Research Article

A hybrid approach of intelligent systems to help predict absenteeism at work in companies

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Abstract
In recent years, several surveys have been conducted on absenteeism and how this affects the routine of conducting productive operations in companies. Therefore, having criteria for predicting absenteeism at work can help managers in contingency actions reduce financial losses due to the absence of a worker in their workplace. The objective of this work is to apply the artificial intelligence concepts of a regularized fuzzy neural network, which combines the benefits of artificial neural networks with the fuzzy set theory to obtain more accurate results in predicting corporate absenteeism. The database called absenteeism at work, taken from the UCI Machine Learning Repository, which captured elements of a Brazilian company, was applied in a fuzzy neural network model that allows the calculation of the regressors, defining the estimate of the lack of hours of an employee. The results of the experiments prove that the intelligent model can help in the creation of a specialist system that assists in the prediction of absenteeism.

Keywords Fuzzy neural network · Absenteeism · Extreme learning machines · Regression problems

1 Introduction

Companies seek to reduce costs and maximize profits to remain competitive in the marketplace. Employees are crucial elements for the company to achieve its goals, from the simplest to the highest positions, and all are part of a larger purpose in the organization. One of the most significant problems that affect companies, increasing their costs and making it difficult to achieve their goals, is absenteeism. Absenteeism is considered as the absence of an employee in your work environment [1], in a justified way or not. When the phenomenon occurs, a task, activity, or decision-making may not be performed, and as a result, the costs increase, or the overhead of work for other company employees may result in decreased quality or demotivation of people [2]. Recent research list characteristics that can cause absenteeism at work like Some sickness [3–5] as well as personal reasons [6], financial difficulties [7], lack of motivation [8], incoherent performance of managers [9] among other reasons [10, 11]. Such factors combined can lead to many absences from an employee in their work period. The work of Mangkunegara and Octorend [12] addresses the essential aspects that affect the presence of employees in companies. Already in Da Silva and Marziale [13] and Alharbi et al. [14], the evidence is presented about the lack of people in the nursing area. More recent work, such as Isosaki [15], addresses the absenteeism of the Nutrition and Dietetics Services workers in Brazilian hospitals, and the paper of Simoes et al. [16] cites illnesses that lead to absenteeism among forest company workers. In the literature, there are also works in the last decade that use artificial intelligence

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concepts to make predictions in various ways about the lack of employees for the job, such as Martiniano et al.[17], Rajab and Sharma [18], Martiniano et al. [19] and Ferreira et al. [20]. In this work, absenteeism will be considered an absence of work related to diseases justified by a medical certificate, in the same way, that was done in the work of Martiniano et al. [17], including using its base as a reference for the appropriate analyzes.

The fuzzy neural networks are considered promising for using neural networks together with fuzzy logic. Thus the learning and computational power of the neural networks, the capacity for representation, and the reasoning of the fuzzy logic are combined [21]. They can act as pattern classifiers such as the Souza [22] and de Campos Souza et al.[23] model that treats real bases using the neuron and nullneurons, respectively. De Campos Souza and De Oliveira [24] who use the neural network model based on nullneurons and the time series forecasting in Souza and Torres [25] and regression problems Souza et al. [26] using logical neurons. Finally, a regularized version using unineurons is proposed by Souza, Silva and Torres [27] and a pruning model using f-score have introduced by Campos Souza in [28]. Therefore, it is a hybrid model with significant scope and relevance of works done in the literature [29–37]. The objective of this paper was to apply the database collected by Martiniano et al. [17] in a fuzzy neural network model regularized to regression problems seeking to predict absenteeism at work, thus creating a rule-based expert system. The paper is organized as follows: Sect. 2 presents the theoretical basis of absenteeism and neural networks, Sect. 3 presents a fuzzy neural network for prediction of absenteeism in companies, Sect. 4 describes the tests and results of the research. Finally, Sect. 5 presents the conclusions about the work done in the prediction of absenteeism by fuzzy neural networks.

2 Literature review

2.1 Concepts of absenteeism

Absenteeism is a word of Latin origin and means "to be away, away or absent." More directly, absenteeism is nothing more than the absence of the employee in the work environment. The same refers to the number of hours of work lost, whether due to absences, delays, justified or not, which decreases the productivity of companies. The most common causes of this phenomenon are those protected by law, which in this case the employee has the right to be absent from work for reasons such as vacations, marriage, death, and birth, and ignored causes, such as health problems, delays, family factors, or various circumstances that influence the employee's non-compliance with working hours [38]. There is also the unjustified shortage of the worker who generates rebates on his payroll but still can disrupt the operational level of the company. Turnover summarizes theory and research on the links between employees and organizations, including the processes by which employees become linked to work for organizations. These agents differentiate many quality factors within organizations since a significant change in staffing can reveal serious management problems [1]. The employee's frustration with the lack of benefits policy also generates self-reported levels of absenteeism. The same happens not to fulfil its full working day, is motivated to the constant delays or happens to be slow in the fulfilment of its functions [39]. When there is absenteeism at work, the employer often has not only the cost of the employee who is not performing the activity assigned to him but also has to choose not to achieve the production target generated by the absence of the employee in question or replace [17]. In the same way, it can be seen that there is a significant increase in labor costs. Figure 1 shows the present forms of absenteeism in companies.

