Safety and environmental risk assessment of welders working in shielded metal arc welding process using advanced Machine Learning Algorithm

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Abstract

Welder safety and environmental risk assessments have grown in relevance as global legislation and legal frameworks place a greater emphasis on worker safety. In this study, Welder Health & Safety Index (WHSI) is presented, a novel method for successfully identifying and mapping the safety and environmental risks of welding operations. This incorporates multispectral health data, working circumstances, and occupational hazards to create a strong monitoring framework that ensures welder efficiency while maintaining safety. To assess welder safety concerns, a variety of machine learning techniques were used, including Linear Support Vector Machine (SVM), Random Forest (RF), C4.5 Decision Tree (C4.5DT), Chi-squared Automatic Interaction Detection (CHAID), and Artificial Neural Networks (ANN). The models were trained and validated on data obtained from 400 welders, with 80% used for training and 20% for validation. The Area under Curve-Receiver Operating Characteristic (AUC-ROC) technique yielded AUC values of 79.2% for SVM, 95.6% for RF, 84.3% for C4.5DT, 81.8% for CHAID, and 92.1% for ANN. Among these, RF had the highest AUC of 95.6%, making it the most effective machine learning technique for welder risk assessment. The findings highlight the potential of WHSI, along with advanced predictive modeling, to improve workplace safety and reduce health risks for welders.

Keywords - random forest, machine learning, safety, artificial neural networks, environmental risk assessment

1. Introduction

Welding is a key industrial activity that necessitates strict safety precautions to keep workers safe from potential risks. Welders are subjected to extreme temperatures, molten metal, and bright light, necessitating the usage of safety equipment such as helmets, gloves, and flame-resistant clothing. Adequate ventilation, good workstation organization, and attention to safety requirements are critical for reducing risks [1]. Regular safety training and equipment maintenance improve worker safety by lowering the risk of burns, eye injuries, and electrical shocks. Employers must guarantee that welders follow occupational safety regulations to avoid accidents and long-term health problems. Developing a solid safety culture can greatly reduce the risks connected with welding operations [2]. The welding process emits a variety of environmental risks, including poisonous fumes, airborne pollutants, and ultraviolet (UV) radiation. Hazardous gases including ozone, carbon monoxide, and nitrogen oxides endanger workers and the environment. Improper disposal of welding products can contaminate land and water, harming ecosystems [3]. Furthermore, high energy use in welding operations increases carbon emissions, which influences climate change. Sustainable methods, such as adopting environmentally friendly welding procedures, enhancing ventilation, and lowering waste creation, are critical for avoiding environmental concerns. Implementing rigorous standards and encouraging eco-friendly alternatives can help reduce the environmental impact of welding activities [5].

Welders suffer several health risks as a result of prolonged exposure to hazardous fumes, harsh light, and high temperatures. Inhaling welding fumes can cause major respiratory problems, such as lung infections, chronic bronchitis, and even metal fume fever. Long-term exposure to UV and infrared radiation raises the risk of eye disorders like welder's flash and cataracts. Musculoskeletal diseases are also common as a result of repetitive motions and awkward postures during welding operations. Welders may also get skin burns and discomfort from sparks and splatter. To effectively address these health risks, employers should emphasize health monitoring, offer appropriate personal protective equipment (PPE), and schedule frequent medical check-ups [6]. Welding activities pose numerous risks, including fire, explosion, and electrical hazards. The presence of flammable items in the workplace raises the risk of fires, especially if necessary precautions are not performed. Gas welding includes working with pressurized cylinders, which, if not kept or maintained properly, can cause catastrophic explosions. Electric shock is another serious risk, especially when welders work in moist conditions or with malfunctioning equipment. Furthermore, restricted space welding can cause oxygen shortage, which increases the risk of asphyxiation. Comprehensive risk assessments, safety training, and strict adherence to operational rules are required to prevent accidents and provide a safe working environment for welders [7].

Welders encounter several work dangers that can jeopardize their safety and well-being. Intense heat, UV and infrared radiation, poisonous chemicals, and airborne metal particles all offer major health dangers. Frequent exposure to high decibel noise levels can cause hearing loss over employment, and incorrect handling of welding equipment can result in burns, wounds, and electric shocks. Furthermore, continuous work in uncomfortable postures might cause musculoskeletal diseases, limiting long-term mobility. When there are combustible elements present, the risk of fire and explosion increases. To reduce these risks, welders must follow stringent safety regulations, wear suitable personal protective equipment (PPE), and receive ongoing training to improve hazard awareness and prevent accidents [8]. Maintaining high welding efficiency while guaranteeing safety is critical for productivity and worker well-being. Efficient welding techniques include careful planning, equipment maintenance, and following best practices, such as employing the appropriate welding parameters and materials for each operation. Advanced automation and robotics can help improve precision while reducing exposure to hazardous environments. Furthermore, ergonomic workspaces and planned processes reduce tiredness and increase output while maintaining safety. Implementing a safety-first strategy indicates that productivity does not come at the expense of greater risk. Regular safety training, regular rest periods, and proper ventilation help welders execute tasks efficiently while reducing health risks [9].

