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Smart Belt Design by Naïve Bayes Classifier for Standard Industrial Protection Equipment Integration

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ABSTRACT

One of the main objectives of various companies between the industrial sector is the reduction of accidents, ranging from minor injuries to the death of workers. In order to prevent previously affected hazards, the fusion of Internet of Things and Industry 4.0 technologies has been chosen, being key tools for the detection and notification of personnel of anomalies detected in the environment, generating Industrial Protection Equipment (PPE) with the ability to predict, detect and report anomalies in the environment. This article proposes the design of a belt capable of being integrated into standard industrial protection equipment, this component being able to detect the operator's condition from the presence of falls thereof, detection of noise levels, gas detection Toxic and notifications to the worker or nearby personnel of the anomaly detected. The information collected is processed by Artificial Intelligence (AI) techniques through Cloud Computing, highlighting during the investigation process the Naïve Bayes classifier to detect real risk situations in risk environments, alerting with 90% accuracy about different situations that can put the life of users at risk.

Keywords: OHS, Condition monitoring, Artificial Intelligence, Naïve Bayes, e-Health.

Computing Classification System: Hardware Integrated circuits Interconnect Input / output circuits. Information systems Information systems applications Decision support systems Expert systems.

1 Introduction

The objective of the proposed device is contributing to the field of occupational safety and health (OHS) as an additional tool, reducing the probability of suffering illnesses, injuries, absences caused by accidents in working hours or fatal accidents which impede the performance of the worker during his daily activities(Leonavičiūtė, Dėjus and Antuchevičienė, 2016)(Grant, Christianson and Price, 2007) . Likewise, it contributes to aspects of the application of intelligent systems focused on the early detection of risks in the worker's environment along the addition of models responsible for predicting or notifying the presence of risks detected with a better precision.(Sánchez, Vara, Criado, González, Tejedor and Corchado, 2019)(Sánchez, 2019) Therefore, it is essential to notify these results to the worker or staff, so communication components are incorporated to transmit and receive the information between the electronic system and Cloud Computing techniques.(Sánchez, Rodriguez and Manuel, 2020)
The rest of this paper is organized as follows: Section Related Work reviews the state of the art. The hardware architecture and system connections are described in Section Methodology. Section Discussions and conclusion outlines the conducted case study conclusions are drawn from the results.

2 Related works

The key factors in the increase of work accidents are consequence of the lack of individual protection equipment, worker's performance and the knowledge of the operator about the safety and health conditions in his work. Although the use of ropes and safety harnesses has been proposed in building sectors, these have shown inefficiencies in building sectors where the worker needs more autonomy and mobility (Leonavičiūtė et al., 2016). The use of protective equipment in industrial and construction sectors has been implemented with the objective of decreasing injuries and fatal dangers in the worker, however there are aspects which, if not detected in time, can cause long-term consequences in the worker. In view of this situation, the implementation of electronic components in PPE and PPE has been proposed, detecting risks in the environment thanks to the information gathered by the sensors that act as agents in the environment (Podgorski, Majchrzycka, Dabrowska, Gralewicz and Okrasa, 2017).
The use of intelligent PPE is designed to predict and detect anomalies in the worker's environment. In order to achieve this, it is essential that the worker is able to adapt to current technological capabilities, i.e. that the devices or Smart PPE are comfortable and allow for worker mobility. (Chabot, Delaware, McCarley, Little, Nye and Anderson, 2019) (Akbar-Khanzadeh, Bisesi and Rivas, 1995) As seen in (Barro-Torres, Fernández-Caramés, Pérez-Iglesias and Escudero, 2012) implement PPE with the ability to transmit information between components implemented in the operator's clothing in order to ensure the correct use of PPE in the operator.
The detection of accidents in the workplace is essential to reduce the rate of fatal accidents in the industry, for this reason the use of accelerometers, gyroscopes and magnetometers have been implemented to analyze the abrupt changes in position to provide a notification by messaging or issuing sound alerts to nearby personnel (Krupitzer, Sztyler, Edinger, Breitbach, Stuckenschmidt and Becker, 2019). These components are usually integrated into helmets,

arms or waist. The use of fall detection systems has not only been established for worker care, it has been considered in the detection of falls in older adults, estimating that the cost of treating falls in older adults. Given this, the detection of falls has been detected by devices used in everyday life. (Mellone, Tacconi, Schwickert, Klenk, Becker and Chiari, 2012) uses cellular devices to use accelerometers, gyroscopes and magnetometers to identify falls or abrupt movements in older adults, notifying the individual through an audible alarm or SMS messaging the detection of fall in real time. It also mentions that the algorithm responsible for detecting falls has not been evaluated in real environments. Another case is presented by (Luo and Hu, 2004), which proposes the use of an algorithm for fall detection, which receives information from an accelerometer incorporated into a belt for the detection of falls in older adults.