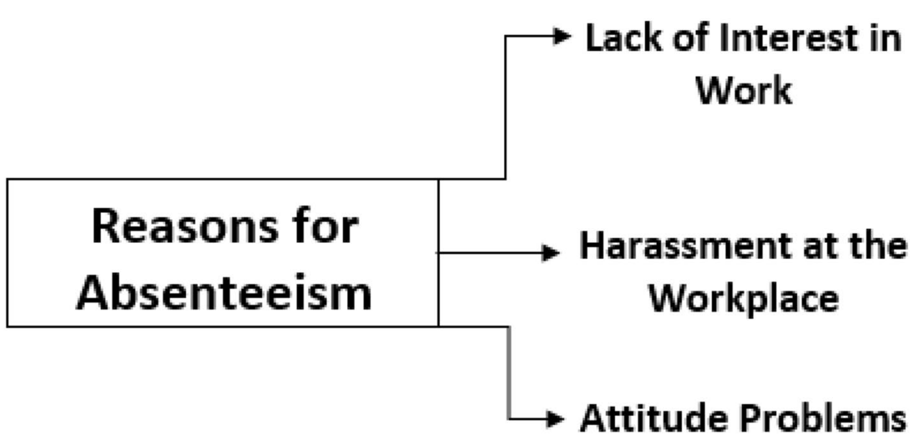


Fig. 1 Main reasons for corporate absenteeism

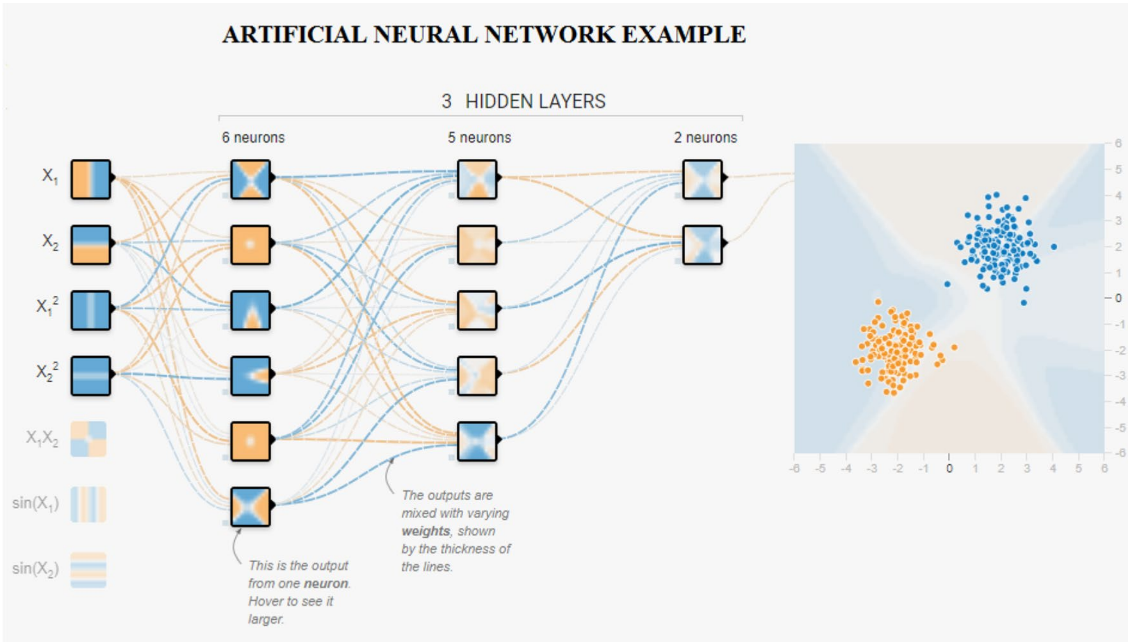


Fig. 2 Artificial Neural Network. Adapted from: https://playground.tensorflow.org/

2.2 Artificial neural networks

Artificial neural networks are computational techniques that present a mathematical model inspired by the neural structure of intelligent organisms and that acquire knowledge through experience. An artificial neural network model may have hundreds or thousands of processing units in its architecture; already the brain of a mammal can have many billions of neurons [40]. A neural network is a computer system composed of interconnected processors (artificial neurons), working in parallel to perform a task employing a nonlinear statistical technique [41]. For this reason, artificial neural networks store knowledge about a theme or set of characteristics, which makes it possible to use related tasks in humans, as it seeks to simulate the behavior of the brain through the learning process. In the area of knowledge, the analogy is made with the forces of connections between neurons, known as synaptic weights [42]. Figure 2 illustrates the format usually used to represent an artificial neural network.

2.3 Artificial neural networks and absenteeism

The concepts of absenteeism and its combination with artificial intelligence techniques have been studied in the literature to provide systems that directly support ways managers act to predict the absence of employees in corporations. Stand out the impact of chest diseases on lack to work [43], in the paper of Karahan and Tetic [44], the total quality program seeks to evaluate relevant characteristics of employee performance in companies, and these indices were assessed through the use of artificial neural networks and data mining techniques. Dynamic systems and models of artificial neural networks evaluated aspects related to the level of satisfaction in the service and therefore aided in the evaluation of absences to the work of the respective employees of a company [45]. The work carried out in [46–50] present studies on absenteeism at work treated through intelligent models.

2.4 Fuzzy systems

The use of fuzzy systems is necessary in cases where the classical approach becomes unfeasible for solving a problem due to the nature of its complexity [51]. Fuzzy systems allow operations usually performed by traditional arithmetic to be implemented in a way that considers the relevance of a variable to its context. The use of membership functions, activation functions, fuzzification, and defuzzification concepts are relevant to the most complex problems that require interpretability [52]. Fuzzy logic is one that mathematically treats inaccurate information usually employed in human communication. It is a multi-valued logic that extends the Boolean logic usually applied in computing [53]. In Fig. 3, we can verify the central concepts related to the fuzzy systems.