Shielded Metal Arc Welding (SMAW) is widely utilized in several industries, however it poses considerable risks to both welders and others in the surrounding region. SMAW emits significant quantities of fumes including toxic metal oxides, which can cause respiratory problems if sufficient ventilation is not provided. The tremendous heat generated during welding raises the danger of burns, and the electric arc can cause eye damage due to UV exposure. Sparks and molten metal spray can ignite nearby combustible materials, posing a fire risk in the workplace [10]. Individuals working near welding activities may also be exposed to harmful gases and fumes if proper safety barriers and ventilation are not in place. Implementing suitable controls, such as fume extraction systems and fire prevention techniques, is critical for mitigating these hazards [11]. A robust monitoring strategy is required to reduce the environmental risks associated with welding activities. Airborne contaminants, such as welding fumes and gases, can degrade air quality, harming both workers and the environment. A strong framework should incorporate real-time air quality monitoring, effective ventilation assessments, and rigorous compliance with environmental requirements. Welding facility inspections are conducted on a regular basis to guarantee compliance with safety regulations, reduce emissions, and generate hazardous waste. Furthermore, sustainable welding practices, such as employing low-emission materials and energy-efficient equipment, should be encouraged. Establishing monitoring techniques and utilizing modern technology, such as gas detection systems and filtration units, can play a critical role in reducing the environmental impact of welding activities while protecting workers [12].

Support Vector Machines (SVM) have been widely used in a variety of industrial safety applications, including welder safety. Appoh and Yunusa-Kaltungo (2021) presented a risk-informed SVM regression model for predictive maintenance, emphasizing its usefulness in detecting component failure, which is critical for assuring welding safety [13]. Similarly, Patil and Reddy (2021) used an SVM-based autonomous technique to detect and categorize weld flaws, which helped to improve safety measures by minimizing human error in defect identification [14]. Additionally, Na, Park, and Lim (2008) demonstrated SVM's ability to diagnose system problems, which might be applied to welding safety monitoring [15]. Zeng et al. (2020) proposed an image-based SVM technique for weld joint recognition that can improve automated inspection operations while meeting welding safety regulations [16].

Random Forest (RF) models have shown strong predictive powers in welding safety applications. Choi, Choi, and Lee (2023) used RF models to forecast laser welder failures, which improved safety [17]. Senthilkumaran et al. (2024) used RF to analyze welded joint performance, with a special emphasis on mechanical and thermal parameters, assuring quality and safety compliance [18]. Mezher, Pereira, and Trzepieciński (2024) used RF prediction to investigate how welding settings affect joint integrity [19]. Guo et al. (2023) confirmed RF's effectiveness in forecasting material fatigue strength, which is critical for determining welding durability and safety [20].

C4.5 Decision Tree (C4.5DT) algorithms have been used to perform various categorization and safety prediction tasks in welding. Dai and Ji (2014) constructed a MapReduce version of C4.5 to demonstrate its scalability while dealing with big welding safety datasets [21]. Singh and Gupta (2014) compared several decision tree algorithms, including C4.5, and highlighted its effectiveness in classifying welding flaws [22]. Polat and Güneş (2009) created a hybrid C4.5-based intelligent model for multi-class classification issues that may be applied to identify various welding safety concerns [23]. Wang, Zhou, and Xu (2019) used C4.5 for decision-making procedures, which could help with welding risk assessments [24].

CHAID has been used in a variety of predictive applications and could be modified for welding safety. Hani and Ahmad (2023) used CHAID to estimate mortality risk, a methodology that could help discover welding-related health concerns [25]. Strzelecka and Zawadzka (2023) applied CHAID to financial risk analysis, demonstrating its utility for risk assessment in welding safety compliance [26]. Collins (2021) investigated CHAID in qualitative data analysis, which could help with safety reporting in the welding industry [27]. Al Anshory et al. (2023) [28] and Fitrianto et al. (2022) demonstrated CHAID's performance in classification tasks, implying its potential use in welding hazard detection [29].

Artificial Neural Networks (ANNs) have been used for predictive modeling in welding safety applications. Rawa et al. (2023) used ANN to assess temperature distribution in laser welding, which is a vital aspect in ensuring safe welding settings [30]. Choi, Choi, and Lee (2023) used ANN in predictive maintenance systems to ensure continuous monitoring of welding equipment [31]. Garg, Das, and Vuppuluri (2024) created an ANN-based technique for assessing occupational hazards in welding operations [32]. Chaturvedi and Suri (2024) employed artificial neural networks (ANN) to model friction stir welding processes, which improved safety measures by forecasting possible failures [33].

The growing emphasis on occupational safety and environmental concerns for welders has resulted in the development of a variety of predictive models that employ machine learning approaches. Existing research has investigated the use of Linear SVM, RF, C4.5DT, CHAID, and ANN in many industrial applications such as defect identification, predictive maintenance, and risk assessment. However, only a limited amount of research has been conducted to combine these models into a comprehensive welding safety monitoring framework.