Designs a belt for analyzing the previous body postures (Prado, Reina-Tosina and Roa, 2002), mobility and the energy expenditure of the worker by an embedded system integrated to the belt to identify causes that lead to falls of the worker or how changes in daily activities alter the physical state of the worker. This concept was implemented by (Williams, Doughty, Cameron and Bradley, 1998), where píezoelectric shock sensors are implemented to detect the impact and a mercury tilt switch to detect the orientation of the individual when a fall occurs. (Sabatini, Ligorio, Mannini, Genovese and Pinna, 2015) implements a barometric altimeter sensor in order to detect the vertical speed and body height, identifying modifications in the movement of the individual in order to detect impacts caused by falls of the individual, identifying true positives and true negatives during the analysis process. (Wu and Xue, 2008) implements a fall detector interconnected with an inflatable device, the method proposed in this investigation is the detection of falls based on the exceeding of a pre-set threshold value, detecting the probability of a fall event with a time less than 70 ms before impact.

With the implementation of Industrial Internet of Things (IIoT) in the industrial sector it is possible to provide PPE with the ability to transmit the information obtained to a web server where the information is stored and processed. Although it is possible to analyze the detection of falls depending on whether the value obtained by the embedded system exceeds an established threshold value or using techniques of Machine Learning (ML) and Supervised Learning, the latter being more sophisticated generating results with greater accuracy (Sarma, 2009) (Pozna, Precup, Tar, Škrjanc and Preitl, 2010) proved to be successful in various applications. This is done thanks to the previous compilation of information, which is processed by means of Neural Network (NN) models, Convolutional Neural Networks (CNN), Decision Trees, Random Forests, etc. This last one can be visualized in (Nam, Kim and Kim, 2016) where techniques of Big Data are implemented in a smart belt with the objective of analyzing the abnormal indices of obesity depending on the position of the carrier of this device. (Fang, Li, Luo, Ding, Luo and Li, 2018) proposes the use of a model in charge of checking and determining the use of PPE for steeplejacks by means of computer vision. In order to prevent falls during maintenance operations, it proposes an ASC classifier to detect steeplejacks that are passing through a window, and then a Convolutional Neural Network (CNN) classifier is used to judge whether a steeplejack is carrying safety equipment. Thanks to the implementation of ML and Supervised Learning it is possible to provide PPE with the predictive capability, focusing

its capabilities to be implemented as a Predictive Industrial Protection Equipment (PPPE), obtaining a result with greater accuracy with respect to the implemented ML models (Nowaková, Prílepok and Snášel, 2017) (Gil, Johanyák and Kovács, 2018).
It is also possible implementing sensor fusion which generates consequently higher accuracy in AI techniques because they provide additional information to the user's environment. As shown in (Gjoreski, Lustrek and Gams, 2011), accelerometers integrated to embedded systems, placed in the arm or waist of the individual were implemented in order to detect positions that suggest the fall of the individual, improving the accuracy of the implemented AI techniques. (Boutellaa, Kerdjidj and Ghanem, 2019) implements the fusion of wearable sensors using a covariance matrix for feature extraction, highlighting an efficiency in fall detection. (Huang, Chen and Liao, 2018) proposes the use of an electronic system placed on the belt of the individual with fall detection capability based on body behavior, in this case the device presents an accuracy of 70-80% when implementing Vector Support Machines.
During the process of obtaining data in real environments it is essential not to overfit the models implemented in ML because they can present problems in real applications compared to the evaluation stage (Krupitzer et al., 2019). During the data collection process, the different situations in which the sensor correctly detects the presented situations must be investigated, that is, by means of tests it has the capacity to detect those situations that represent the 4 possible cases: (Noury, Fleury, Rumeau, Bourke, Laighin, Rialle and Lundy, 2007)

- True Positive: The fall occurs and is detected
- False Positive: A fall is detected by the device but does not occur
- True Negative: No drop detected by the device and no drop declared
- False Negative: A fall occurs and the device does not detect it