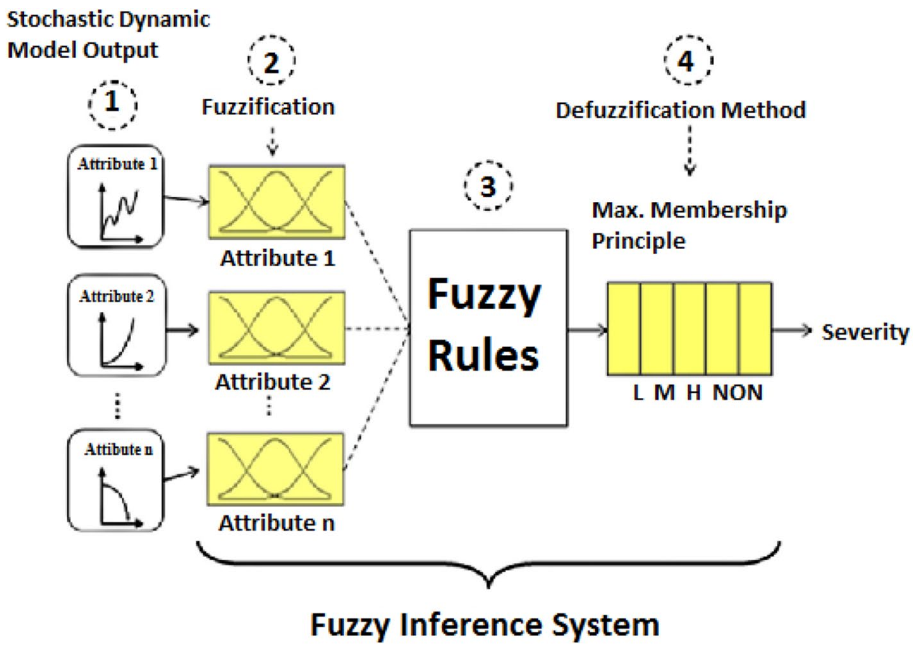


Fig. 3 Fuzzy inference system

2.5 Fuzzy logical neurons

According to Hell et al. [54] numerous models of neurons have been proposed, but their classification is divided into three distinct types, varying according to the use of fuzzy logic concepts in the construction of their structure:

- Fuzzy neurons with non-fuzzy inputs combined with fuzzy weights (Type I).
- Fuzzy neurons with fuzzy inputs that are connected with fuzzy weights (Type II).
- Fuzzy neurons described by fuzzy logic equations (Type III).

Logical neurons are functional units that combine logical aspects of processing with learning ability through the system of fuzzy rules. They can be seen as multivariable nonlinear transformations between unit hypercubes, or $[0,1]->[0,1]^n$ [55]. Thus, neurons and and or (Fig. 4) add the values of fuzzy relevance $\mathbf{a} = [a_1, a_2, \ldots, a_3, \ldots N]$ initially combining them individually with their weights $\mathbf{w} = [w_1, w_2, \ldots, w_3, \ldots N]$, $a, w \in [0,1]^n$ to combine these results in the following way [55]:

$$z = \mathrm{AND}(a;w) = T^n_{i=1}(a_i\ s\ w_i) \quad (1)$$

$$z = \mathrm{OR}(a;w) = S^n_{i=1}(a_i\ t\ w_i) \quad (2)$$

where *S* and *s* are *s-norm* (product) and *T* and *t* are *t-norm* (probabilistic sum).

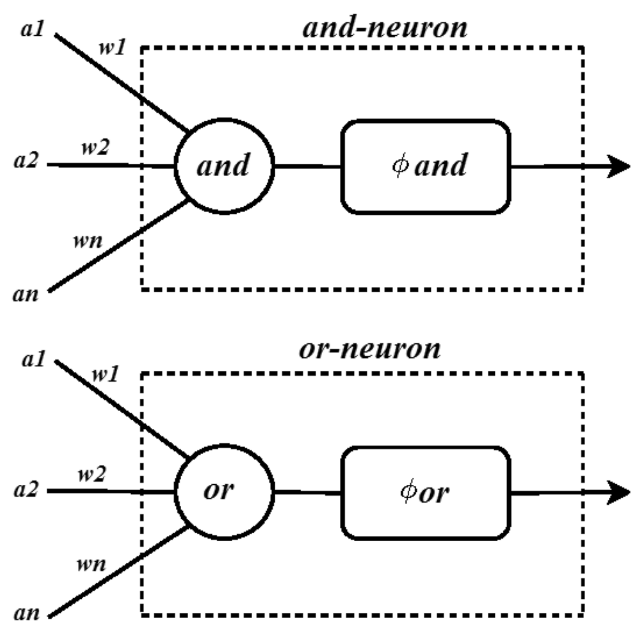


Fig. 4 Fuzzy logical neurons. Adapted from: https://www.semanticscholar.org/paper/Universal-approximation-with-uninorm-based-fuzzy-Lemos-Kreinovich/97a9aecb120f2aee5f9207d677cdc4deac2dd5b0

2.6 Uninorms

In the fuzzy logic, there are moments that the use of calculation operators can improve the model responses. Therefore the flexibilization of its use is a factor that can improve the results of elements that use fuzzy.

