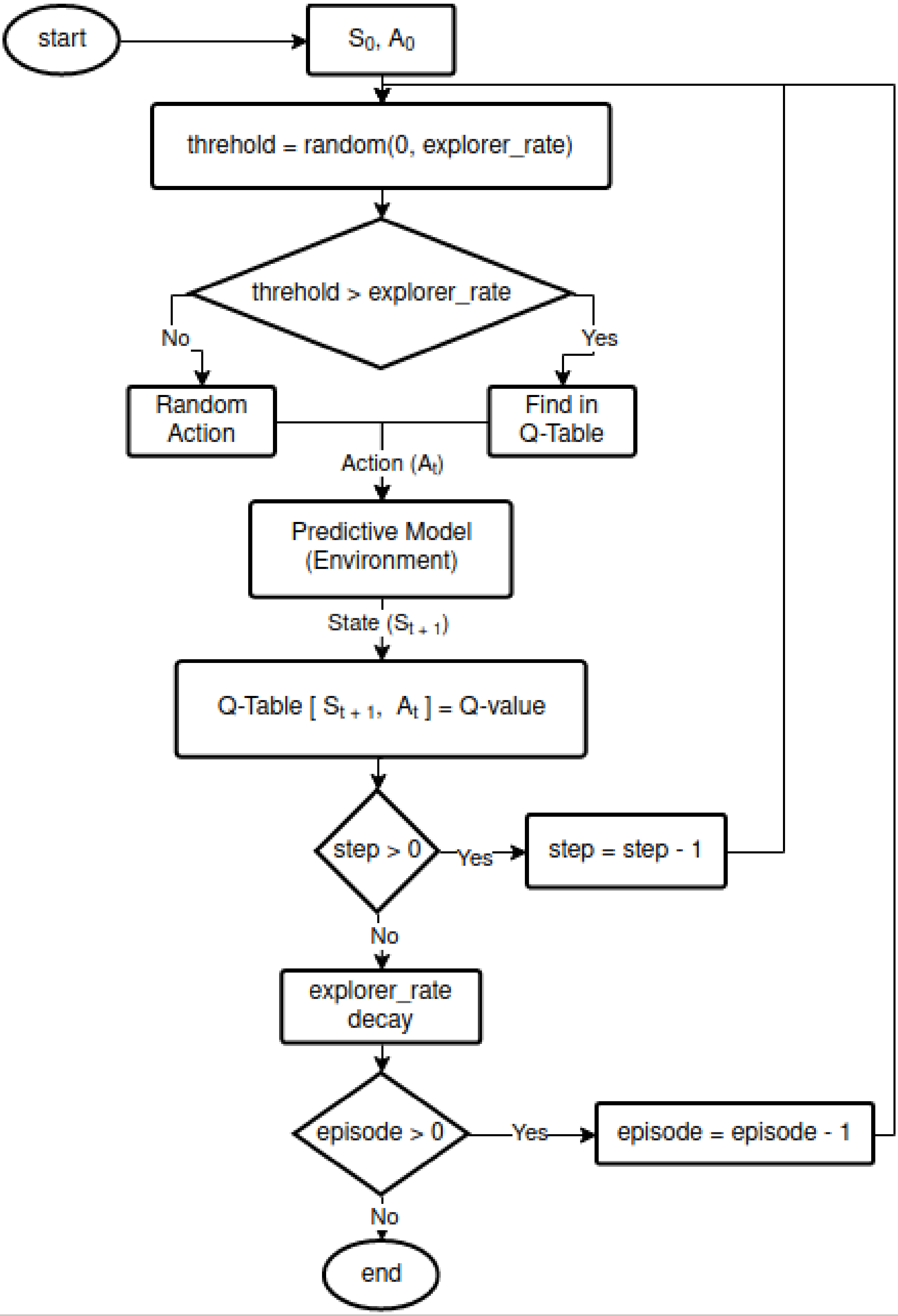
Where α is a learning rate with value 0.1 in this research

In the next stages, it is necessary to define a geometry modeling simulation to validate the behavior of this technique.

5.3.1 Train weld bead geometry modeling

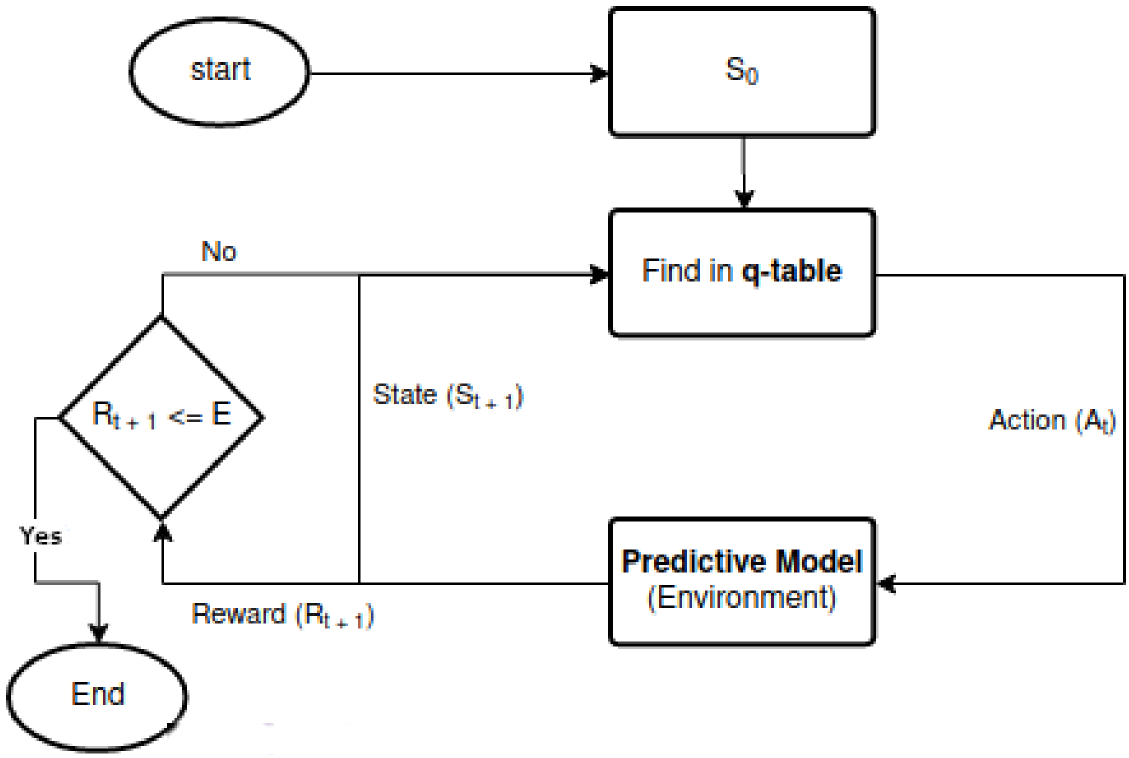
The training was carried out with the experimental data of the real GMAW process. The equation 5.6 is used an iterative process to calculate the *Q-values*, which are stored in a matrix table named *Q-table* with states x actions dimensions. *Q-table* guide to the best action for all possible states to obtain the objective state, like Figure 5.7 shows. It was defined the weld bead dimensions to goal, in this case *(height = 2.20 mm, width = 7.73 mm, depth = -2.50 mm)* The start action parameters over control variables, in this case *(voltage = 20.0 v, wire-rate = 5.8 mm/s, welding velocity = 8.2 mm/s)*. The initial state for these parameters on stable situation are *(height = 2.18 mm, width = 5.48 mm, depth = -2.95 mm)* The number of episodes was 100 and the maximum steps by episode 100 to reach better control values. After obtaining *Q-table* can be found the actions to goal the objective weld bead dimensions by initial parameters.
Once the training has been carried out, it is possible to apply the Q-Table obtained to optimize the process, as shown in the Figure 5.8.