3 Methodology

The methodology used for the development of the electronic system is the methodology of Systems Software Embedded Platforms (SPES) under a quantitative approach (Pohl, Broy, Daembkes and Hönninger, 2016), with the purpose of identifying the different components that make up the requirements that such a system must have, the design, and logical and technical aspects. According to this, the requirements viewpoint is focused on the design of an electronic system located in the worker's belt, which monitors, through sensors, the worker's environment and his/her posture when performing such tasks.
From the functionality viewpoint, the capacity of this electronic system is described. In this case, the information is communicated through IEEE 802.11 protocols, using the coverage range provided by this technology and its response capacity to the device. The information transmitted from the device is stored in a local server in order to present the chief personnel with a history of the anomalies detected during a period of time. In the database configured to store the information, this information is retransmitted to be processed by means of Cloud Computing techniques, ending up with the result of the monitoring of the device, which is

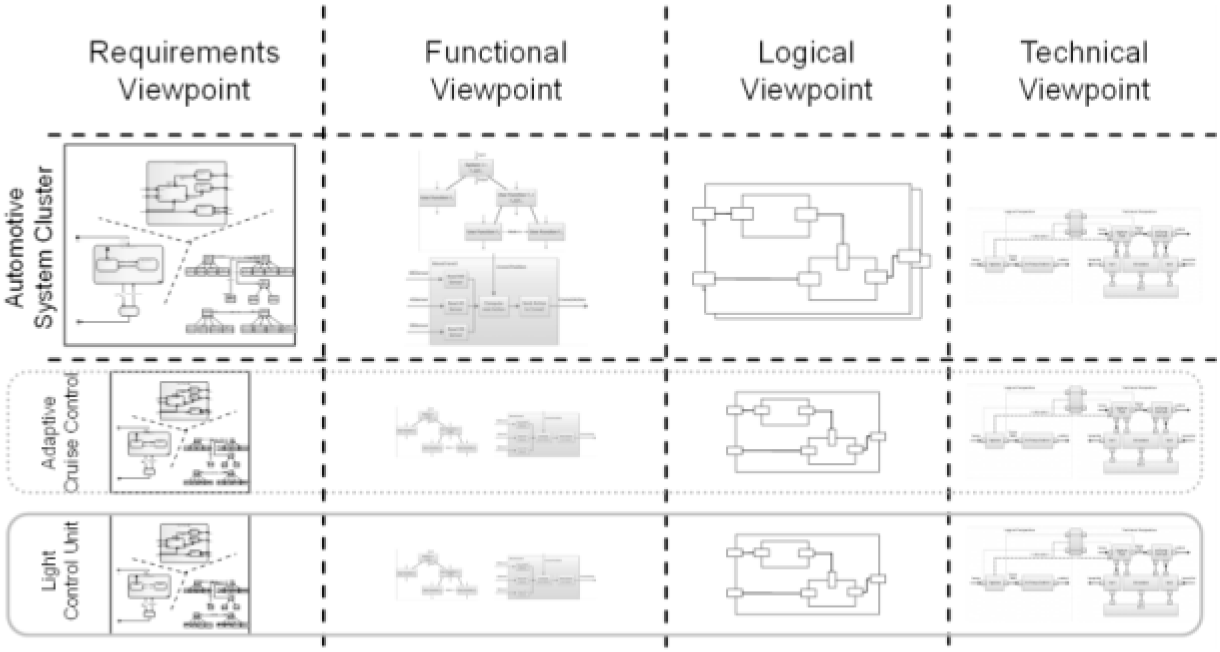

Figure 1: Software Platform Embedded Systems (SPES) Methodology.

transmitted to the worker's electronic system to issue a notification to the latter or to nearby personnel in order to take precautionary measures.

