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Detection of asynchronies in mechanical ventilation by predictive analysis: Applications in Machine Learning

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Abstract. This study aims to present the detection of asynchrony in mechanical ventilation through predictive analysis using machine learning technology. In which the mechanical ventilator is responsible for the improvement of gas exchange and the reduction of respiratory difficulty presented by the patient. With the use of a mechanical ventilator, a relatively common phenomenon can occur, known as patient ventilator asynchrony (PVA), where there is a mismatch between the ventilatory needs demanded by the patient's respiratory center. For this, a literature review on the topic was carried out, which refers to a case study through materials and articles accessed in the virtual environment with the help of research platforms such as Google Academic, Scielo and Pubmed, so that the asynchrony could be analyzed. ventilator patient (VPA) in mechanical ventilator equipment (MV), its classification and management, as well as the interaction for the knowledge of health professionals for a better identification of asynchrony, with the incremental possibility of using machine learning technology (Learning of machine). Therefore, the graphical introduction by machine learning is one of the premises of this article, so that predictive analyzes help the nurse or clinical staff to detect and distinguish more quickly and practically the occurrences of asynchrony, identifying the patterns and having the solutions so that it can better assist the patient in a moment of crisis. As a result of the article, the implementation of the reported analysis models can help to fight the new coronavirus pandemic (COVID-19), since it is possible to predict the necessary configurations for these patients, once with the projected model and in effective functioning, a challenge to be described is the development of the machine learning method applicable in the software of current fans and also a model with the necessary processing capacity for this technology.

Keywords. Big Data, double trigger, deep learning, late cycling, ineffective effort.

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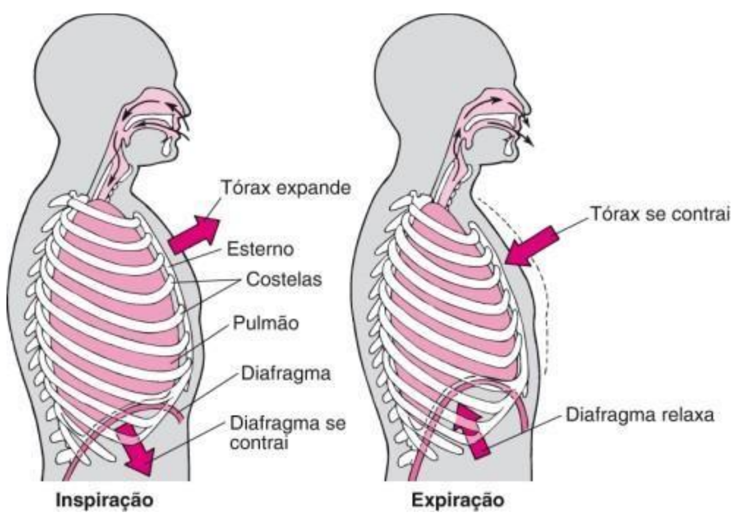
Introduction.

According to Pereira (1996), the main function of the pulmonary ventilator is to send air to the lungs, allowing the exchange of gases that should occur naturally and also assisting in the movement of expiration, removing pressure, acting as an artificial lung replacing the patient's deficient lung.

Human respiration occurs because of the various processes that the human body performs, among them, gas exchanges are carried out by the cardiovascular system and the movement of the lungs due to the respiratory system. During the inhalation of air, the diaphragm contracts and lowers along the intercostal muscles, increasing the ribs causing an increase in the rib cage. During exhalation of air, the pressure inside the lungs decreases, the ribs return to their natural position, and the air is expelled through the airways. (PEREIRA, 1996).

Figure 1 - Diaphragm functioning in breathing



Source: (MSD, 2021)

According to Carvalho, et al (2007), mechanical ventilation (MV) is a support technique for the treatment of patients with acute or chronic respiratory failure. It can be classified as invasive mechanical ventilation (IMV), where an endotracheal tube or a tracheostomy cannula is used. Non-invasive ventilation (NIV) uses a mask to connect the patient to the mechanical ventilator. (BRAZILIAN INTENSIVE MEDICINE ASSOCIATION, 2013).

The mechanical ventilator is able to improve gas exchange and slow down the respiratory difficulty presented by the patient, allowing the restoration of the lungs and

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airways and avoiding complications in clinical procedures. (BRAZILIAN INTENSIVE MEDICINE ASSOCIATION, 2013).

