Journal of Mines, Metals and Fuels, *73(3): 771-782; 2025. DOI: 10.18311/jmmf/2025/47391*

Print ISSN : 0022-2755

Journal of Mines, Metals and Fuels

Contents available at: *www.informaticsjournals.co.in/index.php/jmmf*

Role of Individual and Occupational Factors on Injuries among Contractual Workers in Surface Mines-Machine Learning Approach

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Abstract

This study integrates data analysis and machine learning techniques to investigate workplace injury prediction and mitigation in surface mining operations. Injury data (from March 2023 to Aug 2024) was collected from mechanised limestone mines in Raipur, Chhattisgarh, encompassing 446 workers' demographic details, health data and workplace conditions. The methodology involved exploratory data analysis, linear and non-linear regression models and advanced machine learning algorithms such as XG Boost, random forest, decision tree, and Bayesian ridge regression. risk factors namely skill level (semi-skilled), age (mean 43 years), experiences (mean 14 years), designation, qualifications, health status, work environment, and safety culture were analysed to predict injury occurrences. The results reveal that near misses and minor incidents are significant early indicators (T-value 1.35) of severe injuries, emphasising proactive safety measures. Among the models evaluated, XG Boost well performed with a training R-squared of 0.95 and test R-squared of 0.43, demonstrating its superior ability to generalise and capture complex relationships in the data. The analysis found that injuries are moderately common for contractual workers (mean: 0.90 per instance), with significant variability in near misses (mean: 8.05). Standardised working conditions, such as uniform duty hours (8 hrs.) and leave entitlements (30 days/year), contribute to the occurrence of injuries (t-value 1.35). Proactive measures to be taken in addressing factors like worker skill levels, availability of safety features and positive attitudes toward safety, are crucial for mitigating injuries at workplaces.

Major Findings: *From the study it can be concluded that the factors namely fire (T-value=5.64), experience (T-value=4.69), skill level (T-value=5.08), positive attitude towards safety (T-value=3.68), medical facilities (T-value=4.35), working conditions of the site (T-value=5.23) and available equipment with safety features (T-value=4.55) are the significant factors that contribute to the occurrence of the injuries among contractual workers in surface mines. The machine learning algorithm models namely extreme gradient boost (XG Boost) performed best for the prediction of the injuries data consider for the study with training data set, (R-squared 0.95) and testing data set (R-squared 0.43).*

Keywords: *Contractual Workers, Individual, Machine Learning, Occupational Factor, Surface Mines*

1.0 Introduction

Injuries in surface mines can range from minor bruises and sprains to severe fatalities, with profound consequences not only for workers but also for the industry's productivity and reputation[1,2,3]. mine management and miners need to be educated and sensitized on the dangers of this operation. Provision of safety gears and positive safety culture must be a top priority for management[2]. The lack of management commitment, worker's refusal to report minor injuries or near misses and the cost involve in training employees on health and safety in the

