applied system innovation

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Evaluation of the Performance of Neural and Non-Neural Methods to Classify the Severity of Work Accidents Occurring in the Footwear Industry Complex

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Abstract: In the footwear industry, occupational risks are significant, and work accidents are frequent. Professionals in the field prepare documents and reports about these accidents, but the need for more time and resources limits learning based on past incidents. Machine learning (ML) and deep learning (DL) methods have been applied to analyze data from these documents, identifying accident patterns and classifying the damage's severity. However, evaluating the performance of these methods in different economic sectors is crucial. This study examined neural and non-neural methods for classifying the severity of workplace accidents in the footwear industry complex. The random forest (RF) and extreme gradient boosting (XGBoost) methods were the most effective non-neural methods. The neural methods 1D convolutional neural networks (1D-CNN) and bidirectional long short-term memory (Bi-LSTM) showed superior performance, with parameters above 98% and 99%, respectively, although with a longer training time. It is concluded that using these methods is viable for classifying accidents in the footwear industry. The methods can classify new accidents and simulate scenarios, demonstrating their adaptability and reliability in different economic sectors for accident prevention.

Keywords: machine learning; workplace accidents; shoes industry; deep learning; accuracy

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Citation: da Silva, J.M.N.; da Silva Braz, M.L.; da Silva, J.G.; Bispo, L.G.M.; dos Santos Leite, W.K.; de Araujo Vieira, E.M. Evaluation of the Performance of Neural and Non-Neural Methods to Classify the Severity of Work Accidents Occurring in the Footwear Industry Complex. *Appl. Syst. Innov.* **2024**, 7, 85. https://doi.org/10.3390/asi7050085

Academic Editor: Cheng-Fu Yang

Received: 22 July 2024
Revised: 2 September 2024
Accepted: 12 September 2024
Published: 15 September 2024

1. Introduction

The digitalization process of manufacturing operations (Industry 4.0 or I4.0) has significantly changed work activities [1]. I4.0 has expanded the use of automation by integrating cyber technologies and the physical world [2]. In parallel, governments and organizations have been directing the digitalization process towards more excellent care for the environment and human beings, a paradigm called Industry 5.0 or I5.0 [3]. One of the key objectives of I5.0 is to ensure that production is human-centered, something that depends on efficient safety management to prevent accidents [4]. Researchers, policymakers, and industry professionals in occupational health and safety have a fundamental role in this process in the Brazilian footwear industry.

Work accidents are the third highest cause of death in the world, resulting in more than 7000 deaths and one million physical injuries every day [5]. In Brazil, between 2012 and 2021, more than 22,000 deaths were recorded due to work accidents, of which the year 2021 accounts for 571,000 [6]. Data from the Brazilian Notifiable Diseases Information System (SINAN) total more than 911,000 work accidents between 2006 and 2019 [7]. These alarming statistics underscore the urgent need to address the high incidence of work accidents in the Brazilian footwear industry.

In addition to damaging workers' physical and psychological integrity, accidents result in significant monetary losses. Gonzalez et al. [8] conducted a case study of severe accidents in Brazil and arrived at values totaling more than 18 billion dollars in losses. In poorer regions, the tendency is for occupational aspects to worsen [9]. For example, the northeast region of Brazil had 86,000 accidents in 2013 [10]. Factors such as low wages, precarious occupational relationships, unhealthy work, long working hours, and exploitation of the workforce are expected to be found in different types of work activities in the interior of the Brazilian northeast, something that contributes to a greater chance of illnesses and accidents of work [9,11,12].

Among the sectors of the economy with the highest number of accidents, the footwear industry stands out negatively, as there are many risks inherent in transforming raw materials into finished products [13]. The Brazilian footwear industry comprises around 8000 organizations, which directly employ 340,000 workers and produce more than 908 million pairs per year [14]. Thus, a discrepancy between the size of this market segment and the damage caused to workers is evident.

The Brazilian footwear industry can be positioned as an economic sector with significant occupational risk. Factors such as high pressure for production [15], moral harassment [16], high stress and inappropriate psychosocial conditions [17], excessive use of force or repetitive movements [18], and high cognitive demands [19] are present in the footwear industry. Furthermore, the work organization uses specialist workers with low autonomy and no organizational support [20]. Most academic work found in the footwear industry seeks to prevent ergonomic injuries [21–23], with studies using robust methodologies that seek to prevent workplace accidents based on learning from data on accidents that have already occurred.

The low use of historical information regarding accidents is a worldwide failure. The findings of Stoop and Dekker [24] highlight both the reactive nature of studies focused on accident prevention and the inability of organizations to learn from accidents that occur. Authors, such as Kletz [25], agree that it is difficult to make decisions so that accidents do not happen again and that little is learned from accidents and incidents. Despite a large volume of data and information, occupational safety professionals can only sometimes detect patterns and report variables related to accidents in reports and other documents related to the safety area. A significant investment of time and money is required for these professionals to be able to find patterns that are repeated in workplace accidents. Authors such as Tanguy et al. [26] state that data from industrial reports are valuable for learning lessons from accidents and incidents that have already occurred. However, manual analysis of these documents requires many resources, making it preferable to search for computational solutions.

Alternatively, using neural and non-neural methods can assist in analyzing databases recording accidents and their associated factors. Both types of methods are based on machine learning (ML), characterized by the use of mathematical models implemented in computational routines and capable of identifying patterns to be applied to new similar data in the future and decision-making [27]. Neural methods use the architecture of neurons, including enabling deep layers (deep learning), and promise some superiority in detecting patterns due to self-learning capacity and efficiency in determining optimal solutions [28]. Non-neural methods do not use the architecture of neurons to detect patterns. Still, they can present better solutions than neural methods for several problems [29], with the advantage of being simple and requiring less computational effort and training time [30].

Given the above, this article aims to verify the performance of neural and non-neural methods used to classify the severity of work accidents in the footwear industry complex. Based on the accuracy, precision, recall, and F-Score values, it is expected to define which method performs best in identifying patterns and classifying the severity of work accidents in the footwear industry.

In addition to the novelty of comparing several ML methods to analyze accidents in the footwear industry, this study brings relevant contributions by showing the excellent performance of methods such as 1D convolutional neural networks (1D-CNN) and bidirectional long-short-term memory (Bi-LSTM) to classify occupational accidents, something little explored by previous studies. The findings of this research suggest that neural and non-neural methods performed well in classifying accidents at work in the footwear industry. Methods such as 1D-CNN and Bi-LSTM performed better but required a long training time. Methods such as random forest (RF) and extreme gradient boosting (XGBoost) presented relatively lower performance. However, they require less training time and are still viable alternatives for occupational safety managers in the footwear industry.

This article is organized as follows: Section 1 presents the introduction of the article, highlighting the topic, relevance, and objectives of this article. Section 2 presents a brief review of the related work. Section 3 indicates the methodology used, highlighting the study design, data collection, study variables, classification methods (non-neural and neural), classification model performance, and the importance of factors in classification. Section 4 presents the results, highlighting the characterization and distribution of accidents, the result of model comparison, and the importance of different factors. Finally, Sections 5 and 6 discuss the research's main findings, including the study's implications and limitations and the conclusion of this article, respectively.