The uninorms are the generalization of *t-norms* and *s-norms* by relaxing the constraints related to the neutral elements. Instead of values 0 and 1 for *t-norm* and *s-norm*, respectively, the neutral element is allowed to assume values in the unit interval. One of the main characteristics of the uninorm is that it no longer has the so-called neutral element, now being called the entity element [56]. Through this identity element, the uninorms extend *t-norms* and *s-norms* by varying the value g in the interval between 0 and 1 allowing the alternation between an *s-norm* ($g = 0$) and *t-norm* ($g = 1$). The uninorm used in this work is expressed as follows [56]:

$$U(x,y) = \begin{cases} g\,T(\frac{x}{g},\frac{y}{g}), & \text{if } y \in [0,g] \\ g + (1-g)\,S\left(\frac{x-g}{1-g},\frac{y-g}{1-g}\right), & \text{if } y \in (g,1] \\ \varphi(x,y), & \text{otherwise} \end{cases} \tag{3}$$

and

$$\varphi(x,y) = \begin{cases} \max(x,y), & \text{if } g \in [0,0.5] \\ \min(x,y), & \text{if } g \in (0.5,1]' \end{cases} \tag{4}$$

2.7 Unineuron

The unineuron uses the uninorm concepts to perform more simplified operations according to the activation functions of the fuzzy neurons. Its formatting allows the unineuron to use either concepts of a neuron *and*, or a neuron *or*. [56] explain important concepts about a unineuron. The processing of neurons occurs at two levels. At the first level of L_1 locations, the input signals are combined individually with the weights. In the second, at a global level of L_2, a global aggregation operation is performed on the results of all first-level combinations. Traditional logical neurons use *t-norms* and *s-norms* to perform the described operations.

1. each pair (a_i, w_i) is transformed into a single value $b_i = h\,(a_i, w_i)$;
2. calculate the unified aggregation of the transformed values $\mathbf{U}\,(b_1, b_2 \ldots b_n)$, where n is the number of inputs.

The function p, called relevancy transformation, is responsible for transforming the inputs and corresponding weights into individual transformed values. A formulation for the p function can be described as [57]:

$$p(w,a) = wa + \bar{w}g, \tag{5}$$

using the weighted aggregation reported above the unineuron can be written as:

$$\mathbf{z} = UNI(w;a) = U_{i=1}^{n} p(w_i, a_i). \tag{6}$$

2.8 Fuzzy neural networks models

Fuzzy neural networks are characterized by neural networks formed of fuzzy neurons [58]. These neurons are implemented utilizing triangular rules (*t-norm* and *s-norm*), which generalize the union and intersection operations of classical sets allowing them to be applied in fuzzy sets. Thus, the neural network is now seen as a system interpretable through rules, preserving the learning capacity of the artificial neural network [54]. This type of intelligent model can extract knowledge like the data used in the problem, bringing it to concepts closer to being interpreted by humans. The partitioning of data in the feature space can define the semantic interpretation of the location of the data [55]. Thus a fuzzy neural network can be defined as a fuzzy system that is trained by an algorithm provided by a neural network.

The fuzzy neural networks can be classified concerning how their neurons are connected. This form of connection defines how the signals will be transmitted on the network. In general, there is feedforward where the fuzzy neurons are grouped in layers, and the signal travels the whole network in a single direction, usually from the input of the model to its output generating an expected result. Fuzzy neurons in the same layer have no connection, and their networks are also known as non-feedback networks [59]. This type of connection is the most common among fuzzy neural network models, where we can mention the models developed by Lemos et al. [56, 57], Yucel et al. [60], Silva et al. [61], among others. Finally, some networks are used with feedback, also called recurrently. In this type of fuzzy network, neurons are also gathered in layers, but there is information feed in neurons in the same layer, and may even happen with the fuzzy neuron itself or even in previous layers if they exist. In this type of network, the signal travels the network in two directions, different from feedforward networks and can represent states in dynamic systems [42]. Figure 5 shows the architecture of a hybrid algorithm called ANFIS [62].

The fuzzy neural networks have been used recently in several problems of science. These hybrid models have outstanding performance in problem detection, and extraction of fuzzy rules in the field of breast cancer [63], Pulsar detection [64] and SQL Injection attacks [65]. Therefore, this model has outstanding and extremely varied performance in solving complex problems, regardless of the nature of the problem.

3 Fuzzy neural networks in the prediction of absenteeism in companies

3.1 Fuzzy neural network architecture

The model used in this work is the same one developed by De Campos Souza et al. [25], but the *or* neuron is replaced

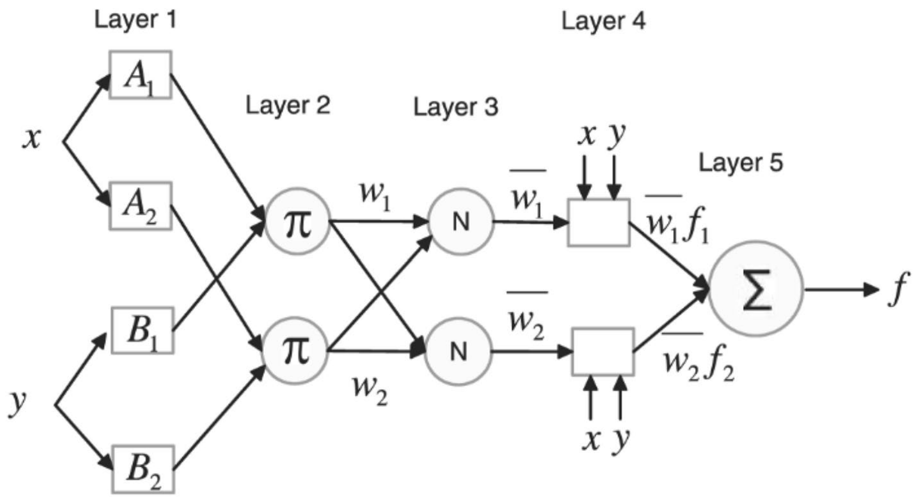


Fig. 5 ANFIS model. Available in: https://www.computer.org/csdl/trans/lt/2012/03/tlt2012030226.html

by *unineuron*, due to its capacity of universal approximation [66, 67]. Although the fuzzy neural network is designed initially for time series problems, the model and the output nature of the linear neuron allows the same model to be adapted so that the output variable is the predictor of the other input variables. The first layer of the fuzzy neural network is formed of neurons whose activation functions are membership functions of the fuzzy sets defined according to the partition of input variables from the genfis technique [62]. For each input variable x_{ij}, M is defined as fuzzy sets A_j^m, m of 1,..., M whose membership functions are the functions of activation of the corresponding neurons, which in this case will be of Gaussian membership functions centered in 0.5. Therefore the outputs of the first layer are the degrees of membership associated with the input values, that is, $a_{jm} = \mu_{A_j}{}^m$ for j=1, ..., N and $m = 1, ..., M$, at where N is the number of inputs and M is the number of fuzzy sets for each input variable [25].