There are references to the use of artificial airways since 2000 BC, however, it was only at the end of the 19th century, with the worldwide outbreak of poliomyelitis, that mechanical ventilation became a therapeutic modality, where subatmospheric pressure ventilation was distributed around the patient's body to assist their respiratory muscles. (SLUTSKY, 2015).

In 1876, Alfred Woillez developed the first functioning iron lung, however the first lung to be widely used was the one developed by Drinker and Shaw in 1929, for the treatment of patients with poliomyelitis. (DRINKER, SHAW, 1929).

Figure 2 - Iron Lung developed by Philip Drinker (1894-1972) in 1930-1939.

Source: (COLLECTION, 2021)

Mechanical ventilation is one of the most frequently performed procedures in the ICU environment, being essential for maintaining the life of patients with acute respiratory failure. (WUNSCH, et al, 2010).

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Figure 3 - OrangeMed, Inc NKV-550 Mechanical Ventilator

Source: (ORANGEMED, 2020)

In turn, ventilator patient asynchrony (VPA) is a decoupling between the ventilatory needs demanded by the patient's respiratory center and the adjustments that are programmed in the mechanical ventilator, which may be demands of time, flow and/or pressure, in which it is considered a relatively common phenomenon, with incidence rates between 10% and 85%. (HOLANDA, MARCELO ALCANTARA, et al, 2018).

Because it is a condition that can develop several complications, which can lead the patient to death, in this way it must be detected quickly and with high accuracy. (CARVALHO, 2021).

According to Rocha et al. (2018), The interaction between the patient and the mechanical ventilator can make achieving the main objective easier or more difficult. Programming the IMV for the patient is not a simple process, as it takes into account the pathophysiology and evolution of the disease. Time is normally only considered a "battle" with the mechanical fan.

PVA is defined as “a lack of coordination between two events (initiation of patient effort and mechanical ventilator assistance) that should occur at the same time.” (GAROFALO et al., 2018).

The most common types are triggering, such as ineffective effort; self-trigger and double-trigger, premature or late cycling, and insufficient or excessive flow. All are detected by visually

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inspecting the volume-time, flow-time and pressure-time curves, all respectively on the mechanical ventilator screen. (HOLANDA, MARCELO ALCANTARA, et al, 2018).

Where, according to Holanda, Vasconcelos, Ferreira and Pinheiro, et al (2018), the ventilator's gas supply must fully meet the patient's needs, but this interaction of the patient and mechanical ventilation depends on the ventilator's response to the patient's respiratory effort, which in turn depends on the patient's response to ventilator breathing. If this patient-ventilator coordination fails, install an asynchronous system.

Ineffective triggering is when the ventilator cannot recognize the patient's effort, an invalid trigger occurs. It may occur due to insufficient effort or insufficient sensitivity configuration, that is, respiratory muscle weakness, dynamic hyperinflation (auto-PEEP), mechanical inspiration time longer than the patient's nerve time, or nerve command inhibition. This can happen during inspiration or expiration. Double triggering occurs in 2 consecutive patient-triggered respiratory cycles, the interval between which is less than half of the mean inspiratory time (IT), and the mechanical inspiratory time is relatively short compared to the patient's nerve time. (HOLANDA, MARCELO ALCANTARA, et al, 2018).

In turn, the self-triggering happens when the ventilator is turned on and the patient does not need to make any effort. May be related to extended expiration time without PEEP, cardiogenic oscillation, hiccups, low trigger threshold, water in the circuit, or leaking in the circuit. Flow asynchrony is the desynchronization that occurs whenever the flow of the ventilator does not match the flow of the patient.

Unsynchronized flow is a common problem and inspiratory flow is probably the most frequently incorrectly programmed ventilation parameter. (HOLANDA, MARCELO ALCANTARA, et al, 2018).

Finally, insufficient inspiratory flow occurs when the regulated flow cannot be increased by patient effort, as in the volume control (VCV) mode. In pressure control (PCV) and pressure support (PSV) modes, this happens when pressure adjustments are insufficient, related to the balance between demand and the patient's ability to ventilate. Excessive Inspiratory Flow: Occurs in the VCV when the flow is greater than required by the patient, or in the PCV or PSV due to high pressure or rapid rise time. (HOLANDA, MARCELO ALCANTARA, et al, 2018).