2. Related Work

The use of machine learning methods has become common in the area of accident prevention and safety, including occupational safety. Some studies have focused on identifying the location of traffic accidents and analyzing the severity of injuries caused in non-occupational scenarios [31–33]. These studies focused on analyzing data related to traffic accidents. Thus, studies such as that by Arteaga et al. [34] used methods such as extreme gradient boosting (XGBoost) and random forest (RF) to classify the severity of traffic accidents. Chen and Chen [35] used methods such as logistic regression, regression trees, and RF to classify the severity of road accidents. It is also possible to identify studies focusing on analyzing parameters related to food safety [27].

However, the literature also presents some applications of neural methods in work activities. The study by Xu et al. [36] classified accidents and assessed their severity using a convolutional neural network in hot work. This same study found the leading causes of these accidents, highlighting the absence of mechanisms for detecting dirty gas and fuel. Cheng et al. [37] used a gated recurrent unit (GRU) neural network to help classify accidents on construction sites, contributing to a better assessment of future safety projects in construction. Other studies use multiple neural methods to ensure the best choice of model. Antwi-Afari et al. [38] compared the performance of different neural network methods, such as long short-term memory (LSTM), bidirectional long short-term memory (Bi-LSTM), and GRU, in the classification of WMSDs in construction industry workers, which demonstrated the algorithms' ability to capture bad postures in real time.

However, professionals widely use non-neural methods in occupational and non-occupational settings. Most studies have compared the performance of these methods. Özkan and Ulaş [39] used RF, k-nearest neighbor (KNN), the gradient boosting method (GBM), and recursive partitioning and regression tree (RPART) methods to predict the causes and consequences of occupational accidents in the metallurgical sector in Turkey. Goh and Ubeynarayana [40] used algorithms such as RF, KNN, decision tree (DT), naive Bayes (NB), linear regression (LR), and support vector machine (SVM) to classify accident narratives in the construction industry. Tixier et al. [41] analyzed the predictive ability of RF and stochastic gradient tree boosting (SGTB) methods to determine the injury type related to occupational accidents in construction industry reports. In the mining and civil engineering sectors, it is worth highlighting the study by Rivas et al. [42], which compared statistical methods, such as logistic regression, with predictive methods, such as decision rules, Bayesian networks (BN), SVM, and classification trees (CT), finding that these models were superior to conventional statistical models. Matías et al. [43] compared the explanatory capacity and predictive potential of methods such as BN, CT, SVM, and extreme learning machines for events involving falls at work in the industrial, mining, construction, and service sectors.

More recently, studies in accident prevention have focused on using neural methods. Text classification of occupational injury reports was improved by the non-negative matrix factorization model method in a study by Chen et al. [44]. Text classification to identify injuries from work-related accidents was also used by McKenzie et al. [45]. Accidents in chemical industries were analyzed using machine learning by Tamascelli et al. [46]. Their findings suggest that the wide–deep model proved helpful for building predictive models to predict accident severity. Graph-based convulsive networks were developed by Pan et al. [47] to automatically classify occupational safety reports, indicating the type of accident and the type of injury caused by the accidents.

Similarly, Luo et al. [48] used an explosive neural network for automatic text classification in accident reports from the construction industry. In addition to text classification, Paraskevopoulos et al. [49] proposed a multimodal framework capable of training machine learning algorithms through images present in reports. A multimodal analysis involving data structuring and natural language processing was employed by Khairuddin et al. [50] on an extensive database of U.S. OSHA Severe Injury Reports. There are also literature reviews on ML methods in the industry [51,52].

However, applying ML and DL methods in the context of occupational safety in the footwear industry is a relatively unexplored area. While Rmadi et al. [53] used the decision tree method to assess the risk of WMSDs in footwear industry workers, and Zokaei et al. [54] employed a neural network algorithm to predict musculoskeletal disorder risks, these studies focused on ergonomic risks and did not compare the performance of different ML and DL methods. Therefore, this study is the first to evaluate the performance of various neural and non-neural methods in classifying the severity of accidents in the industrial footwear sector, making it a unique and valuable contribution to the field.

3. Methods

This section presents the characteristics of the study design; in addition to the data collection process, it presents the study variables (features) taken from the safety reports, the classification methods (non-neural and neural), the tested hyperparameter settings, the performance parameters of the classification model, and the determination of the importance of the factors in the classification.

3.1. Study Design

This exhaustive longitudinal study collected data from forms, reports, documents, and notices of work accidents in shoe factories in northeastern Brazil. The data collected are related to work accidents between 2016 and 2022. In total, 1259 accidents were recorded, which occurred in all 21 sectors present in the industrial complex.

3.2. Data Collection

The factories selected for data collection are part of a complex of industries responsible for making components and assembling footwear. The industrial complex's factories are units of a multinational company with several factories and commercial offices in Asia, North America, South America, and Europe. The shoes are made of PVC and are intended for men and women.

The industrial complex employs around 5500 workers and operates three daily shifts of 7 h and 20 min from Monday to Friday. On Saturdays and Sundays, shifts are 6 h long, with a workforce equal to 85% and 10% of the total. Footwear production involves 104 manufacturing and management tasks in sectors such as administration, finishing, warehouse, vulcanization (autoclave), mixing (Banbury), insertion of small components, distribution center, dry mixing (dry blend), industrial engineering, plastics manufacturing, injection molding, innovation, laboratory, maintenance, mills, pin application, presses, quality, work safety, screen printing, and stabilization.

The data on accidents, crucial for our understanding of workplace safety, were meticulously collected from documents within the company. Professionals with extensive occupational safety engineering and medicine training completed these documents. The engineers diligently entered professional information about the injured worker and chronological information about the time of the accident and the sector in which each accident occurred. Occupational doctors provided detailed information about the type and severity of the injury caused by the accident. This comprehensive information was then meticulously tabulated in an electronic spreadsheet for subsequent analysis, ensuring the reliability of our findings.

3.3. Study Variables

Our data collection process was thorough and meticulous. We gathered chronological data of the accident and worker's return after the accident, along with sociodemographic and professional information about the victims, sectors in which the accidents occurred, injured body region, type of injury suffered, and severity of the accident. These variables are the foundation of our research, providing a comprehensive understanding of workplace safety and health measures. We even collected specific chronological information, such as the day, month, and year of the accident and the day, month, and year of the worker's return after the accident, to ensure the accuracy of our timeline.

The sociodemographic information collected involved sex (male and female), age (in years), and marital status (married, single, and divorced). The professional data involved total time at the company (in years), time in the current role (in years), work shift (first shift, second shift, third shift, and general shift), and sector (all 21 sectors already mentioned).

Regarding the accident, information was collected about the need to leave work due to the accident (yes or no), the need to open a work accident report (WAR), the injured region (head, eyes, neck, chest, back, the region between shoulders and wrists, region of hands or fingers, the area between legs and calves and ankles or feet), the type of accident (sprain, contusion, back pain, eye injury, strain, dislocation, fracture, amputation, injuries caused by animals, injuries caused by electric shock, cuts, and burns), and injury severity (superficial injury and severe injury).

3.4. Data Preprocessing

The data in the spreadsheet originated from standardized reports used by the constituent companies within the industrial complex. To validate the reliability of this information, we randomly selected 100 reports and cross-referenced their data with the content in the spreadsheet. Fortunately, no discrepancies were found between the reports and the spreadsheet data.