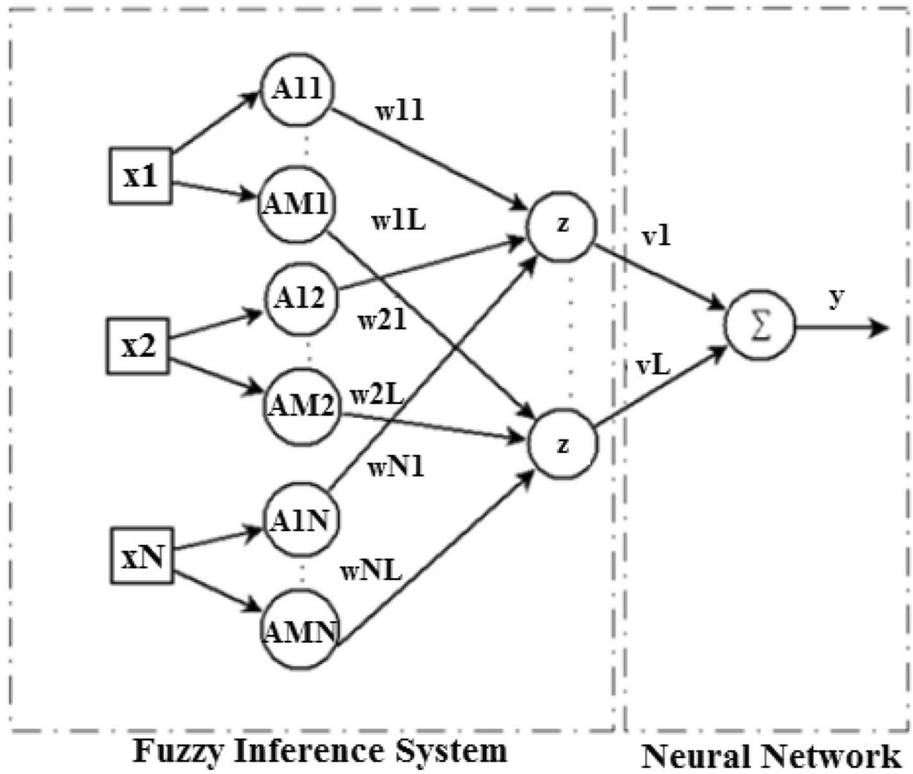
The second layer is composed of neural logic neurons. The unineuron is the neuron using the created network. Each unineuron performs a weighted aggregation of some outputs of the first layer as previously stated. For each input variable j, only one output a_{jm} is set to the lth neuron. Each neuron of the second layer is associated only $n_l < n$ To generate more efficient network topologies [25], the matrix of weights **w** is sparse. To conclude, the third layer constitutes a single-layer artificial neural network responsible for aggregating all the outputs of the fuzzy system of the second layer, providing an output to the network. The network structure is shown in Fig. 6. For this, a linear neuron is used:

$$y = \sum_{j=0}^{l_s} f(z_l v_l) \tag{7}$$

where $z_0 = 1$, v_0 is the bias, and z_j and v_j, $j = 1, ..., l$ are the output of each fuzzy neuron of the second layer and their corresponding weight, respectively.

The training model for fuzzy neural networks based on the model proposed [25], where the model is capable of generating interpretability in the results obtained by the network, suggests a partition of the input data, the using fuzzy logical neurons of the unineuron type and helping in the definition of the network topology we will use an algorithm based on the regularization theory to find the most significant neurons in the model. The algorithm generates a more small network, with the most relevant neurons within the context of the problem and due to the fuzzy logic neurons used. We can visualize the network as a set of incomplete fuzzy rules of the if/then type. The proposed learning algorithm initially defines the first layer neurons by the grid division of each domain interval of the input variables into M fuzzy sets. In the partition by a grid, the strategy is simple: The fuzzy sets are obtained directly through the separation of the input space. In this paper, we are using uniform features of these sets. To avoid the so-called cost of dimensionality [62] because of the exponential relationship between the number of entries and the number of membership functions in this paper, we used the random selection of a membership function for each input variable, where M, in this case, will be twice the value of input space samples, limited to 500 membership functions. Then we use the fuzzy neuron outputs of the model to define many candidate unineurons (L_c) one representing the percentage of L where $L_c < L$. By definition when L<200 used $L_c =$ 100 % of L. Otherwise, the chosen percentage can select candidate neurons. This percentage allows the selection of essential neurons of the first layer [25]. After defining the candidate neurons, the final architecture of the network is defined using the selection of