Figure 4 – Example of ineffective effort asynchrony

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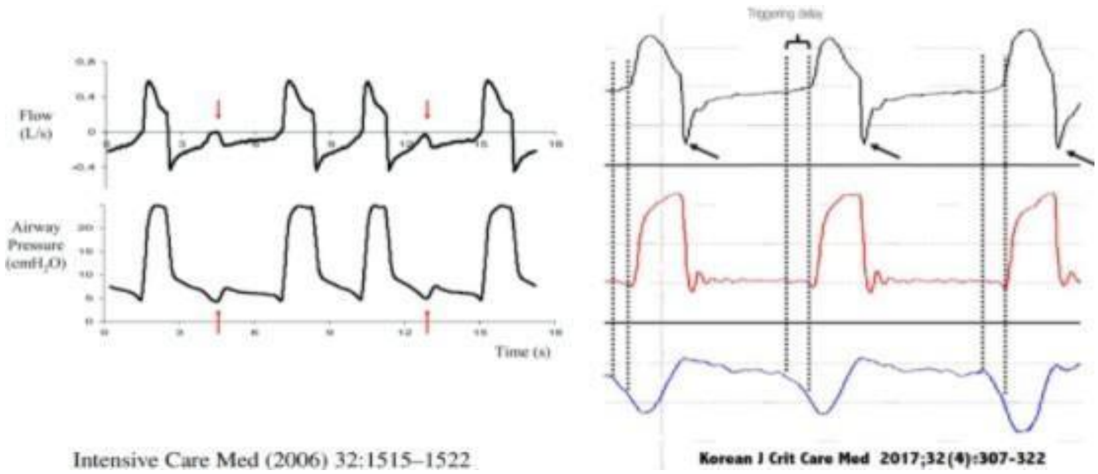

Source: (THILLE et al, 2006)

Asynchrony can cause several adverse clinical effects, such as discomfort, dyspnea, worsening of gas exchange, increased work of breathing, diaphragmatic muscle damage, sleep interference, increased need for sedation and neuromuscular blockade, increased ventilation time, and increased mortality. (HOLANDA, MARCELO ALCANTARA, et al, 2018).

For the result to have a positive reach, patients undergoing ventilatory support need to understand the principles of mechanical ventilation, at the same point it is necessary to keep in mind the needs and care of patients, as well as broad communication between team members. physician about the goals for that patient, about their therapy, plans for weaning and about the patient's tolerance for changes in ventilatory parameters. The nurse is responsible for monitoring the ventilator, thus having the function of observing the type of ventilator, the control modalities, its tidal volume parameters, respiratory rate and fraction of oxygen inspiration. (RODRIGUES, et al., 2012).

Therefore, the presence of nurses is fundamental in ICUs, while their presence has been increasingly distanced from ventilatory support, “perhaps because of the numerous attributions they are deprived of, or because there is another professional category providing this type of assistance, as well as as by the deficiency of their knowledge”. (RODRIGUES, et al., 2012).

An increasing number of studies have demonstrated a low percentage of VPA recognition using waveform analysis. (COLOMBO et al., 2011). Furthermore, the recognition rate is inversely related to the prevalence of VPA in recognition surveys of asynchrony analysis by characteristic curve recognition among professionals. (RAMIREZ, et al., 2017). “In our study, the percentage of HCPs who were able to identify all VPAs was quite low” (19.5%). (RAMIREZ, et al., 2021).

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The effectiveness shown in studies carried out involving Machine Learning (ML) for the automatic identification of thoracoabdominal asynchrony in children, allows us to relate to graphic analysis and asynchrony in mechanical ventilation. (RATNAGIRI, et al., 2021).

Machine learning is a branch of computer science that deals with algorithms that learn from experience and improve their performance over time. The focus is to use the language to detect patterns in the data, aiming at automating the most complex tasks and/or making predictive models. (ARAUJO, et al., 2020).

Unlike machine learning, which after having the input data interpreted and passed on to decision making and there is an output, when this data passes the input, it is forwarded to what are known as hidden layers and, in deep learning, the system will be arranged in several hidden layers, that is, the data will pass through several branches and nodes in order to have an even greater filtering and precision in the system's output. This type of system can address and relate several features, for example, an image can be represented by intensity value per pixels, set of edges, regions of particular shape, etc. These distinct characteristics, when arranged and analyzed by a deep learning system, make the result more reliable since several variables are evaluated in the patterns studied by the system, making the prediction more and more accurate. (ONGSULEE, 2017).

In this work, machine learning technology plays the fundamental role of interpreting the data as it is provided or from previously granted data, and using it to reduce the probability of asynchrony during the use of a mechanical ventilator, by deducing a possibility of occurrence when performing an analysis of the data itself and acquired learning, avoiding several complications resulting from the treatment. (SHOBHA, RANGASWAMY, 2018).