3.1 Electronic system

In the technical viewpoint, the use of an ATMEGA microcontroller is established in order to collect and process the information received from the sensors which are responsible to monitor the worker's environment. In this case the MPU6050 sensor was used, which contains an accelerometer and a MEMS gyroscope, presenting a 16-bit resolution, which means that it divides the dynamic range into 65536 fractions, these apply for each X, Y and Z axis. In the case of detection of sounds at high frequencies, a KY-038 sensor is used, which is a transducer that converts the sound waves into electrical signals, incorporating a microphone together with an LM393 comparator, which allows the reading of both an analog and a digital value. Additionally, a button is integrated to the electronic system with the purpose of alerting anomalies detected by the worker. In the aspect of detection of harmful gases in the area is implemented a sensor BME680, responsible for measuring both the environmental temperature, the presence of moisture and barometric pressure of the environment. These components are integrated with each other in order to provide monitoring of the operator's environmental conditions. The information transmission component is an ESP32 module, which integrates IEEE 802.11 and IEEE 802.15 technologies in order to transmit the information collected from the components described above to a local server. Likewise, in order to notify the personnel that wears this electronic system or people close to it, a horn is integrated to emit beeps to notify about the detected anomaly. In order to provide a visual alert to the worker or staff attached, a WS2812 Integrated Light Source is added to the electronic system which integrates RGB LEDs with a controller chip in a small surface mount package controlled through a single cable. Finally, at this stage the above components are integrated into a circuit along with a 3.7V lithium battery as a power source as shown, see Figure 2.

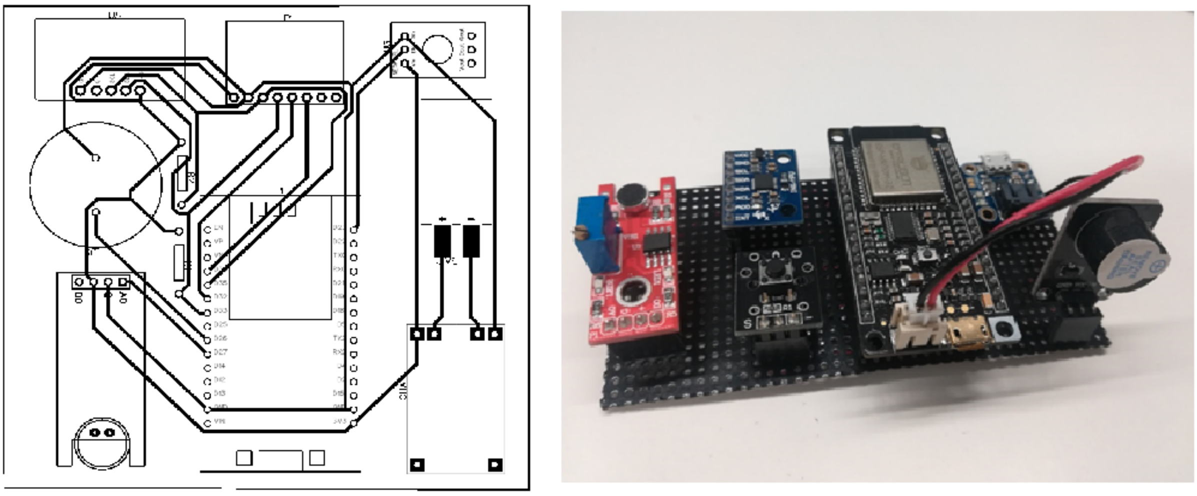

Figure 2: Electronic system circuit design.

3.2 Logical Viewpoint

The logical viewpoint of the electronic system collects information from the components responsible to monitor the worker's environment as well as the energy percentage of the lithium battery. Specifically, in case of detecting a battery percentage lower than 15%, a color code is emitted on the LED strip integrated to the belt in order to notify the low battery of the electronic system. After collecting the information, it is transmitted to the local server via JSON. Likewise, with the aim to notify the worker previously about the detected anomaly, threshold values are established to report the anomaly detected in the first instance. If the anomaly is confirmed by means of Cloud Computing, the information is retransmitted to the electronic system, being notified more frequently by the device.
During the modeling process the methodology Cross Industry Standard Process for Data Mining (CRISP-DM) was used, see Fig. 3. (Kelleher, Mac Namee and D'arcy, 2015).
The process of the methodology is described below, from understanding the data to modelling and evaluation. The data used in the information acquisition system are:

- Battery
- Decibels
- Axis Difference
- Button

For each of the possible situations to which the worker is subjected in an environment that ranges from normal to a hostile point, labels were created to determine the current situation of