Figure 5.7: Algorithm of reinforcement learning train



Source: Produced by author

Figure 5.8: Algorithm of reinforcement learning model

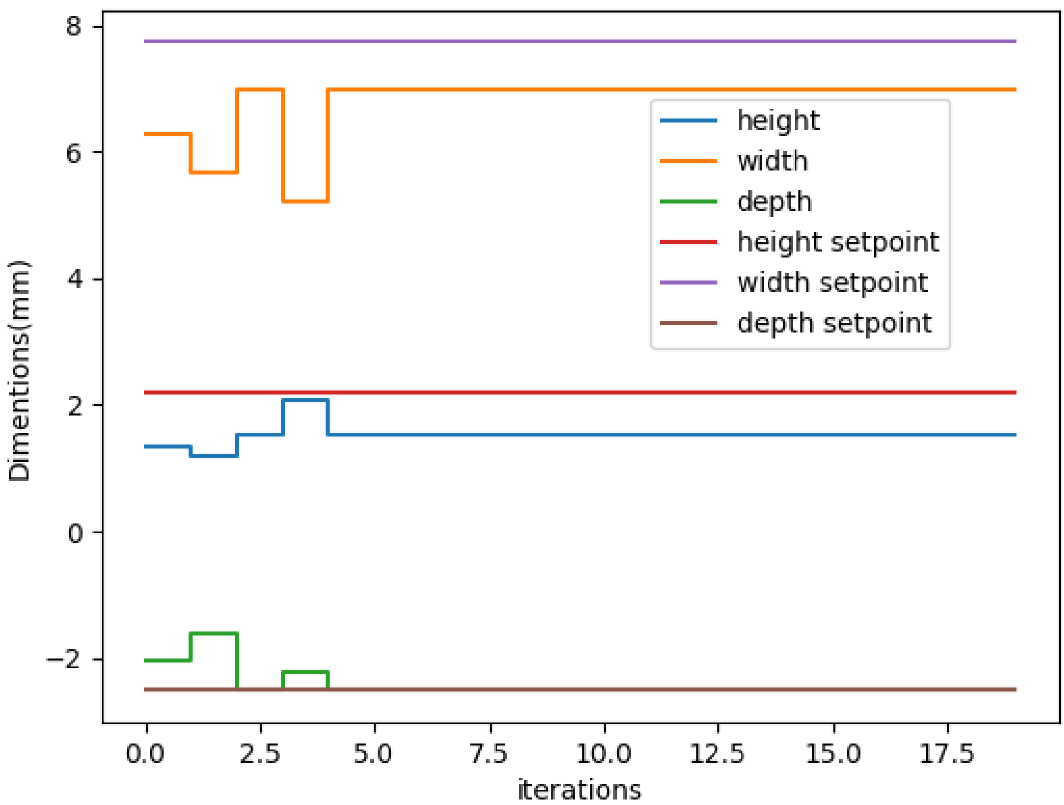


E is the error allowed to the system.
Source: Produced by author.

5.3.2 Drop Volume Methodology: simulation

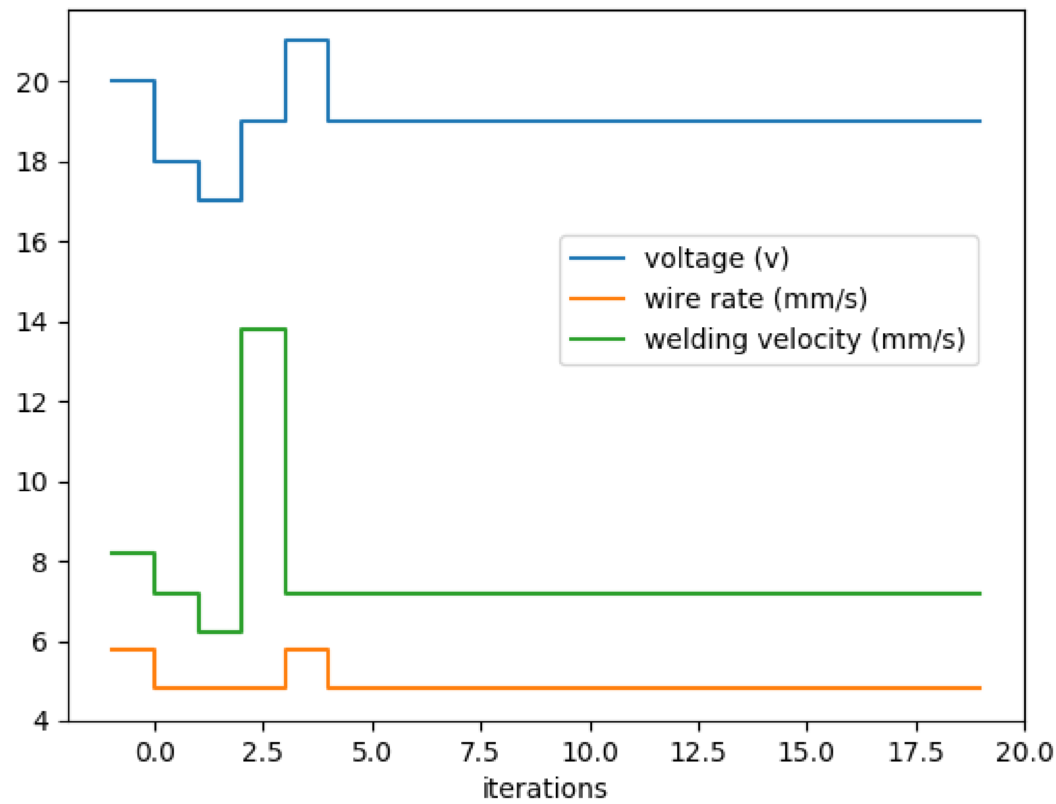
The Figure 5.9 shows the simulation of the weld bead geometric parameters. It can be seen how after the 4th iteration the model reaches the three optimal values. The three geometric values obtain are the three minimums possible, permitted by the volume model, to goal the geometric objective.