As with the different models of mechanical ventilation equipment, there are three types of machine learning that can best adapt to a given situation and/or demand, namely:

Supervised machine learning: a learning method where a set of data is previously provided, where they will be adopted as a standard and used as a reference for the data to be later analyzed. (SHOBHA, RANGASWAMY, 2018).

Unsupervised machine learning: method of learning where there is no human intervention on the data collected and used when there is a large amount of unlabeled data to be interpreted. (SHOBHA, RANGASWAMY, 2018).

And reinforcement learning: a learning method where there is no sample or previous data set, it is developed through trial and error, receiving help in its deductions about what is correct and what is incorrect. (SHOBHA, RANGASWAMY, 2018).

Predictive analytics is the application of algorithms to understand the structure of existing data and to generate prediction rules. Its application of algorithms to understand the structure of existing data and generate prediction rules. Algorithms are used to estimate f and to minimize reducible errors. Whether they are less flexible or more flexible. (SANTOS, et al, 2019).

Neural networks work as a complex system to assist in the learning and assimilation of machine results by making connections between data through "nodes". The system obtains and/or stores different results over time and these data, whether structured or not, can be better verified by the machine, since through the analysis of the data linked to the corresponding nodes, a pattern is identified that corresponds to the information present in your neural network. (MEHLIG, 2019).

Neural networks are an example of Machine Learning. Neural networks work in such a way that the input of the system receives all the data provided, which will be compared to patterns previously added in the network and a decision will be made through activation, this will be passed on in the network to other connected neurons that at the same time end of the process, at the output of the system, being then linked to each neuron in an output layer, making a prediction possible. (MEHLIG, 2019).

This technology is already widely implemented in the world today, very linked and used to Big Data, both machine learning and neural networks and other similar methods that use large amounts of data, whether structured or not, already use this technology for different branches, such as YouTube video recommendations, where the simple act of not watching the video until the end will have its interpretation by the system, which will be adapting to make better recommendations based on your taste, the same goes for other streaming brands like Netflix and Spotify. Even some personal task organization applications already implement such systems, giving recommendations on when to do them. The possibilities offered by these systems make many complex tasks more organized, concise and clean, as well as more accurate. (MORISSO, 2021).

As an example for the development of a prediction model using machine learning and deep learning, we can mention a prediction of hospitalization cases caused by dengue in Paraíba. Monthly hospitalizations caused by dengue were used as a database, as were monthly rainfall, rainfall, information on water and sewage from previous years, and sewage collection and treatment rates. "To carry out the study and analysis carried out by the system, it was divided into

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several phases and models, making a vast and quick analysis of its database, where the corresponding adjustments were made for the predictions and statistical results". (BATISTA, 2021).

"In some of these scenarios, it was defined whether there would be treatment of unusual observations. Therefore, candidate models were proposed, with: number of hospitalizations, monthly rainfall, sewage collection index and sewage treatment index. With this data, logs (past information for attributes) were added with data from the last few months. Once the models were defined, they were subjected to training through specific techniques, with two hidden layers with 250 neurons being added. Finally, the data were separated into 80% training and 20% testing and, at the end of training, predictions were generated and an error rate was generated using an appropriate technique". (BATISTA, 2021).

In this way, the graphical introduction by machine learning is one of the premises of this article so that the predictive analyzes help the nurse to detect and distinguish more quickly and practically the occurrences of asynchrony, identifying the patterns and having the solutions so that he can better attend the patient in a moment of crisis.

This study aimed to analyze ventilator patient asynchrony (VPA) in mechanical ventilator (MV) equipment, its classification and management, as well as the interaction for the knowledge of health professionals for a better identification of asynchronies, with the incremental possibility of using of machine learning technology.

Materials and methods.

For the creation of this article, the research methodology used was a bibliographic review, which refers to a case study through materials and articles accessed in the virtual environment with the help of research platforms such as Google Scholar, Scielo and Pubmed.

Among the scientific articles chosen, a series of studies and analyzes will be carried out, so that the article is finalized with the greatest amount of information and content, thus creating a better view of problems and solutions around asynchrony in mechanical ventilation.

Finally, a code was generated within the Python software to analyze and identify possible asynchronies in mechanical fans.

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Results and discussion.

In this pilot study, we propose that Machine Learning, using predictive analysis of values monitored by the ventilator, can be an efficient tool in detecting asynchronies and assisting the clinical staff in the identification and management of patients on mechanical ventilation.