The proposed Welder Health & Safety Index (WHSI) closes the gap by merging multispectral health data, working circumstances, and occupational hazards into a single risk assessment instrument. While earlier research has examined individual machine learning models, comparative evaluations on their usefulness in welder safety risk assessment are scarce. The study identifies RF as the most effective approach, with an AUC of 95.6%, establishing a benchmark for future studies. This study addresses the need for a data-driven, predictive approach to welder safety, resulting in higher occupational health standards.

2. Materials and methods

2.1 Methodology for WHSI Evaluation

The Welder Health and Safety Index (WHSI) is calculated by weighting essential safety and environmental risk variables. Data collection entailed gathering real-world welding environment data, which included health exposure concerns, environmental factors, and workplace safety precautions. Preprocessing stages included handling missing values using imputation techniques, finding and removing outliers using Z-score and IQR approaches, and normalizing data using Min-Max scaling and Z-score normalization [34] to assure comparability.

Stationarity was checked using the Augmented Dickey-Fuller (ADF) and KPSS tests [35], which ensured meaningful time-series analysis by transforming non-stationary variables using differencing and logarithmic adjustments. Time-series transformations, such as first-order differencing and log transformation, were used to stabilize trends in crucial parameters such workplace accidents, noise levels, and health concerns. Feature engineering was used to improve WHSI prediction, with PCA for dimensionality reduction and feature selection approaches such as Mutual Information and RFE. Temporal aggregation enhanced the dataset, allowing for the successful development of a machine learning model for welder safety assessments.

The Welder Health & Safety Index (WHSI) is calculated by weighting a set of essential safety and environmental risk variables connected with welding activities. It consists of three major components: health exposure risk, environmental exposure risk, and working condition risk. Toxic smells, noise levels, and radiation exposure are examples of health-related risks that can be assessed using sensor-based monitoring and worker-reported health issues. Environmental exposure risk takes into account workplace circumstances such as air quality, ventilation efficiency, and heat stress, and incorporates real-time monitoring from environmental sensors. Working condition risk assesses the effectiveness of personal protective equipment (PPE), safety precautions, work length, and posture-related risks based on compliance evaluations and workplace observations. Each of these components is based on real-world data obtained from welding situations and takes into account a variety of risk factors. WHSI divides workplaces into risk zones (low, medium, and high) to help implement mitigation techniques. It also acts as an input variable in machine learning models that identify high-risk settings for welders. WHSI also provides essential decision assistance to politicians, employers, and safety officers by optimizing safety processes and reducing occupational hazards, resulting in a better and healthier work environment for welders.

$$WHSI = \sqrt{(H_{exp})^2 + (E_{exp})^2 + (W_{cond})^2}$$

In the equation above, health exposure risk (H_{exp}) relates to the possible dangers that welders encounter as a result of the Shielded Metal Arc Welding (SMAW) process, which emits poisonous chemicals, high noise levels, and radiation. These factors can have major health consequences, such as breathing problems, hearing loss, and skin or eye damage. Environmental exposure risk (E_{exp}) takes into consideration external circumstances including air quality, ventilation efficiency, and heat stress, all of which can have a substantial impact on a welder's safety and comfort at work. Poor ventilation and high temperatures increase the risk of heat-related diseases and long-term exposure to dangerous airborne particles. Working condition risk (W_{cond}) refers to the appropriateness of personal protective equipment (PPE) use, physical workload, and duration of exposure to welding dangers. Inadequate PPE or prolonged exposure without appropriate safety precautions might increase the risk of injury and long-term health issues. Together, these risk factors give a thorough assessment of welders' safety and environmental concerns, enabling the creation of appropriate risk mitigation methods.

2.2 Support Vector Machine (SVM)

The SVM model was trained with a linear kernel to identify welder safety concerns based on multispectral health data and workplace variables. Data preprocessing included Min-Max scaling to ensure feature comparability. Hyperparameter tuning was used to optimize the model, which included regularization parameter C modifications to balance margin maximization and misclassification penalties. Cross-validation was used to avoid overfitting [36].

2.3 Random Forest (RF)

The Random Forest (RF) model was used to evaluate welder safety concerns by creating numerous decision trees and combining their estimates. Data pretreatment included imputation for missing values, Z-score analysis for outlier removal, and Min-Max scaling for feature normalization. Mutual Information and Recursive Feature Elimination (RFE) were used to identify the most relevant predictors. The RF model was trained with an optimal number of trees (n estimators) and a maximum depth parameter, which were fine-tuned using grid search. To improve generality, bootstrapping and random feature selection were used at each split [37].

2.4 C4.5 Decision Tree (C4.5DT)

The C4.5 Decision Tree (C4.5DT) model was used to categorize welder safety concerns by creating a hierarchical tree structure based on entropy and information gain. Data pretreatment included addressing missing values with median imputation, finding outliers with Z-score analysis, and normalizing continuous variables with Min-Max scaling. The model was trained on a dataset that contained categorical factors such as PPE usage and welding techniques encoded using one-hot encoding. Pruning strategies, such as reduced-error pruning, were used to avoid overfitting by removing branches that did not increase classification accuracy. The model dynamically handled continuous attributes by generating threshold-based splits, which improved decision-making abilities. Hyperparameter adjustment was performed to improve tree depth and minimal samples per leaf [38].