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company are major problems[3]. Unsafe act and practices contributed greatly to miens accident and injuries[4]. Working in the industry is commonly associated with a combination of personal and environmental health and safety risks[5].Surface mining is a labour-intensive and physically demanding industry, often characterized by hazardous working conditions[6]. The lack of experience in the activity, insufficient specific knowledge (formal and informal knowledge) about a particular installation and to inadequate training period are causes of accident and injuries[7]. The assessment of age, perceptions of working conditions, safety environment, management and supervision, risk-taking behaviour, mental instability, negative job participation, job dissatisfaction, workplace stress, and workers' poor safety performance can help to control the occupational injuries[8]. The pattern of work-related injury in Iran was almost similar in regard to age, gender, cause and type of the accident, with other parts of the world[9]. The hazards present in a work system and the nature of the job carried out by workers are perceived as important drivers of injury potential of a work system[10]. Prevention should focus on handling material, poor environmental condition, especially addressing workers with no formal education, alcohol consumption, disease, big family size, and risk-taking behavior[11]. The occupational health hazards, accidents and injuries is becoming a major problem due socio-economic impact on work place and occupational health hazards, poor documentation, families of affected workers, livelihood[12]. Safety Integrated Model-training (SIM-t) with the aim of unifying the most effective training methods for adults[13]. Mining industry is labour-intensive and demands exclusive ergonomics strategy/design intervention[14]. The risk factors (personal, including behavioral and work organizational) that influence human error and evaluates those risk factors as predictors of injury occurrences at continuous miner worksites[15]. Many factors contribute to the development of WRMSDs specially in the labour-intensive mining industry[16]. The strategic problem of optimally locating different types of relief facilities across the railway network that could respond to an accident-related emergency[17]. Temporary agency workers are particularly vulnerable, with studies showing they experience a higher incidence of workplace injury, and a greater likelihood of more severe injuries than all other employment types[18]. Contract workers, who often lack the same levels of job security, training, skill level, attitude towards safety and supervision as permanent employees, are particularly vulnerable to workplace accidents[18]. The high-risk nature of mining, coupled with the prevalence of contract workers, presents unique challenges in terms of safety and injury prevention[19]. This research contributes to the development of context-specific safety indicators for the Indian mining industry and demonstrates the potential of Artificial Learning (AI) and Machine Learning (ML) in enhancing contractor workers workplace safety. Future work aims to refine the prediction models, explore additional safety parameters, and extend the study to other mining sectors for broader applicability.

2.0 Materials and Methods

Mine visits were conducted to collect contractual workers' data, to conduct a questionnaire survey of the contractor workers and for discussions with mine

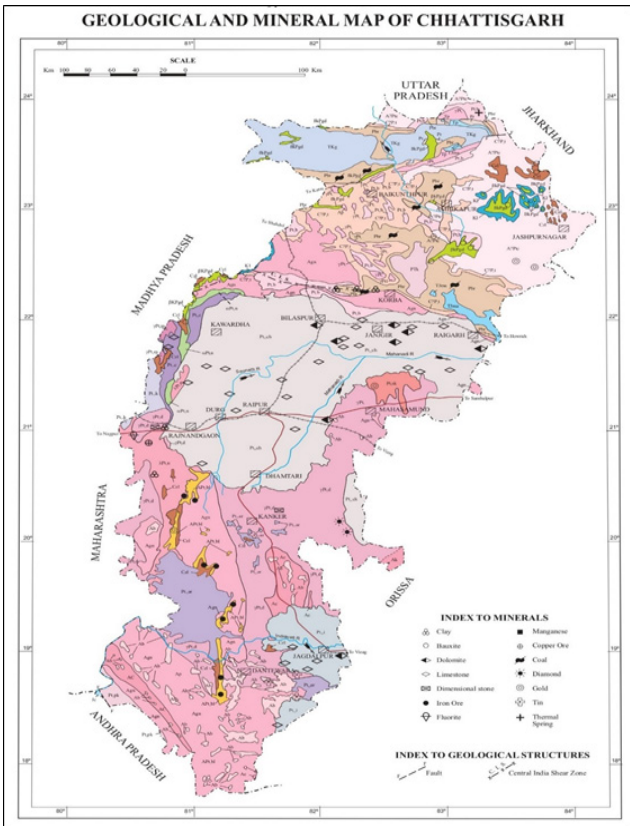


Figure 1. Google location map of study areas.

officials at various limestone surface mines located in the Chhattisgarh geographical region in India. Individual and occupational namely injuries, near miss, age, experiences, skill level, multiskilling training, severity level, and causes of incidents or accidents are collected from historical records of mines and individual factors of contractual workers namely the opportunity to improve safety, medical facilities, working conditions of the site, available equipment with safety features of evaluated and scored evaluated through questionaries' survey. A total of 446 contractor workers working in mines and plants out of them 256 workers got injured in the last one and half years (March 2023 to Aug 2024) participated in the study.