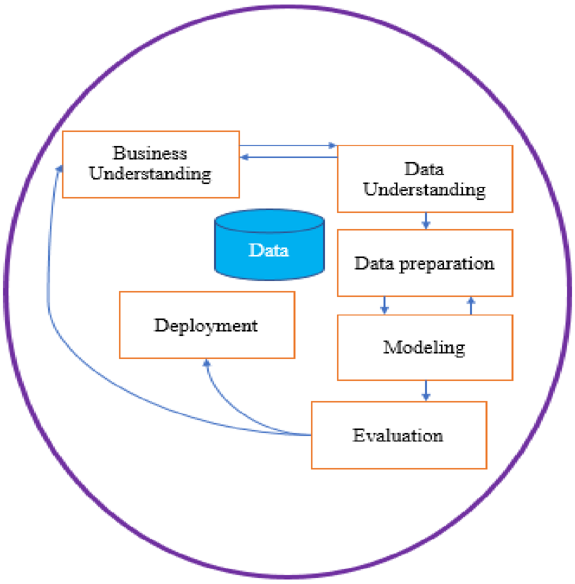

Figure 3: CRISP-DM methodology, used in the development of a bayesian model for the creation of a smart belt

the personnel, Table 1. These labels represent modeling through supervised learning where no clustering of information is required.
What corresponds to the data cleaning were used boxplots to find the data set that was not acquired by the electronic system correctly, Fig. 2 and Fig. 3.

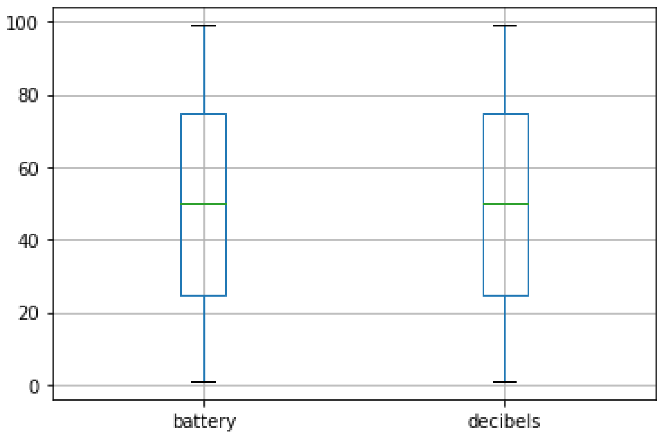

Figure 4: Boxplot for battery and decibels in system data acquisition

They show the boxplot once the data cleaning is done, also, the lines with missing information are eliminated.
In addition the analysis of variance begins with the concepts of linear regression. The analysis of variance permits us to determine if the different treatments show significant differences or if, on the contrary, it can be supposed that the means of their population do not vary (Tarrío-Saavedra, Naya, Francisco-Fernández, Artiaga and Lopez-Beceiro, 2011). Analysis of variance overcomes the limitations of two-way pairwise comparisons, which are a poor method of

Table 1: Labels created depending on the problems presented in the work environment

Problem recorded in the environment	***Label created***
Low Battery	1
Z-axis difference greater than low value	2
Z-axis difference greater than average value	3
Z-axis difference greater than high value	4
High decibels	5
Panic button on	6
Low battery & difference on Z axis greater than low value	7
Low battery & difference on Z axis greater than average value	8
Low battery & difference on Z axis greater than high value	9
Low battery and high decibels	10
Low battery panic button activated	11
Difference on Z axis greater than low value and high decibels	12
Z-axis difference greater than mean value & high decibels	13
Z-axis difference greater than high value & high decibels	14
Z-axis difference greater than low value & emergency button activated	15
Z-axis difference greater than mean value & emergency button activated	16
Z-axis difference greater than high value & emergency button activated	17
Panic button activated & high decibels	18
Z-axis difference greater than low value & high decibels & low battery	19
Z-axis difference greater than mean value & high decibels & low battery	20
Z-axis difference greater than high value & high decibels & low battery	21

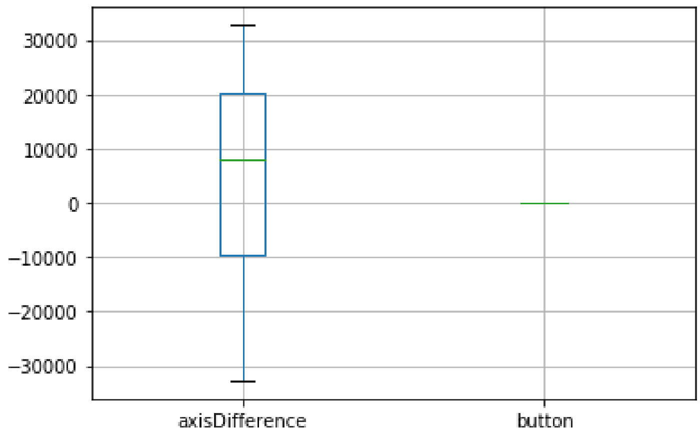

Figure 5: Boxplot for axis difference and button in system data acquisition

determining whether a set of variables with $n > 2$ differ from each other, see Fig. 4 where the Anova analysis is performed on one of the descriptive variables to find significant differences on the labels.