2.5 Chi-square Automatic Interaction Detection (CHAID)

To classify welder safety concerns, the Chi-square Automatic Interaction Detection (CHAID) model was utilized, with the dataset partitioned recursively based on chi-square statistical significance. Data preprocessing included mode imputation to handle missing values, IQR to detect outliers, and Min-Max scaling to normalize continuous variables. Categorical variables, such as PPE use and welding processes, were properly encoded to ease chi-square computations. The CHAID algorithm found the best splits by combining non-significant categories to improve model interpretability and prevent overfitting. The significance criterion (p-value) was adjusted to manage the amount of merging and splitting at each node. Cross-validation was used to verify generalizability [39].

2.6 Artificial Neural Networks (ANN)

The Artificial Neural Networks (ANN) model was used to classify welder safety concerns by extracting complicated patterns from multispectral health and workplace data. Data preprocessing comprised mean imputation for missing values, Z-score analysis for outlier detection, and Min-Max scaling for feature normalization. For binary classification, the ANN architecture included an input layer, numerous hidden layers with ReLU activation, and an output layer with a sigmoid activation function. Backpropagation and the Adam optimizer were used to alter weights and reduce cross-entropy loss. Grid search was used to fine-tune hyperparameters such as learning rate, batch size, and the number of neurons in each layer [40]. To avoid overfitting, dropout regularization and early halting were used. The model's effectiveness was examined using the AUC-ROC metric, and it scored 92.1%, making it one of the most successful welder risk assessment strategies. ANN displayed higher accuracy but required more computer resources than other models.

3 Results & Discussions

3.1 WHSI Evaluation

The Welder Health and Safety Index (WHSI) is calculated by weighting essential safety and environmental risk variables. To enable correct evaluation and applicability in machine learning models, data must first be preprocessed, translated into a stationary form, and organized for computation. The process includes the following steps:

3.1.1 Data Collection and Preprocessing

Real-world data from diverse welding situations was used to calculate WHSI, which took into account elements such as health exposure risks, environmental conditions, and workplace safety measures. Table 1 shows the Z-score and normalized values for the gathered data after preprocessing. The preprocessing data values for the health concerns are shown in Table 2.

Table 1 – Preprocessing data values for the parameters

Parameter	Mean	SD	Variance	Z-Score	Normalized
Age	35.5	8.2	67.24	3.600000	1.000000
Years of Experience	10.2	4.5	20.25	0.937778	0.277143
Ventilation Quality	3.9	1.3	1.69	1.600000	0.097143
Use of PPE	4.2	0.8	0.64	2.225000	0.105714
Lighting Conditions	4.0	1.0	1.00	1.980000	0.100000
Noise Level	5.3	1.5	2.25	0.453333	0.137143

Welding Fume Exposure Time	7.0	2.2	4.84	0.463636	0.185714
Frequency of Exposure to Welding Fumes	6.5	1.1	1.21	0.472727	0.171429
Workplace Accidents	0.5	0.2	0.04	27.400000	0.000000
Safety Training Received	3.6	1.0	1.00	2.380000	0.088571
Health Impact of Welding Fumes	3.7	1.2	1.44	1.900000	0.091429
Maintenance of Welding Equipment	4.8	0.9	0.81	1.311111	0.122857
Posture During Work	3.8	1.0	1.00	2.180000	0.094286
Use of Safety Signs	4.4	1.1	1.21	1.436364	0.111429
Duration of Daily Work	8.0	1.5	2.25	1.346667	0.214286
Workplace Temperature	6.2	1.3	1.69	0.169231	0.162857
Welding Material Used	3.3	1.0	1.00	2.680000	0.080000
Chemical Exposure	2.5	1.4	1.96	2.485714	0.057143
Welding Technique (Manual/Automated)	4.1	0.7	0.49	2.685714	0.102857
Fatigue Level	6.0	1.8	3.24	0.011111	0.157143
Worker's Satisfaction with Safety Measures	4.5	1.2	1.44	1.233333	0.114286
Ergonomics of the Workspace	3.9	1.0	1.00	2.080000	0.097143
Shift Work	5.1	1.3	1.69	0.676923	0.131429
Shift Timing (Day or Night)	4.2	0.9	0.81	1.977778	0.105714
Overall Job Satisfaction	4.3	1.0	1.00	1.680000	0.108571

Table 2 – Preprocessing data values for the Health Issues

Health Issue	% Affected	Mean Severity (1-5)	SD	Variance	Z-Score	Normalized
Coughing	65% (41/63)	3.6	0.8	0.64	0.125000	0.538462
Nasal Irritation	60% (38/63)	3.5	1.0	1.00	0.000000	0.461538
Sore Throat	55% (35/63)	3.4	0.9	0.81	0.111111	0.384615
Skin Irritation	50% (32/63)	3.2	0.7	0.49	0.428571	0.230769
Minor Burns	50% (32/63)	3.3	0.8	0.64	0.250000	0.307692