Fig. 6 FNN architecture



a subset of these neurons using a resampling technique. When performing this procedure, we are performing an optimum subset of values and can be visualized as a variable selection problem, returning the most significant neurons (L_s) based on a cost function. Analogously, we can interpret this selection as the choice of the best set of rules capable of representing the input space. The architecture of the fuzzy neural network is shown in Fig. 6, where the *z*-neurons are unineuron fuzzy rules can be extracted from unineurons according to the following example:

$$
\begin{aligned}
&\text{Rule}_{1:}\ \text{If} x_{i1} \text{ is } A_1^1 \text{ with certainty } w_{11} \ldots \\
&\quad \text{and/or } x_{i2} \text{ is } A_1^2 \text{ with certainty } w_{21} \ldots \\
&\qquad \text{Then } y_1 \textit{ is } v_1 \\
&\text{Rule}_{2:}\ \text{If } x_{i1} \text{ is } A_2^1 \text{ with certainty } w_{12} \ldots \\
&\quad \text{and/or } x_{i2} \text{ is } A_2^2 \text{ with certainty } w_{22} \ldots \\
&\qquad \text{Then } y_2 \text{ is } v_2 \\
&\text{Rule}_{3:}\ \text{If} x_{il} \text{ is } A_3^1 \text{ with certainty } w_{13} \ldots \\
&\qquad \text{Then } y_3 \text{ is } v_3 \\
&\text{Rule}_{4:}\ \text{If } x_{i2} \text{ is } A_3^2 \text{ with certainty } w_{23} \ldots \\
&\qquad \text{Then } y_4 \text{ is } v_4
\end{aligned}
\tag{8}
$$

These rules allow the creation of a building base for expert systems [59].

After the construction of the *L* unineurons the Bolasso algorithm [68] is executed using LARS to select the most significant neurons (called L_s). The final network architecture is defined through a feature extraction technique based on l_1 regularization and resampling. LARS is a regression algorithm for high-dimensional data that is proficient in measuring exactly the regression coefficients but also a subset of candidate regressors to be incorporated in the final model.

An efficient way of identifying which neurons are most activated for the problem is to verify through specific selection techniques using regression methods to which neurons are most relevant to a target problem. Insubstantial dimensional issues such as those of the pulsars, the selection of the best neurons allow the execution of the training to be more efficient, avoiding that unnecessary information is taken to the responses of the model. The LARS algorithm can be used to perform the model selection since for a given value of λ only a fraction (or none) of the regressors have corresponding nonzero weights. If λ = 0, the problem becomes unrestricted regression, and all weights are nonzero. As $\lambda_{\max}$ increases from 0 to a given value $\lambda_{\max}$, the number of nonzero weights decreases to zero. For the problem considered in this paper, the z_{ls} regressors are the outputs of the significant neurons. Bolasso can be seen as a regime of consensus combinations where the most significant subset of variables on which all regressors agree when the aspect is the selection of variables is maintained [68]. Subsequently, following the determination of the network topology, the predictions of the evaluation of the vector of weights' output layer are performed. In this paper, this vector is considered by the Moore–Penrose pseudo-inverse [69]:

$$\mathbf{v} = \mathbf{Z}^{+}\mathbf{y} \tag{9}$$

Z^{+} is the Moore–Penrose pseudo-inverse of **z**, which is the minimum norm of the least squares solution for the output weights.

The procedure synthesized as demonstrated in Algorithm 1. It has three parameters:

1. the number of membership functions, M;
2. the number of bootstrap replications, bt;
3. the consensus threshold, λ.

dimensions evaluated. In these dimensions, data were collected that the experts in the subject judged to be more relevant to define the hours of absence of a worker, among them the disease code, length of service, age, BMI, distance from residence to work, if the employee drinks or smoking, height, weight and level of schooling. The predictor variable in this context is the time in hours of absenteeism.

Two tests were performed, where the first one uses all the attributes of the database and the second one carries out the same evaluation with the ten criteria selected by the Relief algorithm [70]. This selection of the best features is necessary to verify if the decrease of the dimensionality of the problem makes it simpler to be evaluated. Figure 7 represents the flow of the tests performed.

Algorithm 1 FNN training

(1) Define membership functions, M.
(2) Define bootstrap replications, bt.
(3) Define the consensus threshold, λ
(4) Get M^N centers in the first layer using Anfis.
(5) Construct L fuzzy neurons with Gaussian membership functions constructed with center values derived from Anfis and sigma defined at random.
(6) Define the weights and biases of fuzzy neurons at random.
(7) Construct L unineurons with random weights and bias on the second layer of the network by the L fuzzy neurons of the first layer.
(8) For all K input samples do
(8.1) Calculate the mapping z (x_i)
end for
(9) Select significant L_s neurons using the lasso bootstrap according to the settings of bt and λ.
(10) Estimate the weights of the output layer Eq. (9)
(11) Calculate the output of the model using an artificial neuron.
(12) Calculate RMSE (Root-Mean-Square Error) Eq (10).

4 Test prediction of absenteeism

4.1 Database used in the text

The database used in the tests was developed in a doctoral work and published in the [17] and was made available to the developer community in UCI Machine Learning[1]. This base has a total of 740 samples with 21

4.2 Materials and methods

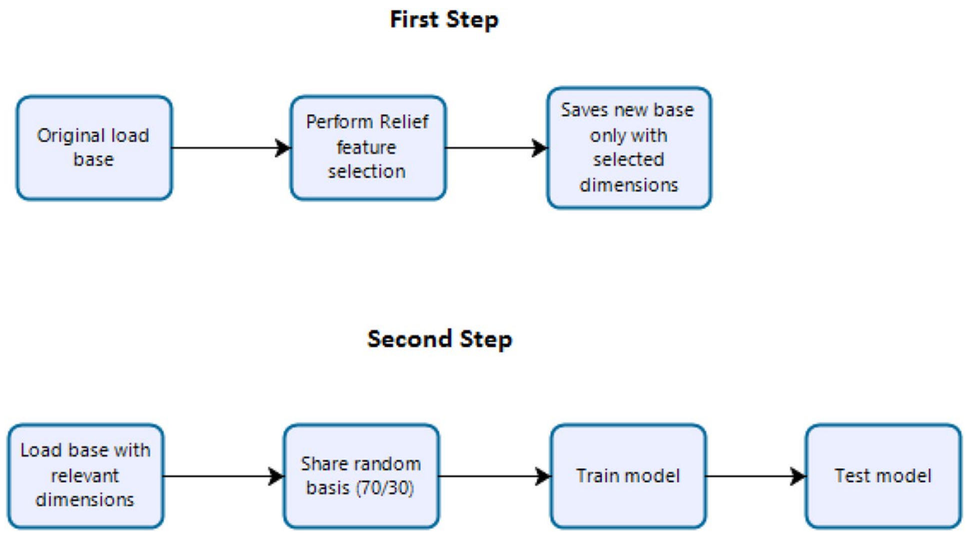
A feature selection method was applied to verify what would be the characteristics of the database using the method Relief[2] on Weka[3]. Figure 8 presents the results of the weights calculated by the technique concerning the attributes collected by the researcher for the definition of absenteeism (highlighting the 10 with the most significant impact).