Only contractual workers who are appointed under the Mines Act, trained under the Vocational Rules (VT) rule, registered under statutory form-A, attendance recorded on Form-D, undergone medical tested Initial Medical Examination (IME)/Periodical Medical Examination (PME) under mines rule are considered in this study. Statistical methods and ML algorithms such as ANOVA, Linear Regression, Random Forest, Decision Tree, Extreme Gradient Boosting, Support Vector, Bayesian Ridge Regression, and Ridge Regression were applied for contractual workers' data analysis to find out the influences parameters which have major role played to occurrences of accidental injuries in surface metal mines. Minitab 17, Kaggle Notebook, Python, Pandas Libraries, NumPy and Matplotlib Software have been used for the analysis of the data set. Optimisation programs to optimise relief facilities across the railway network for accident-related emergencies and programs maximising network coverage, prioritising important rail links, optimising redundancy and minimizing response times, are applied to the North Central Railway zone of Indian Railways, showing that reconfiguring relief facilities increases rail node and rail-link coverage[17]. Figure 1 shows the study areas in Google Maps.

3.0 Results and Discussions

3.1 Data Analysis of Contractual Workers in Case Study Surface Metal Mines

This study includes safety indicators contributing to surface area mine injuries, focusing on individual characteristics and health health-related factors of contractual workers. The aim is to improve safety standards and minimise accidents at mining sites. It suggests modelling training and testing injury data for effective safety measures. The incident data set consist of 256 injuries cases, 190 Nos. of non-injuries cases and 3210 nos. of near miss incidences considered for the prediction of injuries by using XG Boost, Random Forest, Bayesian, Ridge Regression machine learning modelling. Table 1 shows the descriptive statistics of various safety indicators of contractual workers considered in the study.

The study found that significant occurrences of injuries including near misses occurred due to the factors namely, age, experience, skill levels, duty allotted per day, weekly rest day, annual leave entitlement, wages per day, attendance per month, monthly salary and Employees State Insurance (ESI) medical insurance premium costs. The workforce is generally middle-aged, with a mix of experienced and seasoned employees. The average age is 43.1 years, with a mix of seasoned and newer employees. Experience is 13.8 years, with a mix of seasoned and newer employees. The average daily wage is ₹702.70, with a standard deviation of ₹89.66 suggesting variability in pay scales. High attendance rates are maintained, and the monthly salary includes a Provident Fund (PF). The study also shows a moderate need for improvement in safety opportunities, with varying opinions among employees about the adequacy of current safety measures. The availability of medical facilities and safety-equipped equipment is also high, suggesting improvement. ANOVA analysis was carried out to find the impact of each variable on injuries and near-miss incidence by using Python Software. Table 2 shows the T-value and F-value of variables considered in the study.

Table 2, evaluates the impact of various factors on specific safety-related outcomes (e.g., injuries, damages, environmental impact and safety conditions). Using F-values, T-values, and P-values, the analysis identifies the significance and magnitude of each factor's influence. A P-value < 0.05 indicates statistical significance, while higher F-values suggest stronger effects. Significant factors (P< 0.05) are fire, experiences (years), skill level, severity level, positive attitude towards safety, medical facilities, working condition of the site and available equipment with safety features. Fire is the most impactful

Table 1. Descriptive statistics of various safety indicators of contractual workers of the case study mines