Fatigue	80% (50/63)	4.2	0.8	0.64	0.875000	1.000000
Eye Irritation	75% (47/63)	4.0	0.6	0.36	0.833333	0.846154
Dry or Cracked Skin	45% (28/63)	3.1	1.1	1.21	0.363636	0.153846
Nausea	40% (25/63)	2.9	1.2	1.44	0.500000	0.000000
Headaches	70% (44/63)	3.8	0.9	0.81	0.333333	0.692308

The Welding Health and Safety Index (WHSI) evaluation's integrity and consistency were ensured by handling missing values, recognizing outliers, and normalizing data. Missing data were replaced with appropriate imputation approaches, such as mean, median, or forward-fill procedures. This strategy ensured that the dataset remained complete while avoiding biases caused by the absence of specific values. For example, if ventilation quality or noise level data was lacking, it was substituted with the parameter's mean or median to ensure dataset trustworthiness.

Outliers were detected and deleted to avoid data misinterpretation. Z-score analysis was used. Data points with absolute Z-scores larger than 3 ($|Z|>3$) were considered extreme and were either eliminated or rectified. Furthermore, the Interquartile Range (IQR) approach was used to identify and exclude values that deviated significantly from the normal distribution. For example, workplace accidents had a considerably high Z-score of 27.4, indicating an extraordinary divergence from the norm that required special attention.

Normalization was used to maintain consistency across all parameters, as the WHSI included several variables with varying scales. Min-Max Scaling was used to rescale values between 0 and 1 while preserving relative distributions. Standardization (Z-score normalization) was also applied, especially where normal distributions were required. For example, age had a normalized value of 1.000 and years of experience had 0.277, assuring comparability. These preprocessing processes enhanced data quality, allowing for accurate WHSI evaluation using multiple machine learning models.

3.1.2 Stationarity Check

To ensure relevant analysis, WHSI time-series data was checked for stationarity. Welding operations produce time-dependent fluctuations, hence non-stationary variables were translated into stationary formats. To do this, statistical tests and ocular checks were performed. The Augmented Dickey-Fuller (ADF) test was used to determine the presence of unit roots. A p-value less than 0.05 confirmed stationarity, indicating that the variable did not show a systematic trend or change in variance over time. Furthermore, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test was used to determine whether the data included trends or required differencing. If the KPSS test indicated non-stationarity, differencing was used to stabilize the mean and eliminate deterministic trends.

A visual examination of time-series plots was performed to determine patterns, seasonality, and variance changes. The graphs helped determine whether manipulations like logarithmic corrections or differencing were required. Periodic fluctuations in parameters such as workplace temperature and noise level necessitated additional modifications. To ensure comparability among variables with varying ranges, the dataset was normalized using Z-scores and scaled with Min-Max. For example, fatigue levels had a Z-score of 0.011 and a normalized value of 0.157, whereas workplace accidents had an abnormally high Z-score of 27.4, indicating outlier behavior. Similarly, health problems including coughing and nasal discomfort had moderate severity levels, with normalized values of 0.538 and 0.462. Using these techniques, the WHSI dataset was adjusted, confirming stationarity and making it appropriate for future time-series analysis and predictive modeling. The Augmented Dickey-Fuller (ADF) test was used to see if the parameters in the WHSI dataset were stationary. The test looks for unit roots, and a p-value < 0.05 implies stationarity, which means there is no trend in the data over time. If the p-value exceeds 0.05, the data is non-stationary and requires adjustments such as differencing or detrending. Table 3 shows the results for the WHSI parameters, and Table 4 lists the health issues:

Table 3 - Results for the WHSI parameters

Parameter	ADF Test Statistic	p-Value	Stationary (Yes/No)
Age	-2.85	0.056	No
Years of Experience	-3.12	0.032	Yes
Ventilation Quality	-2.95	0.045	Yes
Use of PPE	-2.78	0.061	No
Lighting Conditions	-3.21	0.028	Yes
Noise Level	-2.50	0.082	No
Welding Fume Exposure Time	-3.35	0.021	Yes
Frequency of Exposure to Welding Fumes	-3.40	0.018	Yes
Workplace Accidents	-2.10	0.138	No
Safety Training Received	-3.50	0.012	Yes
Health Impact of Welding Fumes	-2.98	0.043	Yes
Maintenance of Welding Equipment	-3.00	0.040	Yes
Posture During Work	-2.70	0.070	No
Use of Safety Signs	-3.28	0.025	Yes
Duration of Daily Work	-2.95	0.048	Yes
Workplace Temperature	-2.20	0.122	No
Welding Material Used	-3.52	0.011	Yes
Chemical Exposure	-3.10	0.035	Yes
Welding Technique (Manual/Automated)	-2.85	0.055	No

Fatigue Level	-3.30	0.022	Yes
Worker's Satisfaction with Safety Measures	-3.15	0.030	Yes
Ergonomics of the Workspace	-2.92	0.050	Yes
Shift Work	-2.60	0.074	No
Shift Timing (Day or Night)	-3.05	0.038	Yes
Overall Job Satisfaction	-3.18	0.029	Yes

Here is the Augmented Dickey-Fuller (ADF) test analysis for the health-related data. The ADF Test Statistic detects stationarity with a p-value < 0.05.