Thus, we saw in the research that there is a great difficulty for professionals who work with mechanical ventilation to correctly detect and identify asynchronies, in such a way that it implies the adjustment of adequate parameters for the management of patients in asynchrony situations. Historically, asynchronies are directly linked to patient mortality on invasive mechanical ventilation, thus opening possibilities for the development of tools or strategies to assist professionals in the correct interpretation of the graphs indicated by the ventilator, allowing a better parameterization and management of such patients and reflecting on the mortality rate.

Considering that the concept of Machine Learning is a computational tool for data analysis that allows an algorithm to learn from experience and improve its performance over time, we developed this pilot study to justify the use of ML can be applied to Asynchronies in Invasive Mechanical Ventilation being an efficient tool in detecting asynchrony parameters and signaling to users.

The research explored a method of predictive analysis of data that presented satisfactory results and that can be applied to data extracted from ventilation parameters that are monitored by current and most common ventilators in the Brazilian market such as Flow (L/s) and Airway Pressure in (cmH2O), for example. In addition to these parameters, it will be necessary to correlate physiological parameters of each patient in the algorithm, such as predictive weight, height and age.

According to Abujaber et al (2020), machine learning techniques were used to compare the performance between the models and compared to previous studies so that the recommended model achieved better performance and high practicality in supporting clinical decisions. The study aims to introduce a machine learning model that predicts the mortality of patients in the hospital on mechanical ventilator (MV) followed by moderate to severe head trauma.

The study used the following performance comparison techniques: Linear Regression (LR), Random Forest (RF), Artificial Neural Networks (ANNs), C.5 Decision Tree and Support Vector Machines (SVMs) and to conduct the analysis SPSS Modeler 18.2 was used. To prevent overfitting and validate the performance, the data were partitioned into a training model and a test model, the partitioning was performed by analytical software.

The data used were trauma records, from the raw records, a data preparation was carried out with a selection pre-processing where the selection variables were separated, data cleaning and data transformation, from which the partition was performed data in training and testing. In the modeling and evaluation phase, the process was subdivided into two strands, one of Linear Regression (LR) in which the model performed the training, calibration and test of the model, where the model evaluated the significance of the variables, the odd ratio and the importance of predictors. The other branch of Artificial Neural Networks (ANNs), in which it also carried out the training, calibration and testing process of the model.

Based on this, the study went on to the last analysis phase, the visualization and development phase, the models generated Tabulated Models with test results. The results obtained were that both models (Linear Regression and Artificial Neural Networks) with accuracy above 80%, however the linear regression model reached a better general performance compared to the model of artificial neural networks. Finally, it was concluded that the linear regression model was chosen for its best response in the study.

And according to Venkata, et al (2021), the machine learning model was trained and tested with clinical data from feline and canine patients under mechanical ventilation to predict the settings according to the variations in the settings for various respiratory conditions aiming patient survival. The model was successful in generating parameter values for the fan used, with the average of the predicted values and after many tests, thus obtaining values close to the expected.

The study used the technique of Artificial Neural Networks (ANN), where the model has 3 layers, an input layer, two hidden layers and an output layer, in which the selected parameters were the input base that passed through the model and had its predicted data in the output output, based on that, a check was carried out regarding errors and deviations, if any were found, the GPSO was carried out to improve and correct the values so that they could return the input base for a new test.

The model's projection started from the data collection with the patients' observations and the mechanical ventilator settings, after that the filtered values were divided into two strands, an inverse mapping test and the data training with 200 ANN's and reaching the latest updates with the GPSO to improve the performance and training of the ANNS, after the GPSO model has the values, they are estimated and, finally, an error check is carried out.

Finally, the model must be able to predict the parameters of a mechanical ventilator for different respiratory conditions, once the data are available. In view of the novel coronavirus (COVID-19) pandemic, the study by Venkata, et al (2021), reports the feasibility of the article to predict the necessary settings for these patients aiming at a better respiratory condition.

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The use of the Artificial Neural Networks technique as a tool to predict physiological parameters in felines showing that it can be a technique to predict the detected asynchronies and indicate corrections in the parameterization of the ventilator.

A challenge for the implementation of the concept is to develop a method to apply in the software of current fans and what is the necessary processing capacity for this technology.

For this article, the production of a test prototype was designed to demonstrate the expected result of a predictive ML model, to perform it it was necessary to create a fictitious database for testing that had the following parameters x and y, x being the time in seconds and y the flow of air in liters per minute. Thus, with the projected data, the database was tested in a table to verify if it generated a graph similar to the asynchrony selected for testing (Double Trigger), when corresponding with the previously described assertions, the base was tested in Python code, working and being recognized as a table, a graph was generated and it was saved as an image, finally returning as an image with a description registering “Double Trigger” as text.