The first stage of processing consisted of cleaning the data. Accident records with missing data were removed. This approach was used due to the low number of records in this situation. Next, the variables were discretized. The spreadsheet was searched for noisy data, information that the algorithms could not interpret. However, no information of this nature was identified in the database, a testament to the authors' unwavering commitment to data quality. A box-plot graph was constructed to verify the presence of outliers in the factors. Only the age variable presented outliers due to the presence of older workers in the sample. However, the authors chose not to exclude the observations, given the relevance of also considering that older workers can have accidents. The data were also transformed. For this purpose, the normalization technique was used. Thus, the values were standardized between 0 and 1. Since the authors did access a data volume with few features, it was decided not to proceed with any data reduction technique.

3.5. Classification Methods

ML and DL methods, non-neural and neural, were used to classify the severity of accidents. The non-neural methods tested were logistic regression (LR), support vector machine (SVM), and tree structure models such as decision tree (DT), random forest (RF), and extreme gradient boosting (XGBoost). Tree structure models are well accepted due to their effectiveness in processing multifaceted data, flexibility, and ease of interpretation [55], in addition to working satisfactorily with high-dimensional data (due to automatic variable selection) and having an integrated interaction detector [56].

The neural methods tested were multilayer perceptron (MLP), long short-term memory (LSTM), bidirectional long short-term memory (Bi-LSTM), gated recurrent unit (GRU), and 1D convolutional neural networks (1D-CNN).

3.5.1. Non-Neural Methods

The non-neural methods were developed with the help of the scikit-learn [57] and xgboost [58] libraries. All methods are classic and require some coding of variables. The first model tested was logistic regression (LR). A generalized linear model seeks to relate qualitative dependent variables to multiple independent variables. Authors such as Christodoulou et al. [59] suggest that other ML methods do not present significant benefits when compared to predictions made via LR for predicting clinical factors. Thus, LR presented itself as an appropriate method for this study. The algorithm was implemented with penalty type 'l2', tolerance for stopping criterion equal to 0.0001, the maximum number of interactions for convergence equal to 100, and solver type 'lbfgs' (limited-memory Broyden–Fletcher–Goldfarb–Shanno algorithm).

The decision tree (DT) method was also tested. This method seeks to predict a target variable based on the values of other partitioned input variables, giving rise to hierarchical logical diagrams [27]. It is a non-parametric data method with non-linear relationships. This ML algorithm follows a logic of nodes, with the first node being called the decision node, which has several branches connected to leaf nodes, being the output of the decision node [60]. Recently, DT has been successfully used in classification problems in the footwear industry [53]. Therefore, it was one of the non-neural methods tested. The DT algorithm was implemented with the Gini criterion to measure the quality of the divisions in the tree; the division of each node used the best criterion instead of the random criterion, and the minimum number of samples to divide an entire node was equal to 2. The minimum number of samples for each leaf node was equal to 1, and no number of resources was defined to be considered when looking for the best division of the tree.

The random forest (RF) method uses the same principle as DT to generate several trees from vectors with random values, and its main advantage is minimizing overfitting [40]. Authors such as Zhen et al. [61] highlight that RF makes use of the bagging algorithm to generate training data via a sampling process, in which the number of samples generated for training will be equal to the number of samples in the source dataset, making use of the index of Gini to estimate the number of classes in the input data and the heterogeneity of the parent nodes and child nodes of the trees. RF is the most widely used ML algorithm [62]. Therefore, RF was one of the methods used in this article. For the RF algorithm, among the available options, the Gini criterion was used to measure the quality of the divisions in the trees, the square root (sqrt) was used to define the number of resources to be considered when searching for the best division, and the bootstrap as a resampling technique to select training data.

Developed from the improvement of RF-based algorithms (specifically the gradient boosting decision tree), the extreme gradient boosting (XGBoost) algorithm seeks parallel speed and has strong fault tolerance and excellent generalization power [63]. In summary, XGBoost verifies the need to add a new tree to the set of trees initially generated to reduce the residual error (calculated from the results found between the actual value and the value coming from the previously computed set of trees) [61]. As XGBoost has been suggested in the literature as a method capable of classifying injuries caused by accidents [34], we also decided to test this method in this article. The default present in the xgboost library [58] was adopted in the development of this algorithm.

3.5.2. Neural Methods

Several types of neural models and neuron architectures were tested. Like non-neural methods, the models sought to classify accidents based on other factors.

The first neural method tested was the multilayer perceptron (MLP), a structure with an arbitrary number of neurons in input, output, and hidden layers [27]. The MLP is unique in that it is aligned with the logic of brain functioning (neurophysiology), which involves continuously adjusting the weights of its synapses to classify a target variable [28]. This alignment with brain functioning gives MLP a unique potential in classifying work accidents. Although it is one of the first neural networks developed, the application of MLP to classify work accidents in the footwear industry has yet to be explored by previous studies. Table 1 presents the configurations tested for the MLP.

Table 1. Summary of hyperparameters and values tested in the MLP.

Iteration	Hyperparameter	Values
1	Hidden layers	1, 2, 3, and 4
	Number of input neurons	9, 19, 29, 39, 49, and 49
	Number of hidden layer neurons	3, 13, 23, 33, 43, and 53
	Activation function	ReLU, tanh, and Sigmoid
2	Dropout	0.10, 0.20, 0.30, and 0.40
3	Epoch	1000 and 2000
	Optimizer	RMSprop, AdaGrad, Adam, and SGD
4	Learning rate	0.01, 0.001, and 0.005

Another neural network tested was long short-term memory (LSTM). This type of network works with memory cells, which come from complex gate units. Gates work collaboratively and are self-designed, overcoming the naive approach of traditional MLPs [38]. MLPs are accurate when working with recent information, but the LSTM gate structure also has good properties for processing data with long-term dependence [60]. LSTM has rare applications in classification problems, although it has been successfully used to classify accidents in nuclear plants [64]. No studies have been conducted in the footwear industry to classify accidents using LSTM.

The bidirectional long short-term memory (Bi-LSTM) network was also tested. This network operates using two LSTMs in parallel, seeking to process both previous and subsequent information in the database [65]. Authors such as Wang et al. [66] successfully employed Bi-LSTM to monitor the amount of gas emission in underground mining activity and classify the presence or absence of explosion risk. Alhaek et al. [67] classified the severity of traffic accidents using a Bi-LSTM. The use of Bi-LSTM for classifying work accidents is scarce.

Another neural model tested was the GRU neural network. LSTM networks work with the logic of three gates responsible for data input, output, and forgetting. In contrast, GRU makes use of two gates, one for updating (selection of valuable information to be added) and another for redefinition (selection of information to be eliminated) [38]. This simplification in the number of gates makes this network more efficient than LSTM in many situations [68]. A recent review on the use of ML and DL suggests a low use of GRU in security [69]. Therefore, more information is needed about the performance of this network in processing work accident data. Table 2 presents the hyperparameters used in LSTM, Bi-LSTM, and GRU.

Table 2. Summary of hyperparameters and values tested in LSTM, Bi-LSTM, and GRU.

Iteration	Hyperparameter	Values
1	Hidden layers	1, 2, 3, and 4
	Number of input neurons	9, 19, 29, 39, 49, and 49
	Number of hidden layer neurons	3, 13, 23, 33, 43, and 53
	Activation function	ReLU, tanh, and Sigmoid
	Sequence size	30, 60, and 90
2	Dropout	0.10, 0.20, 0.30, and 0.40
3	Epoch	1000 and 2000
	Optimizer	RMSprop, AdaGrad, Adam, and SGD
4	Learning rate	0.01, 0.001, and 0.005

Finally, the last algorithm tested was the 1D convolutional neural network (1D-CNN). This network works according to a hierarchical structure and learns the relationship between input and output data with convolution operations on a one-dimensional matrix [27]. Studies, such as that by Pérez-Sala et al. [70], have observed that 1D-CNN presented the best accuracy for classifying traffic accidents compared to the other models tested. However, reviews did not present studies that sought to classify work accidents using 1D-CNN [52]. Table 3 presents the parameters tested in 1D-CNN.