Figure 5.9: Drop Volume Methodology: modeling geometric parameters



The control error is: *height = 0.68 mm, width = 0.76 mm* and *depth = 0.00 mm*. Generating a margin of less than a millimeter for width and height, an approximation to the objective for depth. The Figure 5.10 shows control parameters. The variations of them in the firsts iterations do not expose sufficient change to make the system unstable.

Figure 5.10: Drop Volume Methodology: control parameters



5.3.3 Drop Frequency Methodology: simulation

The Figure 5.11 shows the geometric control process for drop frequency methodology. The geometric parameters obtained are not better than in the volume model, except the depth.
The control error of this model is: *height = 0.34 mm, width = 1.59 mm* and *depth = 0.32 mm*, with only geometric parameters greater than one millimeter.
The Figure 5.12 shows the values obtained by the control parameters of the frequency model. Like the other model, this has small variations, so instability in the system should not be caused.

Figure 5.11: Drop Frequency Methodology: modeling geometric parameters

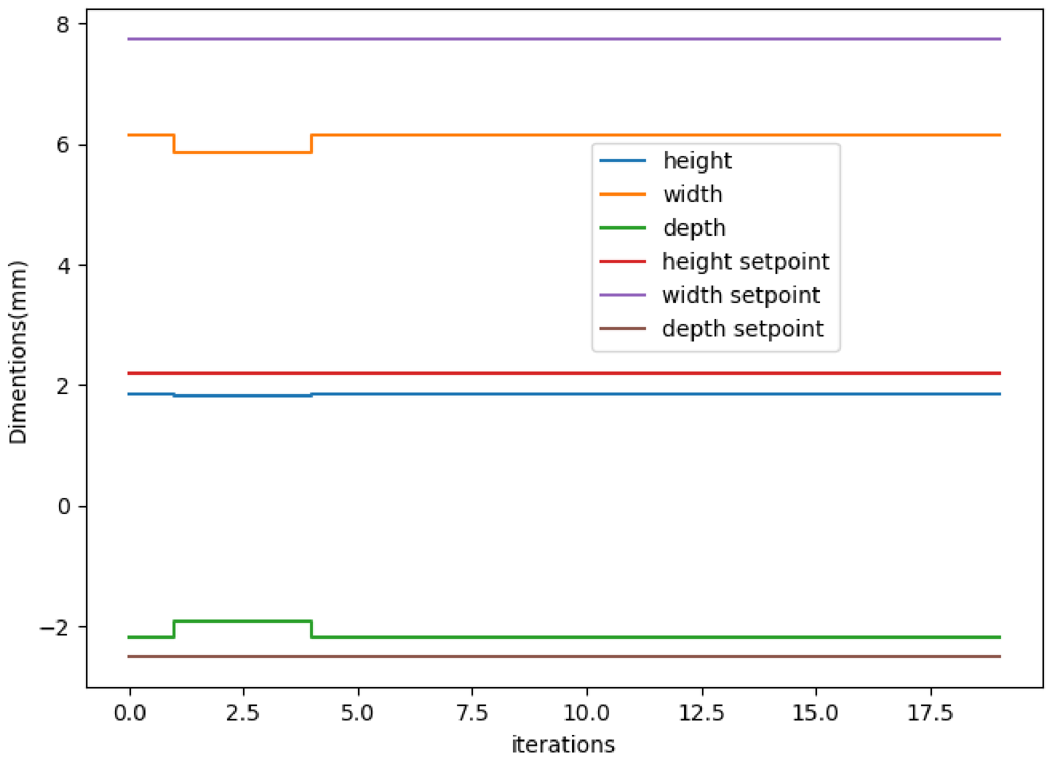
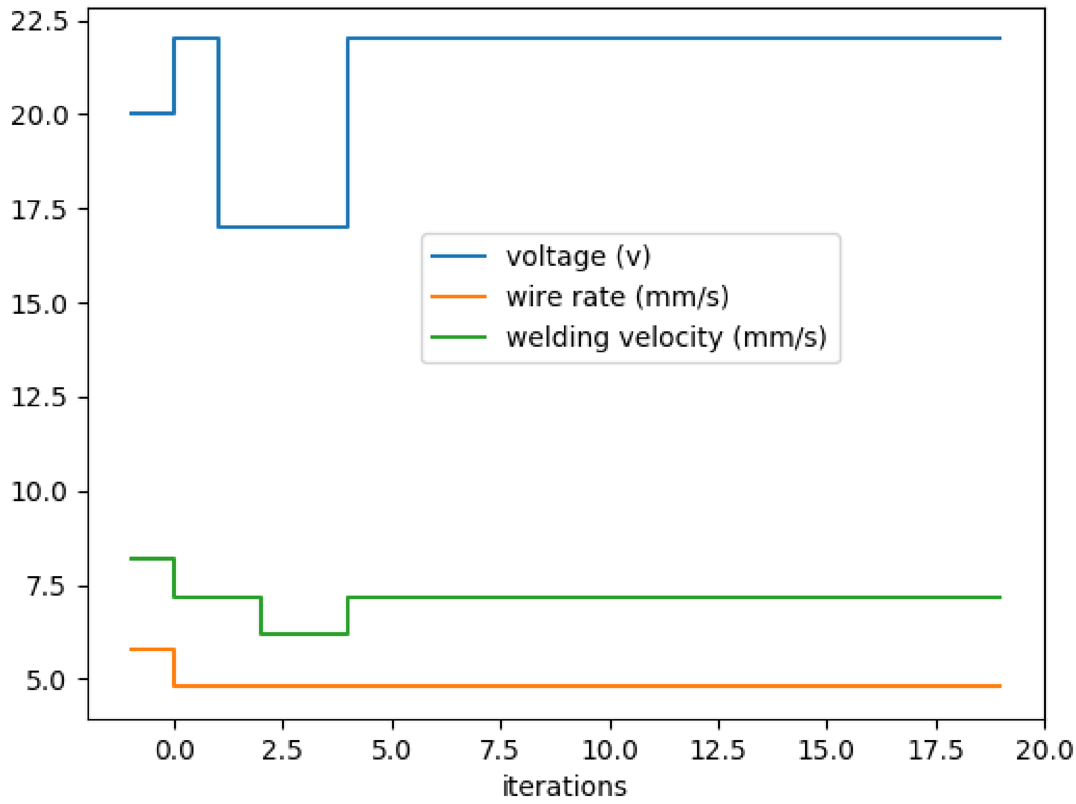


Figure 5.12: Drop Frequency Methodology: control parameters



5.4 CHAPTER CONSIDERATIONS

After analyzing the results in this chapter, it can conclude that the error margins obtained in the stages validate the methodologies and can be applied to a GMAW process with satisfactory results. The deep learning model obtained, proved that images can be classified, calculate unmelted wire length, the consumed wire volume, drop and short-circuit frequency in real-time for a GMAW process. This allows the use of these parameters in predictive and control models in real-time. The SVM algorithm is the one that offers the best results in the prediction of the GMAW process these two methodologies. The weal bead geometry modeling of GMAW process can be developed with the reinforcement learning technique due to the small margin of error that the simulation returns.