To identify an asynchrony within the MV, a prototype model was created using Python, where the premise was that the model represented the final phase of a predictive analysis of an ML model by artificial neural networks, in which the data coming from the MV were analyzed. by the model itself and at the output tip were recorded in a graph that would then return to the user as an image already demonstrating the possible asynchrony. After analyzing the graph, the MV could send a notification or automatically adjust the necessary patterns to correct the recorded asynchrony, thus improving the quality of service and improving the user experience.

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Figure 5 - Example of asynchrony identified by the prototype

In [1]:

```
import pandas as pd
df = pd.read_csv('tcc_base_teste.csv')
df.head()
```

Out[1]:

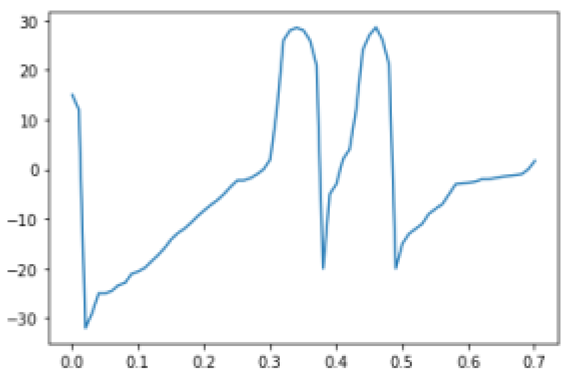
	x;y
0	0.001;15
1	0.011;12
2	0.021;-32
3	0.031;-29
4	0.041;-25

In [13]:

```
import numpy as n
import matplotlib.pyplot as plt

data = np.genfromtxt("tcc_base_teste.csv", delimiter=";", names=["x", "y"])
plt.plot(data['x'], data['y'])

plt.savefig('assindd1.jpg')
```



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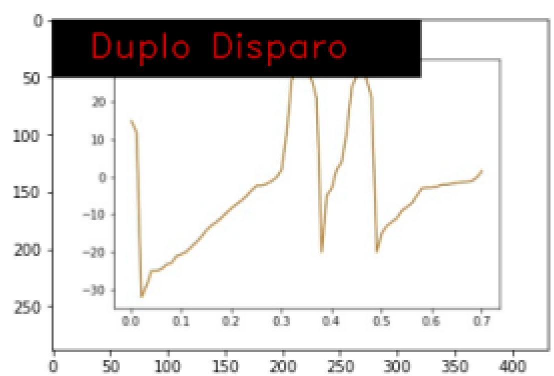
```
In [16]:
import cv2
import numpy as np
import matplotlib.pyplot as plt

img3 = cv2.imread('assindd1.jpg')

x,y,w,h = 0,0,320,50

# Create background rectangle with color
cv2.rectangle(img3, (x,x), (x + w, y + h), (0,0,0), -1)

# Add text
cv2.putText(img=img3, text="Duplo Disparo",org=(x + int(w/10),y + int(h/1.5)), fontF

plt.imshow(img3)

Out[16]: <matplotlib.image.AxesImage at 0x1fc106901c0>
```



Source: (Own Author, 2022)

Conclusion.

After analyzing the case study, it will be possible to implement solutions to correct asynchrony problems in mechanical fans (MV) using Machine Learning, as its functions and capabilities can improve the effectiveness of the MV. Due to the great evolution of ventilators and ventilatory techniques, patients had their health and quality of life expanded, so new ideas and techniques have been studied to further improve this process. One of the biggest problems found is in fact the asynchrony generated between patient-machine, where the machine's effort to help the patient may be insufficient or vice versa. Thus, the application of Machine Learning to correct this phenomenon will be of paramount importance, since the excess effort of both the patient and the machine would be discarded, maintaining the comfort and safety of the patient. It is worth mentioning that knowing the type of asynchrony that is occurring is essential, because,

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with the right direction, the device can be corrected, leading to a better use, among the errors mentioned during this analysis, we have: Ineffective shooting; Double trigger; Auto trigger; Stream asynchronies; Insufficient inspiratory flow and Excessive inspiratory flow.

Thus, it is possible to conclude that the use of Machine Learning along with the prototype could detect these failures and automatically create a solution or alert the person in charge to carry out a preventive correction of the system, avoiding possible complications generated by the various types of asynchronous errors.

Disclosure. The authors report no conflicts of interest in this work.

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