In the same way, the analysis of Fisher allows us to establish significant differences over pop-

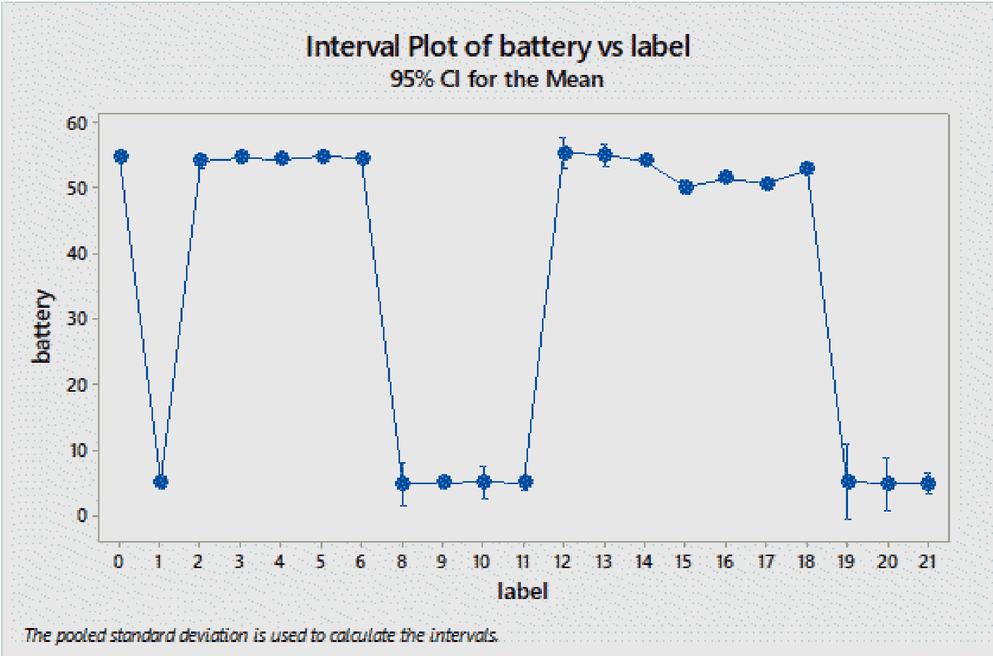

Figure 6: ANOVA, analysis of variance of each descriptive characteristic with respect to the dependent variable

ulations, our labels, with the ability to identify whether characteristics are shared in similarity (Raymond, 1995).

Fisher Pairwise Comparisons

Grouping Information Using the Fisher LSD Method and 95% Confidence

label	N	Mean	Grouping
12	459	55.20	A B
13	855	54.940	A B
5	4240	54.738	A B
0	25664	54.693	A
3	5283	54.530	A B
6	25788	54.460	A B
4	33571	54.256	B
2	2590	54.066	A B
14	5572	54.062	A B
18	11717	52.728	C
16	6091	51.451	D
17	36504	50.495	E
15	2945	50.059	E
19	79	5.152	F
10	399	5.085	F
1	2514	5.0796	F
9	4015	4.9843	F
11	2663	4.9726	F
21	1084	4.8967	F
8	251	4.873	F
20	153	4.869	F

Figure 7: Fisher, contingency analysis with respect to the number of labels given

See Fig. 5 where it can be seen that in reality there are not 21 populations or labels, there are 5 as they share significant characteristics.