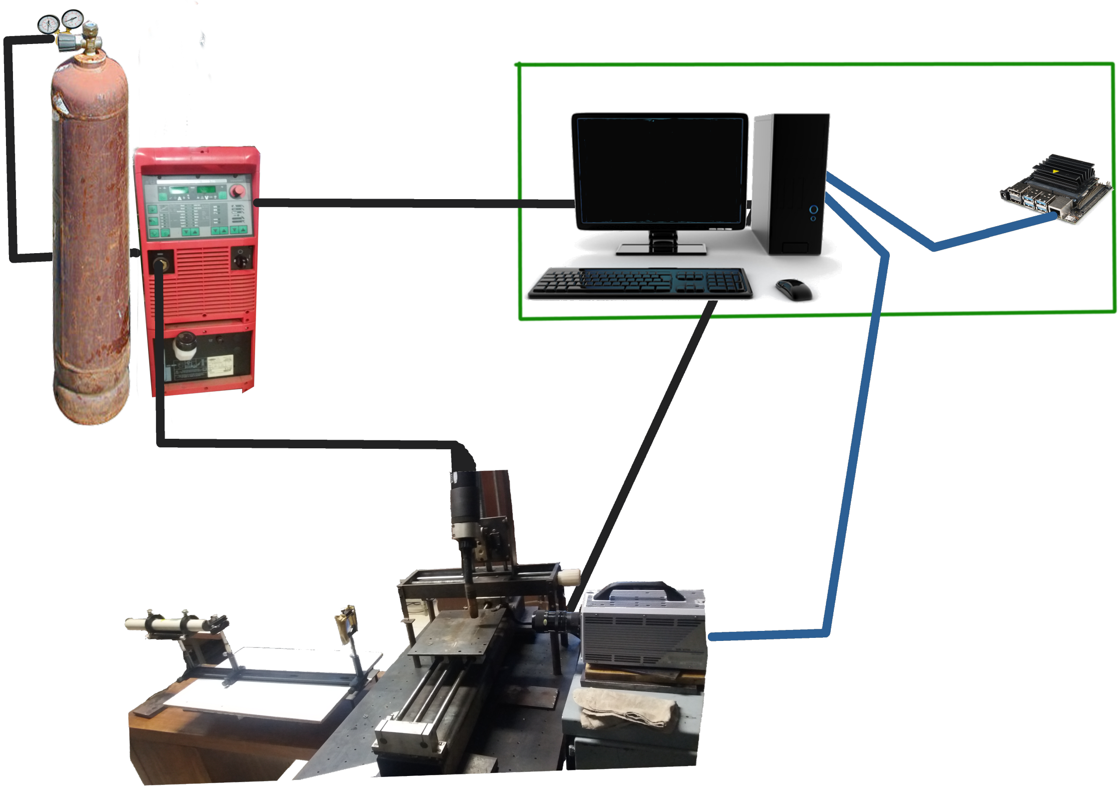
6 DESIGN AND DISCUSSIONS OF RESULTS

This chapter pretend shows the design proposed for the final system and the new technology used them. An analysis of the response times of this system will also be carried out. his chapter, the discussion of the results of this research work was developed.

6.1 DESIGN

The proposed design shows the equipment used for experiments in the GRACO laboratory of Brasilia University. It was proposed to add Jetson nano to process all modeling information, pass it to the computer, and communicate with the other equipment. It is shown in Figure 6.1. Jetson nano is an embedded system-on-module (SoM) and developer kit. Useful for deploying computer vision and deep learning, Jetson Nano runs Linux and provides 472 GFLOPS (floating-point operations, per second) compute performance with 5-10W of power consumption (eLinux 2020). The international cost is approximately 99 dollars.
This equipment reduces costs. It has excellent computational performance with low energy consumption. The average response time for frequency models and volume models are 0.25 ms and 18.25 ms respectively. In future developments, it may be possible to place the desktop pc functionalities in the Jetson nano. But for this, drivers of the welding source, the welding table, and the high-speed camera must be developed.
According to this, it necessary an additional network interface card in the computer. This must have the characteristics of maximum speed 1 Gps (gigabit per seconds), same as onboard. This would allow image transmission less than 0,5 ms. These cards have an approximate price of 7 dollars. The communication was developed through a web service, structured as shown Figure 6.2.
In the computer container, the welding supply driver and welding table driver are software packets developed in previous research. CxN packet is in charge gathers the image of the camera, sending it to the selected model, receiving the control parameters, and passing them to the welding supply and welding table. In jetson nano container, are both frequency-based models and volume-based models for geometry modeling of GMAW process. This action is repeated until the process is complete.
Based on the information placed, this entire process would have a minimum response time of 19.25 ms and an additional equipment cost less of 106 dollars. Therefore, the proposed design meets the objectives of low computational cost and low monetary cost.

Figure 6.1: Design of the proposed system

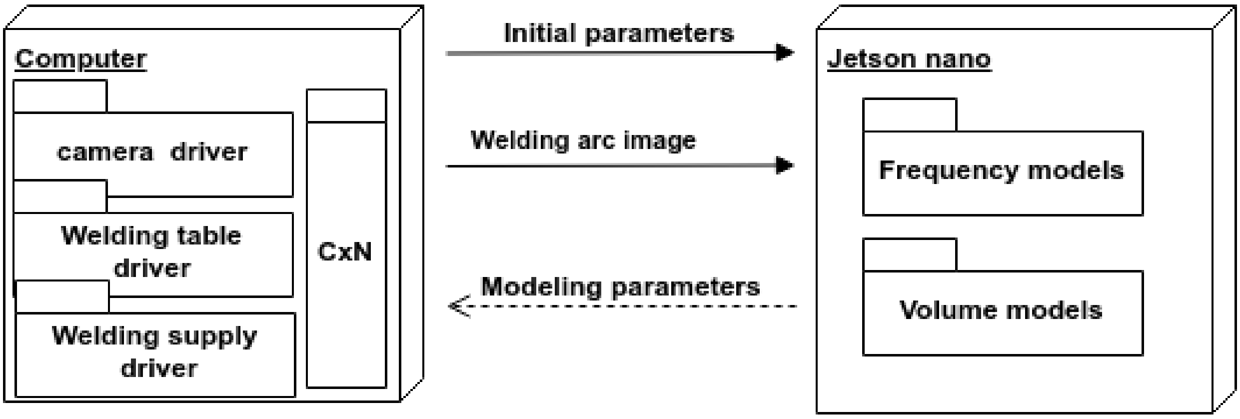


Source: Produced by author

6.2 DISCUSSIONS

The objective of this research was to develop a weld bead geometry model of GMAW process by applying techniques of machine learning, deep learning, and reinforcement learning. The use of these computer science algorithms in welding processes is still new, although there are some applications. In the bibliographic review developed, the little presence of these practices in the welding processes was demonstrated, as shown in Figure 2.5 and Figure 2.6. In contrast to the advantages of these algorithms in various areas, solving problems similar to the main problems in welding processes and lined with new objectives of modern welding manufacturing presented by (Chen and Lv 2014). The potential of learning-based techniques was described because computational resources are becoming cheaper and welding information can be obtained more and more quality information. All these premises aligned with the industry 4.0, where a set of technologies that allow a fusion of physical and digital world to create more intelligent and dynamic systems, like (Brecher 2018) shown.
The articles analyzed where the presence of these algorithms is recognized, but sometimes they do not categorize them as machine learning techniques. The problem is that another series of similar techniques can be ignored and be optimal to generate a better result for a specific case. It