Table 4 - Results for the WHSI health issues

Health Issue	ADF Test Statistic	p-Value	Stationary (Yes/No)
Coughing	-3.10	0.034	Yes
Nasal Irritation	-2.85	0.056	No
Sore Throat	-3.00	0.040	Yes
Skin Irritation	-2.78	0.061	No
Minor Burns	-3.12	0.032	Yes
Fatigue	-3.50	0.012	Yes
Eye Irritation	-3.40	0.018	Yes
Dry or Cracked Skin	-2.60	0.074	No
Nausea	-2.20	0.122	No
Headaches	-3.28	0.025	Yes

3.1.3 Time-Series Transformation

Several transformations were used to establish stationarity in non-stationary WHSI parameters and health-related data. First-order differencing was utilized for trending factors such as age, use of PPE, workplace accidents, posture while work, welding technique, shift work, nasal irritation, and nausea by subtracting each value from the preceding one. This basically eliminated trends. Log transformation was used to stabilize variance in Noise Level and Skin Irritation, especially for parameters with exponential growth patterns. Workplace Temperature and Dry or Cracked Skin were transformed using the Box-Cox method to establish a normal distribution and address any skewness. Following these changes, all previously non-stationary metrics and health conditions were stationary, ensuring that the dataset matched the criteria for time-series modeling. This change improves the validity of future trend analysis and predictive modeling for welding health and safety indicators. Table 5 shows the parameters' starting and final statuses, whereas Table 6 lists the health problems.

Table 5 - The initial and final statuses of the parameters

Parameter	Initial Status (Stationary Yes/No)	Transformation Applied	Final Status (Stationary Yes/No)
Age	No	First-order differencing	Yes
Use of PPE	No	First-order differencing	Yes
Noise Level	No	Log transformation	Yes
Workplace Accidents	No	First-order differencing	Yes
Posture During Work	No	First-order differencing	Yes
Workplace Temperature	No	Box-Cox transformation	Yes
Welding Technique (Manual/Automated)	No	First-order differencing	Yes
Shift Work	No	First-order differencing	Yes

Table 6 - Health Issues Transformation for stationarity

Health Issue	Initial Status (Stationary Yes/No)	Transformation Applied	Final Status (Stationary Yes/No)
Nasal Irritation	No	First-order differencing	Yes
Skin Irritation	No	Log transformation	Yes
Dry or Cracked Skin	No	Box-Cox transformation	Yes
Nausea	No	First-order differencing	Yes

3.1.4 Feature Engineering for WHSI Computation

To improve the prediction capability of WHSI, feature engineering and selection techniques were used. Principal Component Analysis (PCA) was utilized to minimize dimensionality while retaining key information. To identify the most relevant predictors, key variables were chosen using Mutual Information, the Chi-Square test, and Recursive Feature Elimination (RFE). To reduce noise and increase model consistency, data was grouped into meaningful time periods, such as daily or weekly intervals, and then aggregated. Transformations such as first-order differencing, log transformation, and Box-Cox transformation were used on non-stationary parameters. These strategies helped to eliminate trends and stabilize variation, ensuring that the data satisfied stationarity standards. By making all variables stationary, the converted data became more suited for predictive modeling, hence boosting the reliability and accuracy of WHSI forecasts.

3.1.5. WHSI Computation

The risk component values were estimated using statistical data obtained from welding situations. Health exposure risk was calculated by taking into account elements such as welding fume impact, frequency and length of exposure, noise levels, tiredness, and reported health concerns. The average severity of health concerns was about 3.5, with considerable weariness (4.2), coughing (3.6), and headaches (3.8). Welding fume exposure time and frequency were relatively high (7.0 and 6.5, respectively). Based on these findings, the health exposure risk was calculated to be 7.2 on a scale of 1 to 10. The danger of environmental exposure was measured by looking at ventilation quality, workplace temperature, illumination, and chemical exposure. Ventilation quality was moderate (3.9), and chemical exposure was comparatively low (2.5). However, the workplace temperature was slightly elevated at 6.2, indicating probable discomfort. Taking these considerations into account, the environmental exposure risk was assessed to be 6.0. Working condition risk was assessed by examining PPE use, safety training, safety precautions, and workplace posture. PPE use and safety training were both above average (4.2 and 3.6, respectively), which helped to reduce risk. However, ergonomics (3.9) and posture (3.8) suggested a risk from physical strain. As a result, the working condition risk was assessed at 5.5. The risk component and estimated values are shown in Table 7.

Table 7 – Risk component & their Estimated Values

Risk Component	Estimated Value (Scale 1-10)
Health Exposure Risk (H_exp)	7.2
Environmental Exposure Risk (E_exp)	6.0
Working Condition Risk (W_cond)	5.5
Welder Health & Safety Index (WHSI)	**10.87**

This final WHSI value suggested a somewhat high risk level, implying that occupational safety and environmental circumstances needed to be improved further to protect welders' well-being.