Table 3. Summary of hyperparameters and values tested in 1D-CNN.

Iteration	Hyperparameter	Values
1	Hidden layers	1, 2, 3, and 4
	Number of filters	9, 19, 29, 39, 49, and 49
	Kernel size	2, 3, 4, and 5
	MaxPooling	2, 3, and 4
2	Dropout	0.10, 0.20, 0.30, and 0.40
3	Epoch	1000 and 2000
	Optimizer	RMSprop, AdaGrad, Adam, and SGD
4	Learning rate	0.01, 0.001, and 0.005

3.5.3. Classification Model Performance

The data were initially separated into 80% for training and 20% for testing [39]. To classify the performance of neural and non-neural models, we employed the adaptable 10-fold cross-validation method [71]. Utilizing the resampling technique, this procedure ensures that the input data are not precisely the same, allowing our models to be flexible and responsive to different datasets. The neural and non-neural models were trained with ten partition schemes [72], with the input data for training to change in each of the ten repetitions, demonstrating the adaptability of our approach.

After training, four statistics served as the basis for evaluating the neural and non-neural methods:

1. True positive (TP) is the situation in which the method classified an accident with a serious injury as an event that resulted in a severe injury.
2. True negative (TN) is the situation in which the method classified an accident without serious injury as an event that did not result in serious injury.
3. A false positive (FP) occurs when the method classifies an accident without serious injury as an accident with serious injury.
4. A false negative (FN) occurs when the method classifies an accident with serious injury as an accident without serious injury.

From the number of TP, TN, FP, and FN, the values of accuracy (Equation (1)), precision (Equation (2)), recall (Equation (3)), and F-score (Equation (4)) were estimated:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FN} + \text{FP} + \text{TN}} \tag{1}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (2)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (3)$$

$$\text{F} - \text{score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

Thus, accuracy sought to determine the percentage of correct classifications of the method compared to the total classifications made [47]. Precision or sensitivity is a valuable metric for reducing the number of false positive classifications made by the method [27]. On the other hand, recall aims to estimate the effect of false negative classifications made by the method [73]. Finally, the F-score is a performance measure that unifies the trade-off relationship between accuracy and recall [39].

3.6. Importance of Factors in Classification

The recursive feature elimination (RFE) method was used to determine the importance of factors in classifying the severity of accidents. The RFE can be used to select which variables will be used to train the methods based on criteria such as Gini importance and permutation importance [27,40,74]. However, due to the low number of factors, RFE was used in this study only to define the relevance of each predictor for classifying the severity of accidents.

4. Results

This section presents the results, highlighting the characterization and distribution of accidents between the years analyzed, the result of a model comparison involving parameters such as accuracy, precision, recall, and F1-score, and determining the importance of factors related to accidents.

4.1. Characterization and Distribution of Accidents

Table 4 presents the information collected about injured workers, sectors that did not suffer accidents, and information related to the accident. It was found that the majority of accidents occurred among men (93.4%), under 30 years old (66.2%), married (55.4%), working in the second shift (36, 7%), who had been with the company for less than two years (48.5%), and spent two years in the same role (56.2%). Official data from Brazil indicate that men suffer the majority of work accidents [75], especially those up to 24 years of age [76]. Likewise, Brazil is one of the leaders in turnover [77], resulting in a low time of job retention in the same company and function. Hence, the findings align with the operational context of Brazilian companies.

Table 4. Summary of information on accidents and injuries.

Variable	n (%)	Variable	n (%)
Sex		**Injured region**	
Feminine	83 (6.6)	Head	129 (10.2)
Masculine	1176 (93.4)	Eyes	124 (9.8)
Age (years)		Neck	5 (0.4)
Less than 20	87 (6.9)	Chest	13 (1.0)
Between 20 and 24	473 (37.6)	Back	49 (3.9)
Between 25 and 29	273 (21.7)	Shoulders	20 (1.6)
Between 30 and 34	180 (14.3)	Arms and forearms	147 (11.7)
Between 35 and 39	108 (8.6)	Hands and fingers	638 (50.7)
Between 40 and 44	77 (6.1)	Legs and calves	68 (5.4)
Between 45 and 49	34 (2.7)	Feet and ankles	66 (5.2)
Between 50 and 54	20 (1.6)	**Type of injury**	
Over 55	6 (0.5)	Sprain	16 (1.3)

Table 4. *Cont.*

Variable	n (%)	Variable	n (%)
Marital status		Contusion	436 (34.6)
Married	698 (55.4)	Back pain	21 (1.7)
Single	554 (44.0)	Eye injury	107 (8.5)
Divorced	7 (0.6)	Disthesis	25 (2.0)
Shift		Dislocation	16 (1.3)
First	442 (35.d1)	Fracture	62 (4.9)
Second	462 (36.7)	Amputation	3 (0.2)
Third	323 (25.7)	Injury caused by animals	3 (0.2)
General	32 (2.5)	Injury caused by electric shock	3 (0.2)
Company time (years)		Cut	504 (40.0)
Less than 2	610 (48.5)	Burn	63 (5.0)
Between 2 and 4	174 (13.8)	**Sector**	
Between 4 and 6	117 (9.3)	Administration	4 (0.3)
Between 6 and 8	69 (5.5)	Finishing	342 (27.2)
Between 8 and 10	85 (6.8)	Warehouse	10 (0.8)
More than 10	204 (16.2)	Vulcanization (autoclave)	11 (0.9)
Function time (years)		Mixers (Banbury)	95 (7.5)
Less than 2	707 (56.2)	Insertion of small components	13 (1.0)
Between 2 and 4	184 (14.6)	Distribution center	31 (2.5)
Between 4 and 6	102 (8.1)	Dry blenders	14 (1.1)
Between 6 and 8	63 (5.0)	Industrial engineering	12 (1.0)
Between 8 and 10	71 (5.6)	Plastics manufacturing	2 (0.2)
More than 10	132 (10.5)	Injectors	108 (8.6)
Type of return after accident		Innovation	3 (0.2)
Immediate return to work after accident	988 (78.5)	Laboratory	3 (0.2)
Return after care in the infirmary	254 (20.2)	Maintenance	108 (8.6)
Return after home care	17 (1.3)	Mills	131 (10.4)
WAR issuance		Pin applicator	13 (1.0)
WAR was not done	999 (79.3)	Presses	218 (17.3)
WAR was carried out	260 (20.7)	Quality	4 (0.3)
Severity of the accident		Workplace safety	3 (0.2)
Superficial injury	369 (29.3)	Serigraphy	105 (8.3)
Severe injury	890 (70.7)	Stabilizers	29 (2.3)

A high prevalence of accidents is observed in the finishing (27.2%) and press (17.3%) sectors. In most cases, the worker immediately returned to work (78.5%). Findings by Leite et al. [78] highlight that a large part of the footwear industry workers are concentrated in finishing and that this is one of the sectors with the highest absenteeism rates. Most accidents did not result in the opening of a work accident report (WAR) (79.3%). Brazilian data indicate that accidents without WAR increase by up to 47.49% annually [79]. More than half of the injuries occurred to the hands and fingers (50.7%) through cuts (40.0%) or bruises (34.6%). Leite et al. [19] highlight that work in the footwear industry is still manual or semi-automatic, resulting in more hand and finger injuries. The occupational medicine professional classified the majority of accidents as events with serious injuries (70.7%).