Figure 6.2: PC and IA system communication



Source: Produced by author

was obvious in the little presence of model comparisons and infrequent applications of ANN and fuzzy techniques. In the paper's analysis was found a low application of deep learning techniques to process welding arc images. Reinforcement learning techniques have a low presence too. In this way, the novelty of applying these techniques in this investigative work is highlighted. In addition, the little interrelation between the nuclei authors and the few publications of these (Figure 3.3), demonstrate how novel the research are linking these areas.

Consequently, the arc parameters of unmelted wire length, molten wire, short-circuit frequency, droplet volume, and droplet frequency were selected. These parameters can be captured through image processing, which would allow testing these new deep learning techniques. To demonstrate these potentialities, a series of experiments was developed. Experiments 1 and 2 were planned to obtain acceptable variances in the welding parameters, which would allow obtaining a better predictive model. These variances were validated with the statistical analysis of the parameters shown in Table 5.2 and Table 5.3. This requirement is basic to be able to perform optimal modeling applying machine learning, like (Hernandez Orallo, Ramirez Quintana and Ferri Ramirez 2004, Witten and Frank 2005, Marbán, Mariscal and Segovia 2009) exposed.

Experiment 3 was focused on supporting the validation of the deep learning model, plus the approximate calculation of molten wire and droplet volume. The deep learning model was validated with an accuracy of 97,24% that defines the effectiveness of the model in performing a correct detection for both groups ("Short circuit and drop-detachment images" (SCDD) and "No short circuit and no drop-detachment images" (no SCDD)). Another metric that can be calculated with the data from the confusion matrix is Recall (95%). The recall measures the model's ability to detect positive samples. An important value for this research, since it performs the calculations of drop volume and molten wire volume from this detection.

In continuity with the development of the research, the Equation 5.4 was selected to calculate the volume. It is obtained as results of the equations presented by (Choi et al. 2001) and the conditions of droplet detachment detection. This equation makes it possible to calculate, with the same formulation, the molten wire volume and the droplet volume. To allow the generalization of a model (deep learning + volume calculation) in the GMAW process for volume analysis. It is another novelty of this research since most of the volume calculations present in the literature have as a requirement to separate the analyzes by transfer modes. The equation is not exempt from calculation errors, as the author referenced. This error can be considered a systematic error that must usually be estimated by educated guesswork (Mortimer 2013). In turn, this error is assumed by machine learning models so that the permissible error of the model conceives the systematic error of the system. An estimate of the proper functioning of the process (deep learning + volume calculation) is the Figure 5.6. She clearly shows how the unmelted wire length (inverse of arc length) decreases and how the volume of molten wire decreases. It was the objective of experiment 3, and the process (deep learning + volume calculation) captured this function.

Once the arc parameters, the input parameters, and the geometric output parameters have been obtained, the tasks were started to obtain the predictive model. As the bibliographic analysis showed, the predictive model is one of the three learning models presented, the most applied in welding processes. But as a consequence, a generalized two models of the GMAW process were obtained for all transfer modes. A comparison was also made between the two predictive models developed. The Table 6.1 shows a summary of it.

Table 6.1: Comparison of the two methodologies

	Drop Volume Methodology	**Drop Frequency Methodology**
different parameters	unmelted wire length, melted wire volume, droplet volume	short-circuit frequency, droplet detachment frequency
Predictive-model (SVM-RBF) RSME	0.27	0.33
Control error	height = 0.68 mm, width = 0.76 mm, depth = 0.00 mm	height = 0.34 mm, width = 1.59 mm, depth = 0.32 mm
Performance time (Laptop)	130 ms	11 ms
Performance time (Jetson nano)	18.25 ms	0.25 ms

As already expressed, this small difference in the RSME means that any of the two predictive models can be used. Always taking into account the requirements of the system in which it will be applied. Another relevance of this predictive model is that it was proposed to predict three parameters of the geometry of the weld bead at the same time.

The processes, deep learning + (volume or frequency calculation) + predictive model, make up the necessary environment for the reinforcement learning process. As result, the drop volume methodology offers fewer error margins for each geometric parameters, like Table 6.1 shows. But doing the comparison based on response time, the drop frequency methodology has 0.011 seconds on average. Better than the drop volume methodology that has 0.13 seconds. These tests were made on a laptop with RAM: 8 GB, processors: 1.70 GHz x 4, without a dedicated graphics card. Another run test was performed on a Jetson nano. The result was the one shown in the Table 6.1. These increased computational resources improve the run-time of the drop volume methodology.

It would make it more feasible in a production environment but at the same time is less cheaper than the drop frequency methodology. Conversely, the drop frequency methodology would be cheaper by the industry but would have a margin of error that may not be accepted. Another important analysis in drop volume methodology is the drop calculation. Despite being based on formulations of a reference article, this article could introduce another possible errors due to the complexity of the process that occurs in the welding arc.

Others intelligent control techniques, like ANN-fuzzy, has the problem that specialist has to know and define the rules associated to process, which is few probable based on all geometric parameters control and the complex relation between them. (Cruz, Torres and Alfaro 2015) defined 12 fuzzy functions and 7 fuzzy rules for only width control. These fuzzy rules complexities will rise with other control parameters. Q-learning has not this problem how was exposed in this research. The ANN used on intelligent control increases the computational cost compared to other machine learning techniques that can offer the better or same result. The results obtained allow the use of these techniques with good computational performance in terms of training and execution.

7 CONCLUSION

- A bibliographic analysis was developed that showed the new requirements for an intelligent welding process, and the potentialities of machine learning techniques to solve many of these problems were demonstrated. Although this research focused on the GMAW process, this research opens the door to these techniques in other welding processes.

- An efficient resnet model was developed that allows the detection of droplet detachment and the occurrence of short circuits in real-time for a GMAW process. The use of background subtraction technique allowed the visualization of the detachment pattern.

- Functionality was developed with a deep learning model and a physical analysis of the GMAW process, which make it possible to calculate a droplet volume and a molten wire in real-time. Despite the possible systematic error inserted by the deep learning model and the physical formulation used, this analysis can be the beginning of several studies jointly applying physical analyzes and deep learning techniques in the welding arc.