1 https://archive.ics.uci.edu/ml/datasets/Absenteeism+at+work.

2 For more information on the Relief method, see: [70]

3 https://www.cs.waikato.ac.nz/ml/weka/.

Fig. 7 Feature selection process and absenteeism identification



Attribute Evaluator (supervised, Class (numeric): 21 Absenteeism_time_in_hours):

ReliefF Ranking Filter – Instances sampled: all- Number of nearest neighbours (k): 10

Ranked attributes:

0.2412966 2 Reason_for_absence

0.0376806 5 Seasons

0.0283692 3 Month_of_absence

0.0264045 10 Work_load_Average/day_

0.0062557 9 Age

0.0061428 11 Hit_target

0.0030092 16 Social_smoker

0.0021354 13 Education

0.000827 20 Body_mass_index

0.0004599 18 Weight

Fig. 8 Relief results

To perform the tests, we use a notebook with Intel Core i7 processor, 16 GB RAM, 64-bit operating system, 1 TB HD and 128 GB SSD. We also use MATLAB software to perform the tests presented in this paper.'

Using the base mentioned in item 4.1, we conducted the tests that will be better explained in the next section that follows.

4.3 Tests with fuzzy neural network

A total of 30 randomized replicate tests were performed, dividing the total of 730 samples into 70% for training and 30% for testing. In the execution, the following final results were found, where the result is the average of the 30 measurements and the standard deviation of the test is in brackets. The number of Gaussian membership functions (M) is defined by the cross-validation technique in the range of [3–6]. This range meets the criteria of interpretability proposed in the model so that linguistic characteristics are plausible for interpretation. In the model proposed in this paper, consider bt=32 and λ =0.6 were used (previously defined by cross-validation in previous tests using the range of bt = [8, 16, 32, 64], λ= [0.4, 0.5, 0.6, 0.7, 0.8]) and unineuron (defined by the cross-validation method with 10 k-fold. The best values in 50 replicates were chosen).

Other models capable of acting as regressors were used. Linear regression model (LIN R) and extreme learning machine (ELM) [71] were used for regression problems. Multilayer perceptron (MLP) [72], support vector machine (SVM) [73], and naive Bayes (NB) [74] were used. The experiments were replicated in the tool WEKA [75]. The parameters of the models defined in the Weka were also estimated in preliminary tests using 10-k-fold. The proposed model and ELM are applied in MATLAB. An intelligent model that has come to stand out as a universal approximation of functions was proposed by Ponce et al. [76] and worked with concepts of organic chemistry. The model in question is the artificial hydrocarbon network (AHN). Its only parameter, the number of molecules will be the same number of membership functions used in the fuzzy neural network. Its model is implemented in the R language and is available in the featured address.

Table 1 Result of absenteeism test

Model	RMSE Train.	L	L_s	RMSE Test
FNN	**13.66 (0.98)**	500 (0.00)	186.25 (50.23)	**12.91 (2.30)**
LIN R	13.79 (0.57)	186.25 (50.23)	186.25 (50.23)	14.03 (0.87)
ELM	15.21 (1.18)	186.25 (50.23)	186.25 (50.23)	18.27 (1.80)
SVM	14.54 (0.38)	186.25 (50.23)	186.25 (50.23)	16.28 (2.37)
MLP	15.62 (0.91)	186.25 (50.23)	186.25 (50.23)	17.44 (2.89)
NB	13.35 (0.07)	186.25 (22.10)	186.25 (22.10)	14.89 (2.15)
AHN	14.87 (0.18)	–	–	14.69 (3.65)

Bold values indicate the best test results

For the neural network models used in the tests, the parameters involved in the hidden layers of the model were defined randomly. In the linear regression model provided by WEKA, the initial configurations were maintained. All variables were normalized to zero media and unitary standard deviation. The parameters of the hidden layer were sampled from a uniform distribution Un [– 0.5; 0.5]. In this context, they are evaluated through the mean square error (RMSE). The formula for defining your calculation is shown below:

$$\mathrm{RMSE} = \frac{1}{N}\left(\sum_{k=0}^{n} y^k - y'^k\right)^{\frac{1}{2}} \tag{10}$$

Table 2 Results of the 30 measurements using fuzzy neural networks 10 most relevant dimensions of the database according to Relief

Model	RMSE Train.	L	L_s	RMSE Test
FNN	**8.66 (0.46)**	500 (0.00)	75.14 (22.10)	**8.42 (1.04)**
LIN R	10.24 (2.87)	75.14 (22.10)	75.14 (22.10)	9.31 (1.33)
ELM	11.25 (0.98)	75.14 (22.10)	75.14 (22.10)	10.12 (1.04)
SVM	12.66 (0.21)	75.14 (22.10)	75.14 (22.10)	11.24 (2.74)
MLP	13.35 (0.07)	75.14 (22.10)	75.14 (22.10)	10.89 (0.07)
NB	13.35 (0.07)	75.14 (22.10)	75.14 (22.10)	12.31 (2.68)
AHN	11.71 (0.07)	–	–	10.16 (1.17)

Bold values indicate the best test results

For the search of standardization of results, the same number of final neurons of the fuzzy neural network model (L_s) were used as primary neurons of the neural network models used in the test. The activation functions of the ELM, MLP and SVM neurons are of the sigmoidal type.