Figure 1 shows the number of accidents between 2016 and 2022, indicating some randomness in the number of accidents. A total of 2359 days were analyzed, of which 878 (37.2%) included an accident. There were rare peaks of five or four accidents on the same day. On most days analyzed, there were no accidents (62.8%).

Table 5 summarizes the accidents that occurred daily in the years analyzed. On 602 days (25.5%), a single accident occurred. Therefore, days with two or more accidents are rare (11.7%). The result of the Chi-square test shows that the distribution of the number of accidents is different between the years ($\chi 2$ = 84.679; p-value = 0.000). The year 2020 had the highest number of days without accidents (73.2%), representing almost three days without an accident for every four days of work. The years 2016, 2020, and 2022 each featured a day on which five accidents occurred. The years 2017 and 2018 had five and four days in which four accidents occurred, respectively. Such results reinforce the randomness in the number of accidents in the years analyzed.

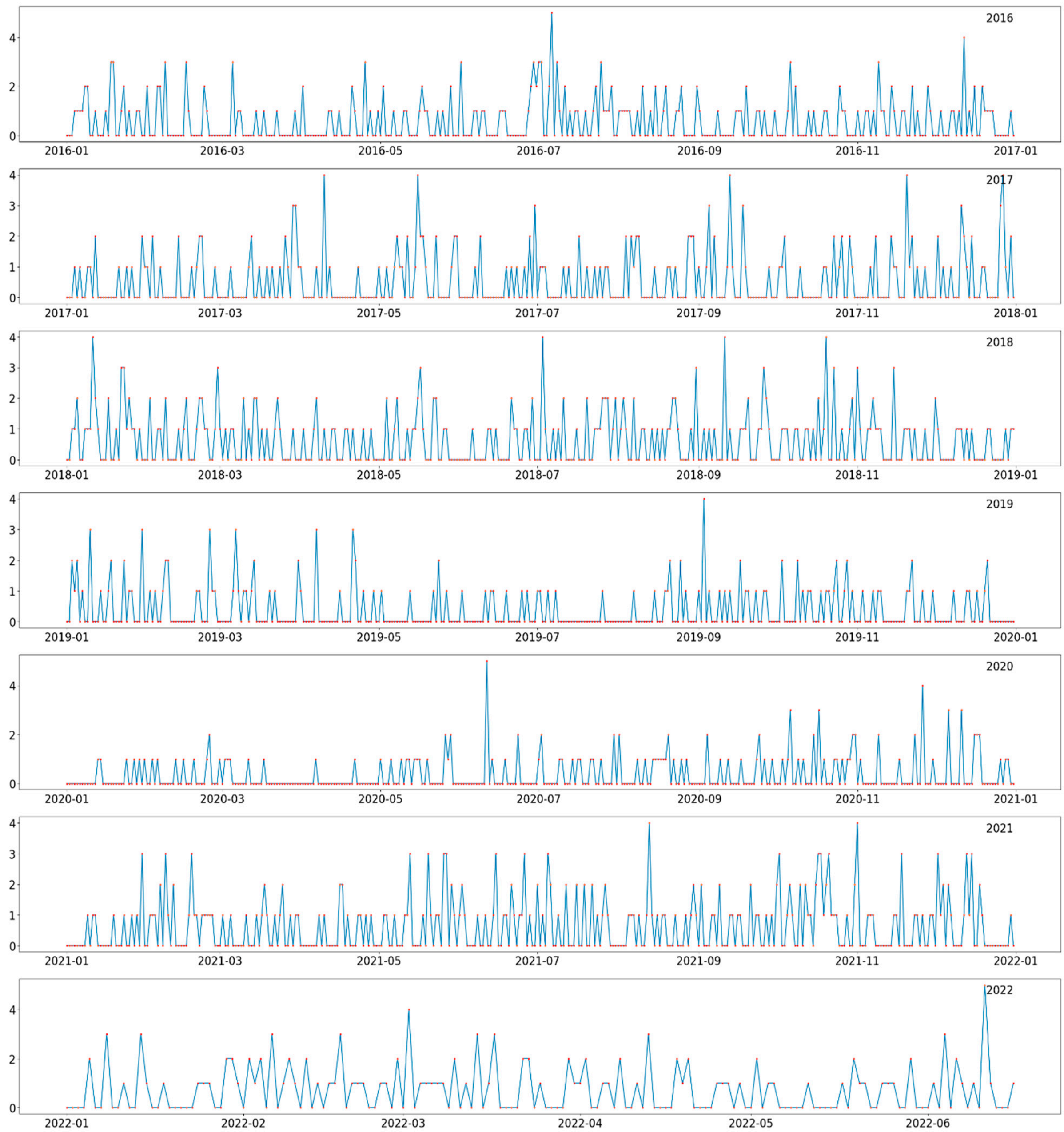

Figure 1. Time series of accidents between 2016 and 2022.

Table 5. Number of accidents in the years analyzed.

No. of Accidents	Years						
	2016	2017	2018	2019	2020	2021	2022
	n (%)	n (%)	n (%)	n (%)	n (%)	n (%)	n (%)
0	223 (60.9)	239 (65.3)	200 (54.6)	263 (71.9)	268 (73.2)	205 (56.0)	88 (52.4)
1	96 (26.2)	78 (21.3)	116 (31.7)	77 (21.0)	74 (20.2)	111 (30.3)	50 (29.8)

Table 5. *Cont.*

No. of Accidents	Years						
	2016	2017	2018	2019	2020	2021	2022
	n (%)	n (%)	n (%)	n (%)	n (%)	n (%)	n (%)
2	31 (8.5)	37 (10.1)	37 (10.1)	19 (5.2)	18 (4.9)	30 (8.2)	20 (11.9)
3	14 (3.8)	7 (1.9)	9 (2.5)	6 (1.6)	4 (1.1)	18 (4.9)	8 (4.8)
4	1 (0.3)	5 (1.4)	4 (1.1)	1 (0.3)	1 (0.3)	2 (0.6)	1 (0.60)
5	1 (0.3)	0 (0.0)	0 (0.0)	0 (0.0)	1 (0.3)	0 (0.0)	1 (0.60)

4.2. Result of Model Comparison

The configuration of the algorithms used in non-neural methods was previously described in the methodology. On the other hand, the process of choosing the best neural network architectures occurred via the hyperparameter tuning process. The best architecture found for the multilayer perceptron (MLP) involved 29 neurons in the input layer, one deep layer with 13 neurons, ReLU activation function, dropout of 0.10, 1000 epochs, 'Adam' optimizer, and a learning rate of 0.01. Regarding LSTM, Bi-LSTM, and GRU, the best architecture involved 29 neurons in the input layer, two deep layers with 13 neurons each, 'ReLU' activation function, 0.10 dropout, 2000 epochs, 'Adam' optimizer, and a learning rate of 0.01. Finally, the best architecture for 1D-CNN involved 29 filters, kernel size equal to 3, a deep layer with 13 filters, MaxPooling equal to 2, dropout of 0.10, 2000 epochs, 'Adam' optimizer, and a learning rate of 0.01. Then, the 10-fold cross-validation method was used to analyze the performance of the neural and non-neural models (Table 6).