- Two models were developed with the Support Vector Machine algorithm with Radial Basis Functionality kernel, giving a low root-mean-square error, showing the possibility of predicting a GMAW process for all transfer modes.

- The two proposed methodologies are analyzed and compared. Its advantages and disadvantages were shown according to its possible application in research and industrial projects. The times obtained using a Jetson nano facilitate the application of either of the two methodologies. In addition, the use of jetson nano potentiates the application of the internet of things (IoT) associated with welding processes.

- A system design proposal was made based on the equipment used in the research, where any of the two proposed methodologies can be applied. An analysis of the computational cost of the entire system and the monetary cost was developed. In conclusion, the feasibility of developing the system and the potential to carry out new research were demonstrated.

8 FUTURE WORKS

- Perform laboratory tests of these methodologies in a GMAW process. It would also lead to the development the proposed system and develop all control software on jetson nano.

- Applying these deep learning techniques and use more modern video sensors, a more in-depth analysis of the arc can be carried out, deepening the studies of molten material, drop analysis, and material losses.

- Extend the techniques analysis of arc welding to other welding processes, like Gas tungsten arc welding (GTAW), Plasma arc welding (PAW), Shielded metal arc welding (SMAW), Submerged arc welding (SAW).

- To develop a research in which all visual events of the welding arc are correlated with the characteristic sound. It would later allow the development of models based on the arc sound.
- To develop other models with other parameters and make comparisons between them to find the most efficient one. Approach the study of the rest of the parameters and their interrelation by applying machine learning techniques.

- To develop other models of reinforcement learning. Compare them and the models proposed in this research.

- To investigate real-time weld bead geometry sensors to be incorporated into intelligent control research. It would simplify the applications of the models and could provide better efficiency.

- To develop a study on the analysis and application of machine learning techniques in orbital welding.

- To develop an investigation of potential internet of things (IoT) and their technologies that can be applied to welding processes.

- To Develop an investigation applying the reinforcement learning technique with an online training.

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ANNEXES

A. WELD-BEAD GEOMETRY CALC CODE

```
import imageio
from matplotlib import pyplot as plt

# initial data depth high
#path_img =  test2_pronta.png
#h_img = 310
#coord_left = (145, 155)
#coord_right = (3549, 74)
#pieceh_left_px = 125
#pieceh_right_px = 127
#pieceh_left_mm = 7
#pieceh_right_mm = 7
#width = False
#name_file =  file_depth_high.csv
#color_high = [10, 54, 128]
#color_depth = [150, 6, 6]

# initial data width
path_img =  test3_pronta.png
h_img = 432
coord_left = (90, 365)
coord_right = (3912, 268)
pieceh_left_px = 516
pieceh_right_px = 530
pieceh_left_mm = 23
width = True
name_file =  file_width.csv
color_high = [150, 6, 6]

# initial data
img_solda = imageio.imread(path_img)


# all functions


def calc_funcline():
    if coord_right[0] != coord_left[0]:
        m = (h_img - coord_left[1] - (h_img - coord_right[1])) /\
                  (coord_left[0] - coord_right[0])
        n = coord_left[1] - m * coord_left[0]
    else:
        print( error )
    return m, n


def values_line(m, n):
```

```
    values = []
    for x in range(coord_left[0], coord_right[0]):
        # images coord are inverse
        values.append(int(n - m * x ))
    return values


def values_high(line):
    values = []
    values.append(0)
    for i, pos in enumerate(line):
        y_pos = pos
        x_pos = coord_left[0] + i
        while y_pos > 0 and not (img_solda[y_pos, x_pos] == color_high).all():
            y_pos -= 1
        if (img_solda[y_pos, x_pos] == color_high).all():
            img_solda[y_pos - 1, x_pos] = color_high
            img_solda[y_pos - 2, x_pos] = color_high
            img_solda[y_pos - 3, x_pos] = color_high
            values.append(pos - y_pos)
        elif y_pos == 0:
            values.append(0)

    values.append(0)
    plt.imshow(img_solda)
    plt.show()
    return values


def values_depth(line):
    values = []
    values.append(0)
    for i, pos in enumerate(line):
        y_pos = pos
        x_pos = coord_left[0] + i
        while y_pos < h_img and not (img_solda[y_pos, x_pos] == color_depth).all():
            y_pos += 1
            # print(y_pos)
        if (img_solda[y_pos, x_pos] == color_depth).all():
            img_solda[y_pos + 1, x_pos] = color_depth
            img_solda[y_pos + 2, x_pos] = color_depth
            img_solda[y_pos + 3, x_pos] = color_depth
            values.append(pos - y_pos)
        elif y_pos == h_img:
            values.append(0)
        # print(pos, y_pos)
    values.append(0)
    # plt.imshow(img_solda)
    # plt.show()
    return values


```

```
def values_geo(line):
    depth = []
    if not width:
        depth = values_depth(line)
    high = values_high(line)
    return depth, high


def calc_coef(index):
    # pixcel ajust
    coef = pieceh_left_px * (pieceh_right_px - pieceh_left_px) / (float(
        (coord_right[0] - coord_left[0]) * index + pieceh_left_px *
        (pieceh_right_px - pieceh_left_px)))
    return coef

def calc_func_deformation():
    if coord_right[0] != coord_left[0]:
        m = (pieceh_right_px - pieceh_left_px) / ( coord_right[0] - coord_left[0])
    else:
        print( error )
    return m

def calc_pieceh_px(m, n, index):
    # pixcel ajust
    pieceh_px = m*index + n
    return pieceh_px

def calc_mm_ajust(value):
    return value * pieceh_left_mm / pieceh_left_px

def calc_mm(value, pieceh_px):
    return value * pieceh_left_mm / pieceh_px

def save_csv(depth, high):
    m = calc_func_deformation()
    n = pieceh_left_px
    with open(name_file,  w ) as f:
        i = 0
        if not width:
            f.write( depth, high \n )
            for v_depth, v_high in zip(depth, high):
                pieceh_px = calc_pieceh_px(m, n, i)
                mm_depth = calc_mm(v_depth, pieceh_px)
                mm_high = calc_mm(v_high, pieceh_px)
                f.write(str(mm_depth) +  ,  +
                        str(mm_high) +  \n )
                i += 1
        else:
            f.write( width \n )
            for v_high in high:
                pieceh_px = calc_pieceh_px(m, n, i)
                mm_width = calc_mm(v_high, pieceh_px)
```

```
                f.write(str(mm_width) +   \n )
                i += 1

        f.close()


if __name__ ==  __main__ :

    m, n = calc_funcline()
    print(" calculated m and n")
    print(m, n)
    line = values_line(m, n)
    plt.plot(line,  r , linewidth=1)
    plt.show()
    print(" calculated line")
    depth, high = values_geo(line)
    print(" calculated geometry")
    print(len(depth), len(high))
    save_csv(depth, high)
    print(" saved geometry")
```