Safety Indicators and Factors as Variables	Description	Data Type	Mean	Standard deviations	Min.	Max.
Injuries and near miss	Dependent Variable	Numeric	8.66	7.07	0	45
Age	Independent Variable	Continuous	43.12	7.99	23	59
Experience	Independent Variable	Continuous	13.81	5.17	2	35
Skill level	Independent Variable	Categorical	2.40	0.69	1	3
Duty allotted per day in hours	Independent Variable	Numeric	8.00	0.0	8	8
Weekly rest day	Independent Variable	Numeric	1.00	0.0	1	1
Yearly leave entitlement in d ays	Independent Variable	Numeric	30.00	0.0	30	30
Wages per day	Independent Variable	Numeric	702.70	89.6	522	778
Attendance per month	Independent Variable	Numeric	26.00	0.0	26	26
Monthly salary including PF	Independent Variable	Numeric	18024.52	3130.74	16926	20228
ESI medical insurance premium	Independent Variable	Numeric	275.00	0.0	275	278
Positive attitude towards safety	Independent Variable	Numeric	9.21	3.90	1.9	17.5
Opportunities to improve safety	Independent Variable	Numeric	8.05	3.45	1.5	15
Medical facilities	Independent Variable	Numeric	13.83	4.09	3	21
Working conditions of the site	Independent Variable	Numeric	8.27	2.76	3	14.99
Available equipment with safety features	Independent Variable	Numeric	8.98	2.89	3	17.51

parameter with an F-value of 31.83 and P-value < 0.001, indicating a strong association with outcomes. Experience (years) strongly affects safety (F = 22.02), experienced workers likely reduce risks. Skill level is highly significant (F= 25.79), skilled workers ensure fewer errors and safer practices. The severity level significant (F = 5.45) highlights the importance of mitigating severe incidents. Positive attitude towards safety, notable impact (F = 13.51), proactive safety attitudes reduce hazards. Medical facilities are critical to mitigating injuries (F = 18.91). Working conditions are the most impactful among site-specific factors (F = 27.37). Available equipment with safety features is critical with F= 20.72, proper equipment minimises risks. Injuries, equipment/ property damages

Table 2. ANOVA analysis of the variables considered in the study

Safety indicators and factors as variables	Description	Data Type	F- value	T-Value	P-Value	Sum Sq. Error
Injuries and near miss	Dependent Variable	Numeric	18.91	1.35	0.18	0.341
Equipment / Property damages	Independent Variable	Numeric	2	1.41	0.16	0.001
Environment	Independent Variable	Numeric	1.51	0.06	0.95	5.43
Fire	Independent Variable	Numeric	31.83	5.64	0.02	2.52
Age	Independent Variable	Continuous	1.81	1.34	0.16	3.76
Experiences (Years)	Independent Variable	Continuous	22.02	4.69	0.015	4.40
Skill Level	Independent Variable	Categorical	25.79	5.08	0.02	0.93
Severity Level	Independent Variable	Discrete	5.45	2.33	0.029	0.001
Monthly salary including PF	Independent Variable	Numeric	1.5	0.07	0.95	2.30
Positive attitude towards safety	Independent Variable	Numeric	13.51	3.68	0.049	0.30
Opportunities to improve safety	Independent Variable	Numeric	1.91	0.01	0.99	3.22
Medical facilities	Independent Variable	Numeric	18.91	4.35	0.04	4.67
Working conditions of the site	Independent Variable	Numeric	27.37	5.23	0.015	3.53
Available equipment with safety features	Independent Variable	Numeric	20.72	4.55	0.02	73.43

and environment ($P > 0.05$) show no significant statistical impact in this study. Monthly salary and opportunities to improve safety are also not statistically significant. A lower sum of squares error (e.g., Severity Level: 0.001, Fire: 2.52) indicates robust predictive power for these factors. Higher variance (e.g., Environment: 5.436) suggests weaker reliability. The analysis highlights both individual and workplace factors influencing safety outcomes. Human factors are experience and skill level are pivotal; experienced and skilled workers can predict and mitigate risks effectively. Attitudes towards safety underline the psychological and cultural dimensions of workplace safety. Workplace conditions are working conditions and available equipment is critical in preventing accidents.

Poor site conditions and unsafe equipment amplify risks. Systemic interventions are medical facilities play a significant role in responding to incidents and minimising long-term impacts. Factors like fire risks and near misses highlight the importance of early intervention and monitoring systems. Injuries, environmental conditions and salary are not statistically significant in this study, possibly due to sampling limitations. Context-specific factors that overshadow their relevance.