When analyzing the average parameters, it was noticed that, except for LSTM and GRU, all methods presented an accuracy greater than 90%. Among the non-neural methods, RF, XGBoost, and DT presented accuracy equal to 95.9%, 95.7%, and 94.4%, respectively. Therefore, tree-based methods performed slightly better than LR (93.7%) and SVM (94.0%). On the other hand, neural methods showed accuracy greater than 95%, such as 1D-COV (95.8%), Bi-LSTM (98.6%), and MLP (99.6%). Thus, when comparing the performance of the three best neural and non-neural methods, it was observed that the neural methods showed slightly higher accuracy than the non-neural ones, with a maximum accuracy gain of 3.7%. However, it is worth noting that both neural and non-neural methods showed a high rate of correct classifications of serious accidents (TP) and non-serious accidents (TN), resulting in high accuracy values.

Regarding accuracy, the non-neural RF and XGBoost methods stood out, reaching 94.7% and 94.6%. Therefore, XGBoost proved slightly more accurate when classifying serious accidents (TP). On the other hand, neural methods such as 1D-COV (99.8%) and LSTM (99.4%) showed accuracy greater than 99%. Therefore, this result suggests that the LSTM method was penalized in accuracy due to its difficulty in correctly classifying non-serious accidents (TN). The 1D-COV method shows great potential due to its high accuracy and precision. When comparing the top results from neural and non-neural models, it was observed that a modest increase in accuracy can reach up to 5.1%.

Regarding recall, the non-neural RF (95.2%) and XGBoots (94.4%) methods presented the best results. However, the recall of the 1D-COV (99.7%) and Bi-LSTM (99.2%) methods was greater than 99%. A discreet maximum recall gain of 5.3% can be observed when comparing the best models. In general, it is suggested that these methods can correctly classify non-serious accidents (TN). Methods such as LSTM, for example, presented recall equal to 82.7%, that is, some difficulty in classifying non-serious accidents, even though their precision (ability to classify serious accidents) was high.

The F1-score, due to its relationship with precision and recall, only reinforced the better performance of the non-neural methods RG (94.8%) and XGBoots (94.4%), and the neural methods Bi-LSTM (99.0%) and 1D-COV (99.7%). When considering all parameters, regardless of the type of method, a ranking can be formed, such that the order must be 1D-COV, Bi-LSTM, MLP, RF, XG, SVM, LR, DT, GRU, and LSTM.

Table 6. Performance of methods in 10-fold cross-validation.

Model	10-Fold Cross-Validation										Mean
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	
LR											
Accuracy	0.970	0.950	0.960	0.931	0.931	0.931	0.921	0.930	0.910	0.940	0.937
Precision	0.887	0.946	0.969	0.929	0.903	0.904	0.936	0.936	0.944	0.927	0.928
Recall	0.908	0.962	0.986	0.929	0.903	0.941	0.945	0.944	0.962	0.927	0.941
F1-Score	0.896	0.953	0.977	0.929	0.903	0.919	0.940	0.940	0.952	0.927	0.934
DT											
Accuracy	0.970	0.931	0.960	0.921	0.960	0.950	0.941	0.930	0.920	0.960	0.944
Precision	0.920	0.896	0.973	0.961	0.902	0.912	0.907	0.951	0.907	0.936	0.927
Recall	0.912	0.888	0.933	0.969	0.876	0.920	0.931	0.951	0.930	0.944	0.926
F1-Score	0.916	0.892	0.951	0.965	0.888	0.916	0.918	0.951	0.917	0.940	0.925
RF											
Accuracy	0.990	0.950	0.970	0.960	0.950	0.970	0.970	0.950	0.920	0.960	0.959
Precision	0.980	0.932	0.984	0.969	0.911	0.907	0.919	0.960	0.930	0.976	0.947
Recall	0.950	0.955	0.993	0.986	0.893	0.931	0.910	0.969	0.955	0.976	0.952
F1-Score	0.963	0.942	0.988	0.977	0.901	0.918	0.914	0.964	0.941	0.976	0.948
XGBoost											
Accuracy	0.980	0.960	0.980	0.941	0.950	0.960	0.941	0.940	0.950	0.970	0.957
Precision	0.953	0.937	0.984	0.953	0.911	0.927	0.921	0.943	0.960	0.968	0.946
Recall	0.953	0.919	0.993	0.953	0.893	0.927	0.938	0.934	0.969	0.958	0.944
F1-Score	0.953	0.927	0.988	0.953	0.901	0.927	0.929	0.939	0.964	0.963	0.944
SVM											
Accuracy	0.941	0.911	0.960	0.941	0.941	0.950	0.950	0.940	0.920	0.950	0.940
Precision	0.968	0.892	0.894	0.952	0.886	0.919	0.934	0.958	0.943	0.993	0.934
Recall	0.959	0.934	0.886	0.952	0.894	0.879	0.944	0.968	0.961	0.982	0.936
F1-Score	0.963	0.909	0.890	0.952	0.890	0.896	0.939	0.963	0.951	0.987	0.934
MLP											
Accuracy	0.961	0.951	0.960	0.952	0.957	0.959	0.962	0.958	0.954	0.961	0.958
Precision	0.959	0.947	0.963	0.960	0.960	0.969	0.966	0.965	0.956	0.955	0.960
Recall	0.986	0.982	0.981	0.972	0.979	0.973	0.980	0.975	0.978	0.990	0.980
F1-Score	0.972	0.964	0.972	0.966	0.969	0.971	0.973	0.970	0.967	0.972	0.970
LSTM											
Accuracy	0.750	0.894	0.872	0.837	0.870	0.745	0.778	0.876	0.915	0.811	0.835
Precision	0.999	0.987	0.990	0.992	0.987	1.000	0.999	0.992	0.990	0.999	0.994
Recall	0.749	0.885	0.861	0.827	0.859	0.745	0.773	0.863	0.905	0.800	0.827
F1-Score	0.856	0.933	0.921	0.902	0.919	0.854	0.872	0.923	0.946	0.889	0.902
Bi-LSTM											
Accuracy	0.993	0.990	0.969	0.996	0.991	0.983	0.975	0.991	0.981	0.990	0.986
Precision	1.000	0.992	0.962	0.999	0.996	0.986	0.970	0.999	0.992	0.997	0.989
Recall	0.991	0.994	0.996	0.996	0.992	0.991	0.997	0.990	0.982	0.989	0.992
F1-Score	0.996	0.993	0.979	0.997	0.994	0.988	0.983	0.994	0.987	0.993	0.990
GRU											
Accuracy	0.889	0.880	0.861	0.858	0.864	0.874	0.861	0.862	0.854	0.874	0.868
Precision	0.953	0.949	0.948	0.964	0.953	0.946	0.964	0.938	0.953	0.958	0.953
Recall	0.903	0.897	0.877	0.865	0.876	0.891	0.867	0.885	0.864	0.884	0.881
F1-Score	0.927	0.922	0.911	0.912	0.913	0.918	0.913	0.910	0.906	0.920	0.915
1D-COV											
Accuracy	0.996	0.997	0.994	0.996	0.999	0.996	0.997	0.994	0.997	0.995	0.996
Precisão	0.995	1.000	0.995	0.997	1.000	0.999	0.999	0.996	0.999	0.995	0.998
Recall	1.000	0.996	0.997	0.997	0.999	0.996	0.997	0.996	0.997	0.999	0.997
F-score	0.997	0.998	0.996	0.997	0.999	0.997	0.998	0.996	0.998	0.997	0.997

Table 7 presents the training times (in seconds) for the methods. The models required 3.48 h to be trained via 10-fold cross-validation. Thus, only about 0.20% of the time was used to evaluate the performance of non-neural methods. The Bi-LSTM neural model required 43.62% of the time to assess the models' performance. The 1D-COV model required 7.10%

of the time to evaluate performance, even though it was the best model with respect to accuracy, precision, recall, and F-score.