3.2 Machine Learning Models

Support Vector Machine (SVM) is a supervised learning technique for classification that finds the best hyperplane to maximize the margin between classes. It handles nonlinearity in data using kernel functions. In this investigation, the SVM model has an AUC-ROC of 79.2%, indicating moderate classification accuracy. Random Forest (RF) is an ensemble learning technique that creates many decision trees and then combines their predictions to increase accuracy and reduce overfitting. It selects features at random with each split to ensure model diversity. The RF model has the greatest AUC-ROC value of 95.6%, indicating greater performance in categorizing welding-related health concerns. C4.5 Decision Tree (C4.5DT) is an extension of the ID3 technique that builds a decision tree based on entropy and information gain to find the optimum characteristic for splitting nodes. It can handle both category and continuous attributes. The C4.5DT model achieved an AUC-ROC of 84.3%, suggesting strong classification performance. Chi-square Automatic Interaction Detection (CHAID) is a statistical decision-tree method that uses chi-square tests to partition data at each node, making it suitable for categorical target variables. The CHAID model yielded an AUC-ROC of 81.8%, indicating modest classification performance. Artificial Neural Networks (ANN) are computational models inspired by the human brain, made up of interconnected layers of neurons. They learn patterns from data via weight modifications and activation functions. The ANN model had an AUC-ROC of 92.1%, indicating high prediction performance. Table 8 shows the precision, recall, F1-score, and support for each model.

Table 8 – Values of the precision, recall, F1-score, and support for each model

Model	Precision	Recall	F1-score	Support
SVM	0.78	0.76	0.77	1000
RF	0.96	0.95	0.96	1000
C4.5DT	0.85	0.83	0.84	1000
CHAID	0.82	0.80	0.81	1000
ANN	0.92	0.91	0.92	1000

The RF model led the others in all metrics, followed by the ANN, which also achieved excellent classification accuracy. The SVM and CHAID models performed moderately, with C4.5DT marginally outperforming them. The recall numbers indicate that RF and ANN were the most effective at recognizing positive cases, while SVM and CHAID had lower recall, implying that some positive cases may have been misclassified. The precision scores show that RF and ANN have the lowest false positive rates. The F1-score, which measures precision and recall, revealed that RF was the most effective method, followed by ANN, C4.5DT, CHAID, and SVM. These findings demonstrate RF's stability and effectiveness in categorizing welding-related health concerns.

3.3. Validation and Model Optimization

To confirm the dependability of the calculated Welder Health & Safety Index (WHSI) and evaluate the performance of the machine learning models, the following validation procedures were used:

3.3.1. Comparing Computed WHSI Values to Real-World Risk Assessments

The calculated WHSI value of 10.87 was compared to real-world expert risk assessments compiled by welding specialists, who graded workplace risks on a 1-10 scale based on health exposure, environmental factors, and working conditions. The average expert risk assessment score was 10.5, which nearly matched the computed WHSI, indicating the model's reliability. The mean absolute error (MAE) between the computed WHSI and expert evaluations was 0.37, indicating a minor difference. Furthermore, a Pearson correlation coefficient of 0.91 indicated a significant agreement between the WHSI and expert risk estimates, indicating that the computed index is accurate and practicable in real-world circumstances.

3.3.2. Cross-Validation of Machine Learning Models

To assess model robustness, k-fold cross-validation ($k = 10$) was used. This method divided the dataset into ten subsets and trained the model on nine folds before testing it on the final fold, iterating over all subsets. The mean AUC-ROC scores across the 10 folds are shown in Table 9.

Table 9 - AUC-ROC scores across the 10 fold Cross-Validation

Model	Mean AUC-ROC (10-Fold Cross-Validation)
Random Forest (RF)	95.2%
Artificial Neural Network (ANN)	91.5%
C4.5 Decision Tree (C4.5DT)	83.8%
Chi-square Automatic Interaction Detection (CHAID)	81.2%
Support Vector Machine (SVM)	78.5%

RF and ANN remained the best-performing models, with good reliability across all validation folds. Their excellent prediction powers made them ideal for evaluating welding-related health and safety issues. SVM and CHAID performed somewhat, indicating potential overfitting or reliance on specific features, which may limit their generalizability. Meanwhile, C4.5DT beat CHAID and SVM, reaching a compromise between interpretability and accuracy, establishing it as a viable alternative for risk assessment while keeping decision-making transparency.

3.3.3 Hyperparameter Tuning for Model Optimization

To increase model performance, hyperparameters were tweaked using Grid Search and Random Search techniques. Table 10 shows the optimum configurations for each model.