3.2 Linear Regression Modelling

The linear regression modelling section provides insights into the relationships between input-dependant variables such as injuries (onsite, offsite, and total) and various outputs as independent factors like qualifications, age, and skill levels. Table 3 shows the summary of linear regression modelling of various injuries namely onsite, offsite and total injuries.

Table 3 shows a weak positive relationship between qualifications and onsite injuries, suggesting that qualifications alone may not strongly explain variations in injuries. Offsite injuries showed no significant effect on qualifications, while total injuries showed a slight negative relationship with age. Skill level had a slight negative relationship with total incidents, suggesting that higher skill levels may reduce injuries slightly. However, the low R-squared value indicates other factors are likely more significant. The results suggest that most models exhibit low R-squared values, indicating that the predictors explain very little variance in injuries or incidents. Some weak positive or negative coefficients hint at minor trends, and there is a need for better predictors, such as safety training, work hours, or environmental conditions.

3.3 Multiple Linear Regression Machine Learning Modelling Through Train Test Split Evaluation Technique for Injuries Prediction.

The analysis uses multiple evaluation techniques to assess the performance of a multiple linear regression model.

The Figure 2 and Figure 3 show the actual vs. predicted injuries in training and testing data respectively in multiple linear regression modelling. The training and testing R-squared scores were 0.049 and -0.11 respectively. The K-Fold cross-validation Evaluation technique was used to evaluate the model's performance. Negative values indicate the model's performance is worse than a simple mean predictor, while positive values suggest the model explains some variance but only slightly. The mean R-squared score was -0.003. The mean R-squared from bootstrapping is -16.0. The Standard deviation of

Table 3. Summary of linear regression modelling of various injuries

Model	Equation	Coefficient	Intercept	Mean Squared Error (MSE)	R-Squared
Onsite injuries vs. Qualifications	Y = 0.0947X + 0.4759	0.0947	0.47	2.24	-0.014
Offsite injuries vs. Qualifications	Y = -0.0071X + 0.0791	-0.0071	0.07	0.08	0.0001
Total injuries vs. Qualifications	Y = 0.0876X + 0.5550	0.0876	0.55	2.33	-0.015
Total injuries vs. Age	Y = -0.0071X + 1.1792	-0.0071	1.17	2.32	-0.007
Offsite injuries vs. Age	Y = -0.0019X + 0.1351	-0.0019	0.13	0.08	-0.010
Total injuries vs. Skill level	Y = -0.1946X + 9.4333	-0.1946	9.43	66.79	0.005

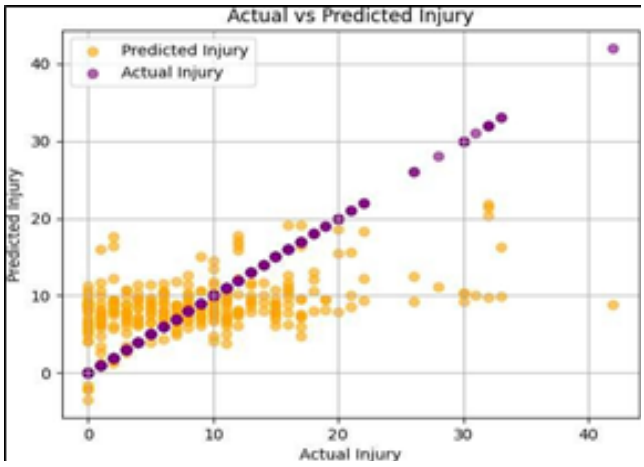


Figure 2. Actual vs. predicted injury train MLR.