Table 7. Times related to training and 10-fold cross-validation.

Model	Training	10-Fold Cross-Validation
LR	0.31	0.50
DT	0.03	0.12
RF	1.35	2.82
XGBoost	2.06	4.09
SVM	1.16	17.7
MLP	3.28	101.77
LSTM	188.71	3338.03
Bi-LSTM	610.38	5457.99
GRU	26.07	2701.02
1D-CNN	95.53	888.44

4.3. Importance of Factors

The RFE method was utilized to assess the importance of each factor in classifying accident severity (see Figure 2). The analysis revealed that factors related to chronological variables (such as the year and month of the accident and the year and month of return after the accident) played a significant role in classifying accident severity. On the other hand, factors such as the age of the injured person, whether a WAR was opened due to the accident, the sector in which the accident occurred, type of injury, location of the injury, and gender were found to have little relevance in classifying the severity of accidents.

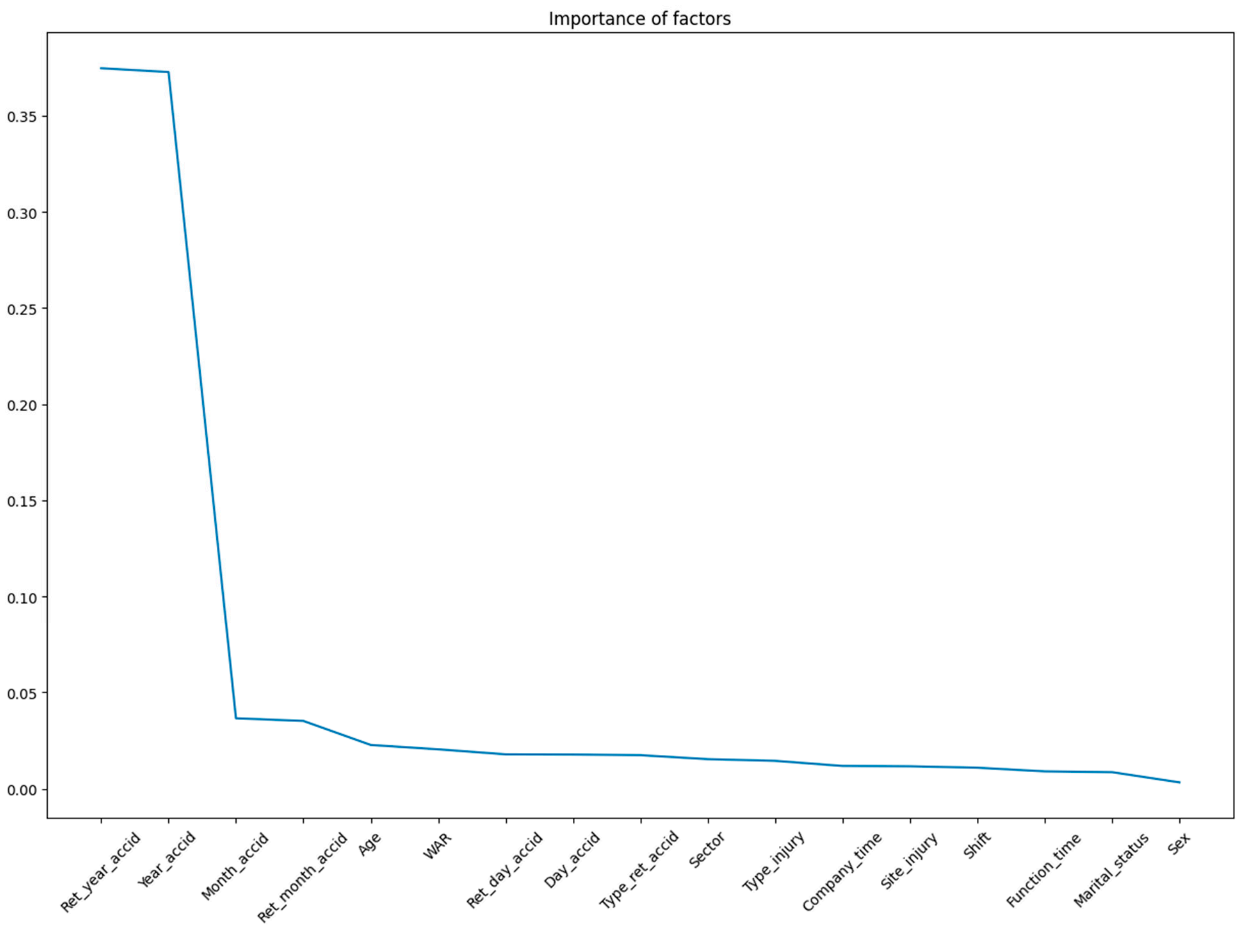

Figure 2. Importance of factors in classifying the severity of accidents.

Legend: Year_accid—year of the accident; Ret_year_accid—return year after the accident; Ret_month_accid—return month after the accident; Month_accid—month of the accident; Age—age of the worker; WAR—whether there was a CAT opened; Day_accid—day of the accident; Ret_day_accid—return day after the accident; Type_ret_accid—type of return after the accident; Sector—sector in which the accident occurred; Type_injury—type of injury; Company_time—company time; Site_injury—injured body region; Shift—work shift in which the accident occurred; Function_time—function time; Marital_status—marital status; Sex—sex of the worker.

5. Discussion

This section discusses the main findings of the research, including practical and theoretical implications and limitations of the study.

Accidents are a cause of suffering for workers around the world [5]. The findings of this research suggest that recording accidents that have already occurred can provide relevant lessons to help prevent new accidents. Authors such as Goh and Ubeynarayana [40] have already highlighted the possibility that the elements present in accidents can help in the construction of prevention strategies to avoid new incidents. Özkan and Ulaş [39] have highlighted the need to look for patterns related to accidents to obtain evidence of the root causes that led to such unwanted events.

The neural and non-neural methods used in this article captured accident-related patterns, proving that some common characteristics are present in them. Therefore, the use of ML can help capture these patterns, providing essential insights for decision-makers in the area of occupational safety. Findings by Arteaga et al. [34] showed that ML methods are crucial tools for understanding the factors related to the severity of accidents. Thus, ML methods have proven suitable for extracting latent knowledge from databases, with the advantage of not employing robust mathematical modeling techniques [51]. Therefore, the use of ML in the area of occupational safety is viable, with great potential to assist hygiene and occupational health managers in the decision-making process [52].