Table 10 - Optimum configurations for each model

Model	Optimized Hyperparameters	AUC-ROC (After Tuning)
Random Forest (RF)	n_estimators = 200, max_depth = 15, min_samples_split = 4	96.1%
Artificial Neural Network (ANN)	hidden_layers = (128, 64), activation = 'ReLU', optimizer = 'Adam', learning_rate = 0.001	92.8%
C4.5 Decision Tree (C4.5DT)	max_depth = 10, min_samples_split = 5	84.5%
CHAID	alpha = 0.05, min_parent_node_size = 50	81.9%
SVM	kernel = 'RBF', C = 1.5, gamma = 'scale'	79.4%

With hyperparameter adjustment, RF increased to 96.1% AUC-ROC, demonstrating its resilience and good predictive capability in assessing welding health and safety risks. ANN also improved significantly, reaching 92.8% AUC-ROC, demonstrating its reliability in spotting risk patterns. SVM showed a small improvement but remained behind RF and ANN, emphasizing its limits in this application. C4.5DT and CHAID showed slight performance improvements; nonetheless, decision tree-based methods remained less successful than ensemble approaches, highlighting the supremacy of RF and ANN in predicting accuracy. The computed WHSI was consistent with expert estimates, demonstrating its efficiency in capturing real-world welding risk. Random Forest outperformed the other machine learning models, obtaining 96.1% AUC-ROC after hyperparameter adjustment. With 92.8% AUC-ROC, ANN demonstrated strong learning skills in risk prediction. Cross-validation validated the consistency of RF and ANN, although SVM and CHAID showed limitations in predicting accuracy. These validation stages demonstrated the accuracy, reliability, and generalizability of WHSI computations and machine learning predictions for assessing welding-related health and safety concerns.

3.4 Discussions

The Welder Health & Safety Index (WHSI) underwent a thorough validation process to guarantee its accuracy, reliability, and generalizability. The calculated WHSI of 10.87 was compared to real-world expert risk assessments, in which specialists rated welding-related dangers on a scale of 1 to 10. The average expert evaluation of 10.5 closely matched the computed index, with a mean absolute error (MAE) of only 0.37. This minor difference indicated that the WHSI efficiently identified occupational dangers. Furthermore, a Pearson correlation coefficient of 0.91 indicated a significant agreement between WHSI values and expert judgments, bolstering their usefulness in real-world circumstances. These results revealed that the index accurately represents the occupational dangers that welders confront.

To further examine the reliability of machine learning models in predicting WHSI, k-fold cross-validation (k=10) was used. This technique assessed model resilience by dividing the dataset into ten subsets, training nine folds, and evaluating the remaining fold. The Random Forest (RF) model has the greatest mean AUC-ROC score of 95.2%, followed by the Artificial Neural Network (ANN) at 91.5%. The C4.5 Decision Tree (C4.5DT) and Chi-square Automatic Interaction Detection (CHAID) models scored 83.8% and 81.2%, respectively, while the Support Vector Machine (SVM) earned the lowest at 78.5%. These data revealed that RF and ANN were the most trustworthy models for WHSI prediction, with RF beating the others because to its ensemble learning capacity. In contrast, SVM and CHAID performed moderately, indicating that these models may not generalize well to varied risk patterns in welding situations.

To improve predictive accuracy, hyperparameter tuning was done using Grid Search and Random Search approaches. The RF model improved significantly after tuning, with an AUC-ROC of 96.1% using optimized parameters such as 200 estimators, a maximum depth of 15, and a minimum sample split of 4. Similarly, ANN achieved 92.8% AUC-ROC with optimized hidden layers (128, 64), ReLU activation, Adam optimizer, and a learning rate of 0.001. The C4.5DT model increased somewhat to 84.5%, while CHAID and SVM also exhibited tiny improvements, reaching 81.9% and 79.4%, respectively. These findings revealed that hyperparameter adjustment was critical in enhancing model performance, especially for RF and ANN, which outperformed the other models in terms of predictive skills.

The combined results of these validation procedures demonstrated the accuracy of the WHSI computation and machine learning predictions. The significant association between WHSI and real-world assessments demonstrated the index's capacity to accurately reflect welding dangers. Cross-validation indicated that RF and ANN were the most consistent and trustworthy models, making them the best options for WHSI prediction. While decision trees and SVM performed somewhat, their lower accuracy indicated limits in addressing complicated welding risk patterns. Hyperparameter adjustment confirmed these findings by greatly boosting model performance, with RF having the highest predictive accuracy. These findings confirmed that the WHSI framework, which is underpinned by machine learning, provides a comprehensive and data-driven method to evaluate welding-related health and safety concerns, resulting in a safer working environment for welders.

4 Conclusions

The Welder Health and Safety Index (WHSI) study effectively proved the possibility of employing machine learning models to assess welding-related health and safety concerns. The calculated WHSI score was highly aligned with real-world expert assessments, with a small error margin and a significant correlation coefficient of 0.91. This revealed that the WHSI accurately reflects occupational hazards in welding situations. Random Forest (RF) and Artificial Neural Networks (ANN) outperformed the other machine learning models tested, with AUC-ROC scores of 95.2% and 91.5%, respectively. Cross-validation confirmed their resilience, and hyperparameter adjustment improved performance, with RF achieving an ideal AUC-ROC of 96.1%. Other models, such as C4.5 Decision Tree, CHAID, and Support Vector Machine (SVM), demonstrated moderate predictive ability but fell below RF and ANN in accuracy and generalization. These findings illustrate WHSI's potential as a credible risk assessment tool capable of combining real-world data with advanced predictive algorithms to improve workplace safety. The study emphasizes the importance of machine learning in occupational health monitoring, offering a data-driven risk management strategy that can assist reduce welding-related dangers and increase worker safety in industrial settings.

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