B. CONVOLUTIONAL NEURAL NETWORK CODE

```
from fastai.imports import *
from fastai.transforms import *
from fastai.conv_learner import *
from fastai.model import *
from fastai.dataset import *
from fastai.sgdr import *
from fastai.plots import *
from tqdm import tqdm
tqdm.monitor_interval = 0
PATH = "../../../metal_drop/data/"
sz=96
arch=resnet18
bs=64

augs = transforms_side_on + [AddPadding(pad=10, mode=cv2.BORDER_REPLICATE)]
tfms = tfms_from_model(arch, sz, aug_tfms=augs, max_zoom=1.1)
data = ImageClassifierData.from_paths(PATH, tfms=tfms, bs=bs)
learn = ConvLearner.pretrained(arch, data, precompute=False, ps=0.4)
learn.opt_fn=optim.Adam

%time learn.fit(1e-2, 3, cycle_len=1, cycle_mult=2)

learn.unfreeze()
lr = np.array([1e-3,1e-3,1e-2])
%time learn.fit(lr, 3, cycle_len=1, cycle_mult=2)
```

C. UNMELTED WIRE CALC CODE

```python
def calc_wire_width(image_array, x, y, xl_ant = 10, xr_ant=15):
    """
    User give coord(x, y) in the wire for algorithm search in the same line
    wire init width and it value.

    image_array: image for wire calc
    x,y: coordenate between wire side
    """
    left = -1
    right = 1
    value_left = x
    value_right = x
    flag_left = False
    flag_right = False
    resized_image = cv2.resize(np.uint8(image_array), (32, 32))
    thresh = edge_detect(resized_image)

    while not(flag_left and flag_right):
        if not flag_left:
            left -= 1
            if thresh[y, x + left] == 255:
                value_left = x + left
                flag_left = True
            elif (x + left) == (xl_ant-2):
                value_left = xl_ant
                flag_left = True


        if not flag_right:
            right += 1
            if thresh[y, x + right] == 255:
                value_right = x + right
                flag_right = True
            elif (x + right) == (xr_ant+2):
                value_right = xr_ant
                flag_right = True
    return value_right, value_left

def calc_unmelted_wire(image_array, h, xl, xr, base_h, e=1, wire_d=1.2, bico=15):
    """
    It detect and calc unmelted wire high dimention

    image_array: image for wire calc
    h: it is high init for search stick out (px)
    xl: x left of wire (px)
    xr: x right of wire (px)
    base_h: high of base system(px)
```

```python
    e: allowed error in width dimention
    wire_d: wire diameter (mm)
    bico: dimention base to bico (mm)
    """

    temp_xl = xl
    temp_xr = xr

    flag = True
    thresh = edge_detect_resize(np.uint8(image_array))

    while ((xr - xl) <= (temp_xr - temp_xl) + e) and h <= (base_h - 2) and flag:
        h += 1
        if thresh[h, temp_xl] != 0:
            if thresh[h, temp_xl + 1] == 0:
                temp_xl += 1

        if thresh[h, temp_xr] != 0:
            if thresh[h, temp_xr - 1] == 0:
                temp_xr -= 1


        # it detect if temp values worked
        if thresh[h, temp_xl] != 0 or thresh[h, temp_xr] != 0:
            flag = False

    h_px = base_h - h-1
    dx = xr - xl
    if dx == 0:
        dx = 1
    h_mm = h_px * wire_d / dx
    unmelted_wire = bico - h_mm

    return h - 5, unmelted_wire
```

D. PREDICTION CODE

```
import pandas as pd
from sklearn.cross_validation import train_test_split
from sklearn.metrics import mean_squared_error
# from fancyimpute import KNN
from knn_impute import knn_impute
from sklearn.externals import joblib
# algorithms
from sklearn.multioutput import MultiOutputRegressor
from sklearn.preprocessing import PolynomialFeatures
from sklearn.pipeline import make_pipeline
from sklearn.linear_model import Lasso
from sklearn.linear_model import ElasticNet
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn.linear_model import LassoLars
from sklearn.linear_model import BayesianRidge
from sklearn.svm import SVR
from sklearn.neural_network import MLPRegressor

# load dataset
df_exp1 = pd.read_csv( parte 1/final/aws_a5_1_all.csv )
df_exp2 = pd.read_csv( parte 2/final/aws_a5_2_all.csv )
df_aws = pd.concat([df_exp1, df_exp2])
df_aws = df_aws.drop([ image ,  time ,  cputime_dif , num ], 1)


# loss data
if df_aws[ wire_l ].isna().any():
    dfwire_l = knn_impute(target=df_aws[ wire_l ],
              attributes=df_aws.drop([ wire_l , volume ], 1),
                  aggregation_method="median",
                          k_neighbors=10, numeric_distance= euclidean ,
                          categorical_distance= hamming
                          missing_neighbors_threshold=0.8)
    df_aws[ wire_l ] = dfwire_l

    dfvolume = knn_impute(target=df_aws[ volume ],
              attributes=df_aws.drop([ volume ], 1),
                          aggregation_method="median", k_neighbors=10,
                          numeric_distance= euclidean ,
                          categorical_distance= hamming ,
                          missing_neighbors_threshold=0.8)
    df_aws[ volume ] = dfvolume

# run model
X = df_aws.drop([ high ,  width ,  depth ], 1)
y = df_aws.drop([ tension ,  velocity ,  weld_velocity ,  wire_l ,  volume ], 1)
```

```
# estimators
ESTIMATORS = {
    "Linear regression": LinearRegression(),
    "Ridge": Ridge(alpha=1.802e-01),
    "Lasso": Lasso(alpha=1.802e-01),
    "ElasticNet": ElasticNet(random_state=0, alpha=1.802e-01),
    "LARS Lasso": LassoLars(alpha=1.802e-01),
    "Bayesian Regression": BayesianRidge(),
    "SVR poly": SVR(kernel= poly , C=1e3),
    "SVR rbf": SVR(kernel= rbf , C=1e3),
    }

# Create an empty dictionary to collect prediction values
y_test_predict = dict()
y_mse = dict()
mim_y = 2.0
df_model_error = pd.DataFrame(index=[*ESTIMATORS])

for i in range(1, 7):
    iteration =  iter +str(i)
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33,
                            random_state=42)
    for name, estimator in ESTIMATORS.items():
    if name ==  SVR poly :
            multiestimator = MultiOutputRegressor(SVR(kernel= poly ,
                              C=1e3, degree=i))
        elif name ==  SVR rbf :
           multiestimator = MultiOutputRegressor(estimator)
        else:
      multi = MultiOutputRegressor(estimator)
      multiestimator = make_pipeline(PolynomialFeatures(i), multi)
    # fit() with instantiated object
        multiestimator.fit(X_train, y_train)

        # Make predictions and save it in dict under key: name
        y_test_predict[name] = multiestimator.predict(X_test)
        y_mse[name] = float(mean_squared_error(y_test,
                           multiestimator.predict(X_test)))
        print(   RMSE for  ,name,  were  ,y_mse[name])
        y_round = round(y_mse[name],2)
        filename =  models/ +name+ _ +str(iteration)+ .model
        # save model
        joblib.dump(multiestimator, filename)

    df_model_error[str(i)] = pd.Series(y_mse, index=df_model_error.index)

df_model_error.to_csv( model_error.csv )
```