This article aimed to verify the performance parameters of neural and non-neural ML methods. These parameters measured the ability of the methods to classify the severity of work accidents occurring in a complex of footwear industries. Based on the values of these parameters, it is possible to evaluate the capacity of the algorithms to classify work accidents that occurred between the years 2016 and 2022. Parameters such as accuracy, precision, recall, and F-score have already been used to compare the performance of ML on large industrial accident databases in the metallurgical sector [39]. However, no previous study has been applied in the footwear industry to assess the severity of accidents via ML methods.

Findings from this research suggest that, in most cases, neural networks have some advantage over non-neural methods when performance parameters such as accuracy, precision, recall, and F-score are analyzed. When comparing the best neural method with the worst non-neural method, the difference was 5.87% for accuracy (1D-COV x LR), in addition to 7.08%, 7.18%, and 7.19% for precision, recall, and F-score (1D-COV x DT), respectively. Findings by Nogales et al. [27] on food safety also suggest that the 1D-COV method may perform better when compared to other ML methods.

Comparison of models that assess the severity of injuries resulting from accidents is scarce, so much so that most studies focus on traffic accidents [31–33], in the construction industry [40,41], in more than one type of work activity [42,43], or based on data from emergency or hospital accidents [46], or in other public reports of accidents with entire populations [45,80]. However, studies with accident severity data in the footwear industry that compare ML methods were not found. On the other hand, McKenzie et al. [45] already highlighted that the records in many accident databases do not categorize the accident as suffered during work activity, making it challenging to analyze by economic sector or occupation.

Still, within the analysis of performance parameters, it is necessary to comment on the fact that the research data are not balanced in terms of the severity of the accidents. This is because most of the accidents analyzed are considered severe. Fully balanced data can be regarded as more of an exception than a rule for real problems [81]. Authors such as Jeni et al. [82] comment that when analyzing performance parameters in the scenario of unbalanced data, problems may occur in determining the parameters, as the algorithms tend to perform poorly in the class with the smallest number of cases. Therefore, the results of this article for the performance of ML methods should be examined with extreme caution. To solve this problem, oversampling [83] and cost-sensitive techniques have proven effective by balancing information loss with computational efficiency [84]. In this paper, no method was employed to minimize possible bias in the classification results of ML algorithms.

It is necessary to highlight the training time factor. The time requirement for training non-neural methods is much lower than the training time for neural methods. While non-neural methods were trained in a few seconds, neural methods required several minutes, reaching a maximum of 1.52 h for Bi-LSTM. As noted by Khairuddin et al. [50], as Bi-LSTM uses more than one LSTM, its training time is expected to be longer. On the other hand, the 1D-COV method was trained in less than 15 min, which is a more viable time from a practical point of view for the industry. Authors such as Cunha et al. [29] have highlighted that some neural methods can be up to 23 times slower and only sometimes perform much better than classical methods, especially when processing a smaller database. Therefore, it is up to health and safety managers to define which methods to use in the case in question, given that non-neural methods such as RF and neural methods such as MLP showed good performance at low training costs. For comparison purposes, 1D-COV presented the best performance at a training cost 315 times higher than that of RF and 8.7 times higher than that of MLP.

5.1. Research Implications

This study is the first to be carried out in a complex footwear industry to evaluate the performance of ML methods and classify the severity of workplace accidents. Tamascelli et al. [46] highlight that using ML to extract relevant database knowledge is a viable way to learn from past incidents and improve industrial enterprises' health and safety systems. Thus, this research sheds light on this possibility in the footwear industry, one of the most common sites of workplace accidents and illnesses [19,85].

Neural and non-neural methods have been successful in classifying the severity of accidents. Thus, this research's findings reinforce that non-neural methods are still viable, even though neural methods may present superior performance. Methods such as FR and XGBoots required less computational effort and training time to be processed. Furthermore, they present low complexity in their interpretation.

Neural methods such as LSTM and GRU showed poor performance in classifying the severity of accidents. These methods have temporal dependence [37] in which the context, which is the output of a previous step, is the unilateral input of the step currently being processed [29]. This characteristic may have interfered with the accuracy of the classifications. Thus, the performance of these methods is enhanced for data that present temporal dependence, such as classification based on time series or text [60], to predict the trend of future data. The Bi-LSTM method showed much better performance. Unlike GRU and LSTM, the Bi-LSTM structure considers the complete data sequence due to its ability to analyze 'forward–backward' information, improving its prediction and performance [50]. Therefore, this study expands the possibility of using Bi-LSTM to analyze databases tabulated in electronic spreadsheets directly to classify the severity of work accidents in the industry.

This is also the first article to test the 1D-COV method for classifying accidents in the footwear industry. Pérez-Sala et al. [70] had already observed good performance of convolutional methods in predicting the severity of traffic accidents. Therefore, this study expands the possibility of using 1D-COV directly on accident data in the footwear industry, as the accuracy of the classifications was greater than 99%.

From a practical point of view, new simulated scenarios or new accurate data can feed the trained neural networks, generating the probable severity of the accident. Therefore, occupational safety managers can use algorithms to build prevention strategies and scenarios for possible workplace accidents.

5.2. Limitations

A limitation of this research was the non-direct use of the texts in the reports. Authors such as Pan et al. [47], Luo et al. [48], and Özkan and Ulaş [39] used artificial intelligence methods to extract information directly from the report texts. In our article, the information was extracted manually by professionals from the industry complex itself, which can lead to errors in data tabulation and some bias in interpreting the information in the reports. Another limitation is that images present in the reports were not used to train the ML methods. Paraskevopoulos et al. [49] suggest a multimodal classification to analyze security reports, considering textual elements and images present in the reports. A final significant limitation was the non-use of techniques that could minimize bias resulting from unbalanced data, which could increase the accuracy of performance parameters [84].

6. Conclusions

Several ML methods were used to classify the severity of accidents occurring in complex footwear industries. In this article, we built a database from reports, work safety and ergonomics documents, accident records, and work accident notices. The accidents present in these documents cover the period between 2016 and 2022. Non-neural methods like RF and XGBoots performed well with low training time and complexity. However, the best performance was found for the 1D-COV and Bi-LSTM neural methods, presenting accuracy, precision, recall, and F-score parameters greater than 98% and 99%, respectively. Thus, due to the shorter training time and better performance compared to Bi-LSTM, 1D-COV presents itself as the most viable method for practical applications for classifying the severity of work accidents in the footwear industry.

Future work could develop algorithms that use natural language processing (NLP) to more accurately and completely extract accident information from footwear industry documents [86]. In the same way that the optimization of hyperparameters can be achieved through genetic algorithms [70], these algorithms can provide a more appropriate input dataset for neural methods. These implementations are expected to make ML and DL algorithms more reliable and robust regarding their classifications.

Author Contributions: Conceptualization and writing—original draft, J.M.N.d.S.; methodology and investigation, M.L.d.S.B.; methodology and investigation, J.G.d.S.; conceptualization and supervision, L.G.M.B.; investigation, W.K.d.S.L.; data curation, E.M.d.A.V. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported with capital funding by the National Council for Scientific and Technological Development (CNPq), through Universal Notice CNPq/MCTI No. 10/2023. The project also received two grants from the Federal University of Alagoas (UFAL), through Notice PROPEP/UFAL No. 5/2023.

Data Availability Statement: The data presented in this study are available upon request from the corresponding author. They are not publicly available due to the need to store private information from the industrial complex.

Acknowledgments: The authors would like to thank the industrial complex managers for providing the information for this research.

Conflicts of Interest: The authors declare no conflicts of interest.

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