Table 1 summarizes the information:

Figure 9 shows the best individual result obtained with the tests of prediction of absenteeism in companies carried out with fuzzy neural networks. This indicates that this

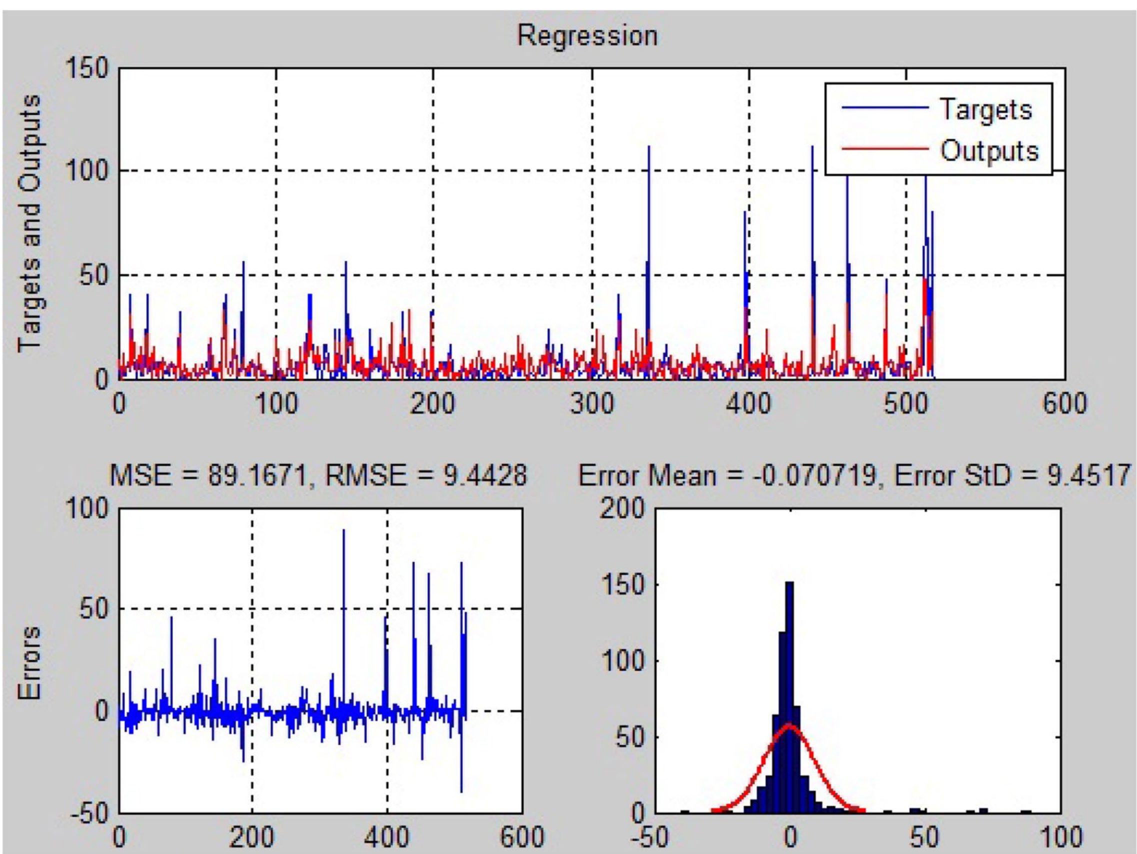


Fig. 9 FNN performance in test

type of model can find better results if another range of values is chosen or the base treated in the reduction in its dimensionality.

The work of [17] obtained a maximum error of 8.79 h. The model of this paper averaged 13 h of error. However, in this paper, the fuzzy rules can help in the construction of a specialist system.

Already in the approach with the ten best attributes to define absenteeism at work, the fuzzy neural network model obtained better results when compared to state of the art (8.42 < 8.79 h).

4.4 Interpretability of the problem based on fuzzy rules

According to the results presented in Tables 1 and 2, the proposed fuzzy neural network had an excellent performance in the identification of absenteeism at work. Fuzzy rules were generated by the system, allowing the results to be seen more clearly to researchers in the area.

The use of fuzzy rules can generate linguistic variables to represent the input space of the training data of the model.

The data of the employee are analyzed, and according to the results obtained through cross-validation, we can conclude the intensity that these data will influence in absenteeism in work according to the fuzzy rules generated by the system.

5 Conclusion

After the tests were performed using the fuzzy neural network model, we conclude that the results of the experiments prove that the intelligent model can help in the creation of a specialist system that assists in the prediction of absenteeism in companies and that it can help to reduce difficulties faced by managers in relation to the possibilities that a specific type of problem may affect an employee, thus causing the absence of the same in the workplace and harming the operation of the company. Although the RMSE was 12.91, it is a more consistent way of predicting the studies. In future works, elements can be identified as outliers in the base, thus allowing better predictions in the absenteeism of companies in general. This problem considered for the study emanates from social importance such as harassment at workplace and attitude problems, which have indirectly affect the economic and financial well-being of an organization. This type of approach allows the construction of expert systems to assist managers in areas that do not use computational resources based on artificial intelligence to improve the management of their teams and to deal with situations that may generate social and financial losses in the organization.

The fuzzy rules generated in this work can help in the training of managers on aspects that can be easily identified in the work routine.

Other models of the fuzzy neural network can be applied in this type of base so that the predictive results are improved. It is worth remembering that expert systems are tools to aid decision-making and a network of fuzzy rules can act in this way.

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Compliance with ethical standards

Conflicts of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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