E. REINFORCEMENT LEARNING CODE

```
import random
import numpy as np
import pandas as pd

class Qtable:

    num_episodes = 10000
    max_step_per_episode = 100

    learning_rate = 0.1
    discount_rate = 0.99

    exploration_rate = 1
    max_exploration_rate = 1
    min_exploration_rate = 0.01
    exploration_decay_rate = 0.001

    rewards_all_episodes = []

    df_exp1 = pd.read_csv( parte 1/final/aws_a5_1_all.csv )
    df_exp2 = pd.read_csv( parte 2/final/aws_a5_2_all.csv )
    df_aws = pd.concat([df_exp1, df_exp2])

    def __init__(self, state, init_action_values):

        self.__obj_state = state
        self.__values = init_action_values
        self.__init = init_action_values
        # values min and max  tension ,  wire rate ,  welding velocity
        self.__extrem_val =[(17,32),(4.8,8.2),(6.2,13.4)]
        # making q-table
        df_state = self.df_aws[[ high ,  width ,  depth ]]
        # index states < high ,  width ,  depth >
        self.state_list ={}

        # columns actions < tension ,  wire rate ,  welding velocity >
        self.action_list = [ +++ , --- , === , ++= , =++ , +=+ , -++ , +-+ ,
                             ++- , +-- , -+- , --+ , +== , =+= , ==+ , =-- ,
                             -=- , --= , -== , =-= , ==- , -+= , -=+ , +-= ,
                             =-+ , =+- , +=- ]

        self.__q_table = pd.DataFrame(columns=self.action_list)

    def calc_reward(self, state):
        dif = 0
        # permited error
        e = 0
```

```
        for i in range(0, len(self.__obj_state)):
            dif += abs(self.__obj_state[i]-state[i])
        return -1*(dif - e) + 10

    def get_action(self, state):
        # get new action
        return pd.Series.idxmax(self.__q_table.loc[state,:])

    def get_weld_values(self, action):
        # variation are values for eachs welding parameter variation
        # variation = (3, 1, 2)
        variation = (2, 1, 1)
        result = [0, 0, 0]
        for index, act in enumerate(action):
            if act ==  + :
                result[index] = self.__values[index] + variation[index]
            elif act ==  - :
                result[index] = self.__values[index] - variation[index]

            if result[0] < self.__extrem_val[0][0]:
                result[0] = self.__extrem_val[0][0]
            if result[0] > self.__extrem_val[0][1]:
                result[0] = self.__extrem_val[0][1]
            if result[1] < self.__extrem_val[1][0]:
                result[1] = self.__extrem_val[1][0]
            if result[1] > self.__extrem_val[1][1]:
                result[1] = self.__extrem_val[1][1]
            if result[2] < self.__extrem_val[2][0]:
                result[2] = self.__extrem_val[2][0]
            if result[2] > self.__extrem_val[2][1]:
                result[2] = self.__extrem_val[2][1]

            self.__values = result
        return result

    def check_state_exist(self, state):
        string = str(state[0])+str(state[1])+str(state[2])
        if string not in self.state_list.keys():
            # append new state to q table
            self.state_list[string] = state
            self.__q_table = self.__q_table.append(
                pd.Series(
                    [-10]*len(self.action_list),
                    index=self.__q_table.columns,
                    name=string,
                )
            )
    # method for offline train
    def get_volume_wirel(self, tupla):
        df_temp =  self.df_aws.loc[(self.df_aws[ tension ] -
                    tupla[0]).abs().argsort()].dropna()
        df_temp = df_temp.loc[(df_temp[ velocity ] -
```

```
                   tupla[1]).abs().argsort()].dropna()
        df_temp = df_temp.loc[(df_temp[ weld_velocity ] -
                   tupla[2]).abs().argsort(),
                                    [ volume , wire_l ]].dropna()
        return df_temp.iloc[0][ volume ], df_temp.iloc[0][ wire_l ]

    def prox_value(self, tuple):
        dict_list ={}
        for index, row in enumerate(self.state_list):
            dict_list[round(abs(row[0] - tuple[0]) + abs(row[1] - tuple[1]) + \
              abs(row[2] - tuple[2]),2)] = index
        sort_dic =sorted(dict_list)
        return dict_list[sort_dic[0]]

    def find_dict_key(self, state):
        for key, val in self.state_list.items():
            if state == val:
                return key

    def learn(self, name, env):
            Q learning algorithm
        # states ( high ,  width ,  depth )
        state = (2.18, 5.48, -2.95)
        self.check_state_exist(state)
        for episode in range(self.num_episodes):

            reward_current_episode = 0

            for step in range(self.max_step_per_episode):
                # exploration-explotation trade-off
                exploration_rate_threshold = random.uniform(0, 1)
                key_state = self.find_dict_key(state)
                if exploration_rate_threshold > self.exploration_rate:
                    index = np.argmax(self.__q_table.loc[key_state,:])
                    action = self.__q_table.columns[index]
                else:
                    index = np.random.choice(len(self.action_list))
                    action = self.action_list[index]

                weld_parameters = self.get_weld_values(action)
                # learning offline
                vol, wire = self.get_volume_wirel(weld_parameters)
                # tension  velocity    volume  weld_velocity  wire_l
                weld_parameters.insert(2,vol)
                weld_parameters.append(wire)

                # return < depth ,  high ,  width >
                new_state = env.predict([weld_parameters])
                new_state = [round(new_state[0][1], 2),
                 round(new_state[0][2], 2),
                 round(new_state[0][0], 2)]
                reward = round(self.calc_reward(state),2)
```

```
                # Update Q-table for Q(s, a)
                print(   step %s of %s ,(step, self.max_step_per_episode))
                self.check_state_exist(new_state)
                key_state_new = self.find_dict_key(new_state)
                self.__q_table.loc[key_state, action] = self.__q_table.loc[key_state,
                                       action] * \
                              (1 - self.learning_rate) + \
                               self.learning_rate * (reward +
                               self.discount_rate *
                               np.max(self.__q_table.loc[
                                          key_state_new, :]))

                state = new_state

                reward_current_episode += reward

                if reward >= 10:
                    break

            # Exploration rate decay
            self.exploration_rate = self.min_exploration_rate + \
                (self.max_exploration_rate - self.min_exploration_rate) * \
                np.exp(-self.exploration_decay_rate * episode)

            self.rewards_all_episodes.append(reward_current_episode)
```