3.3 Naïve Bayes Modelling

Naïve Bayes can be trained very efficiently in a supervised learning environment. Parameter estimation for Naïve Bayes models usually uses the maximum likelihood method. The mathematical basis is described in Eq.(1) (Liu, Blasch, Chen, Shen and Chen, 2013).

$$P(y|x_1, \cdots, x_n) = \frac{P(y)P(x_1, \cdots, x_n|y)}{P(x_1, \cdots, x_n)} \tag{3.1}$$

it can be assumed that Eq. (2).

$$P(x_i|y, x_1, \cdots, x_{i-1}, x_{i+1}, \cdots, x_n) = P(x_i|y) \tag{3.2}$$

for the i-th, this is simplified as follows in Eq. (3).

$$P(y|x_1, \cdots, x_n) = \frac{P(y)P(x_i \prod_{i=1}^{n} |y)}{P(x_1, \cdots, x_n)} \tag{3.3}$$

Given that $P(x_1, ..., x_n)$ is static given the input, it is use sorting rule Eq. (4) and Eq. (5).

$$P(y|x_1, \cdots, x_n) \alpha P(y) \prod_{i=1}^{n} P(x_i|y) \tag{3.4}$$

$$\hat{y} = arg \max_{y} P(y) \prod_{i=1}^{n} P(x_i|y) \tag{3.5}$$

For the current work it was implemented the Gaussian Naïve Bayes algorithm for classification. The probability of the features is assumed to be Gaussian Eq. (6).

$$P(x_i|y) = \frac{1}{\sqrt{2\pi\sigma_y^2}} exp(-\frac{(x_i - \mu_y)^2}{2\sigma_y^2}) \tag{3.6}$$

Once the model is implemented, it is evaluated against the classic measures in the literature, precision, recall and f1-score, see Table 2 where the score of each class on the evaluation measures is observed.

The analysis of ROC (receiver operating characteristic curve) curves are commonly used to present results for binary decision problems in machine learning. ROC curves constitutes a statistical method to determine the diagnostic accuracy of these tests, to determine the cut-off point of a continuous scale at which the highest sensitivity and specificity is achieved, to evaluate the discriminative ability of the diagnostic test and to compare the discriminative ability of two or more diagnostic tests that express their results as continuous scales (Davis and Goadrich, 2006) (Cerda and Cifuentes, 2012). See the Fig. 6 showing the ROC curve for each class, the performance of the Naïve Bayes

Table 2: Evaluation measures for Naïve Bayes in the dataset

	precision	recall	f1-score	support
0	0.82	0.94	0.88	13667
1	0.71	0.95	0.81	2420
2	0.99	0.74	0.85	1235
3	0.98	0.87	0.92	7787
4	0.75	0.97	0.85	2114
accuracy	0.87	34488		
macro avg	0.88	0.86	0.85	34488
weighted avg	0.89	0.87	0.87	34488

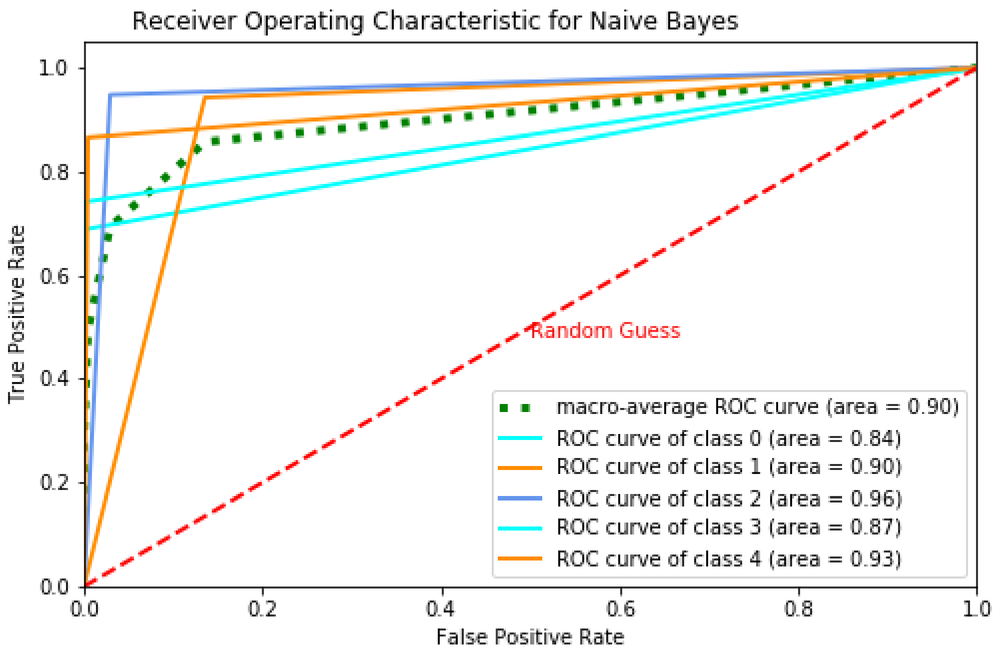

Figure 8: ROC curves for each of the classes represented in the dependent variable

4 Discussions and Conclusions

In (Nam et al., 2016) proposed to develop a wearable device, called Smart Belt, for life-logging, monitoring and analyzing living body data with personal big data processing. In (Krafft, Kullgren, Lie and Tingvall, 2006) studied if there were differences in seat of the driver belt use between cars with and without smart seat belt reminders (SBR).
There are several reasons why accidents of human origin are caused, however in (VAN CHARANTE and MULDER, 1990) three hundred workers who had had at least one injury in the previous 3 years and 300 matched controls were asked about their current use of alcohol, tranquilizers, and cigarettes. Where alcohol consumption, hearing loss greater than 20 dB, and loud noise greater than 82 dB(A) were found to be safety hazards. At this shipyard, the

risks attributable to noise and hearing loss together ac counted for 43% of the injuries. Contrary to the above, this study does not establish whether there is a connection between addictions or the living of the workers conditions. The model is focused on the work environment which can be of risk in different areas.

As well as in (Borges, Barroca, Velez and Lebres, 2009), they presented solutions for WSN applications, and design aspects in the context of patient monitoring. The solution presented whose primary function is to collect the vital data remotely from the various sensors in low-rate wireless personal area network (LR-WPAN) is based on the IEEE 802.15.4 standard. In contrast to the present work where a communication through specialized modules in the transmission and reception of information for Internet of the Industrial Things was used.

Finally in (Noury, Barralon, Virone, Boissy, Hamel and Rumeau, 2003) their purpose was to automatically detect in real time the fall of the person from a single device, worn on the trunk in the *para sagittal* plane. The device includes 2 accelerometers, an 8 bits RISC microcontroller, a buzzer and a push button. It was serially linked to a RF-modem. It was tested on 10 healthy young persons in 15 different situations and exhibits good specificity and sensibility. Compared to the current work has an important simulation, one of the main objectives of the belt is to detect when the worker is at risk due to the geographical area in which it is, ie, falls have to be classified in a specific range to avoid falling into false assumptions, the Naïve Bayes proved to be very effective in cross validation with an accuracy of 90%.

Workplace accidents are a very important problem for worker's care, due to various factors that represent a risk to them. One component to reduce these causes is the implementation of protective measures, especially where it is not possible to determine standards to ensure the integrity of the individual. As a result, it is important to use PPE, such as belts, helmets and other devices that protect the physical integrity of the operator. In view of this, the implementation of an electronic system for the detection of anomalies in the workplace can be an essential support for the care of personnel. Likewise, by means of Artificial Intelligence techniques it is possible to improve the predictive capacity of the electronic system, placing it as an essential step for the improvement of equipment by implementing emerging technologies in PPE.

This article provides the design of an electronic system, which has the ability to detect falls by means of a gyroscope and accelerometer, as well as the ability to detect noise harmful to the human eardrum, transmitting the information collected by the electronic system to a database hosted in the cloud, in addition to implementing Cloud Computing techniques in order to obtain the resulting prediction of these parameters. One of the aspects to highlight during the research process can be the fusion of sensors in order to provide information about the fall of the operator with greater accuracy than that presented by a single device, because it can provide a significant change when verifying whether a fall occurs or is just a false positive. Likewise, an essential component for the reduction of accidents is the continuous training of the workers before the changes produced during the development of a construction, being essential the acquisition of knowledge regarding the prevention measures, experiences of other users or knowledge regarding the correct use of PPEs.

Naïve Bayes being a model that implies that the presence or absence of a particular characteristic is not related to the presence or absence of any other characteristic, given the variable

class.
Naïve Bayes has an acceptable performance in terms of multi-class classification, for the current job a set of 21 different characteristics were presented in work environments with risk of falling or being in conditions where the air or volume in decibels was a danger to the worker. The model classified with an average of 90% accuracy under ROC curves, this implies the improvement in the safety services provided to industrial areas.
The reduction in populations, the number of labels, for any model represents an improvement in model learning, and as shown in the assessment table, Naïve Bayes is a model with a performance greater than 85% even when the data sets are not balanced. This is extremely important, since the world around us is never balanced.

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