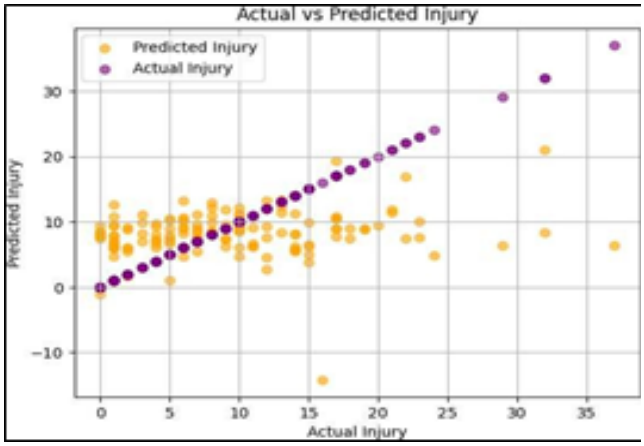


Figure 3. Actual vs. predicted injury test MLR.

the R-squared from bootstrapping is 5.22. The multiple linear regression model currently performs poorly across all evaluation techniques, likely due to insufficient and weakly predictive features, noisy data, and possible overfitting. The training-test split evaluation technique shows a low R-squared value, suggesting a weak fit even on the training data. The testing R-squared value is negative, indicating overfitting and poor performance on the test set. The K-fold cross-validation evaluation technique shows mixed performance across folds, with negative values indicating poor model performance in specific folds. The bootstrap evaluation technique shows a massive negative value, indicating extremely poor performance. Key findings from these techniques include poor predictive power of features, overfitting on training data, insufficient or noisy data, and model instability. Recommendations for improvement include feature engineering, increasing sample size, exploring non-linear models, regularization techniques, data normalization and stratified cross-validation. Addressing these limitations through better feature selection, larger datasets, and non-linear modelling approaches can lead to more reliable and accurate predictions.

3.4 Regression-Based Machine Learning Modelling for Injuries Prediction.

The study compares various regression models for injury prediction, focusing on their performance on training and test data. The Extreme Gradient Boosting Regression (XG Boost) model fits the training data exceptionally well, explaining 95% of the variance. However, it struggles to generalise to test the data, particularly for higher injury severities. Random Forest regression outperforms these models in terms of generalisation, balancing training and test performance well. The Figure 4 and Figure 5 show actual vs. predicted injuries in training and testing data set of case study contractual workers respectively in XG Boost regression modelling. The Figure 6 and Figure 7 show actual vs. predicted injuries in training and testing data set of case study contractual workers in random forest (RF) regression modelling. The Figure 8 and Figure 9 show actual vs. predicted injuries in training and testing data set of case study contractual workers in decision tree regression (DTR) modelling. The Figure 10 and Figure 11 show actual vs. predicted injuries in training and testing data set of case study contractual workers in support vector regression (SVR) modelling. The Figure 12 and Figure 13 shows actual vs. predicted injuries in training and testing data set of case study contractual workers in Bayesian ridge regression (BRR) modelling. The Figure 14 and Figure 15 shows actual vs. predicted injuries in training and testing data set of case study contractual workers in ridge regression modelling (RR).

Table 4 presents the performance of six models for injury prediction, including XG Boost, Random Forest, Decision Tree, SVR, Bayesian Ridge Regression, and Ridge Regression. XG Boost has the highest training R-squared (0.950), explaining 95% of the variance in the training data. SVR and Decision Tree have lower training R-squared values, suggesting they are less effective at explaining the variance in the training data.

Table 4. Performance analysis of predictions model

Statistical measure and machine learning algorithm models	XG Boost Regression	Random Forest Regression (RF)	Decision Tree Regression (DTR)	Support Vector Regression (SVR)	Bayesian Ridge Regression (BRR)	Ridge Regression (RR)
Training R-Squared	0.95	0.63	0.59	0.49	0.57	0.61
Test R-Squared	0.43	0.045	0.36	0.22	0.39	0.34
Mean R-Squared (K-Fold)	0.39	0.40	0.24			
Mean R-squared (Bootstrapping)	0.74	0.59	0.49			
Standard Deviation Bootstrapping	0.04	0.032	0.04			

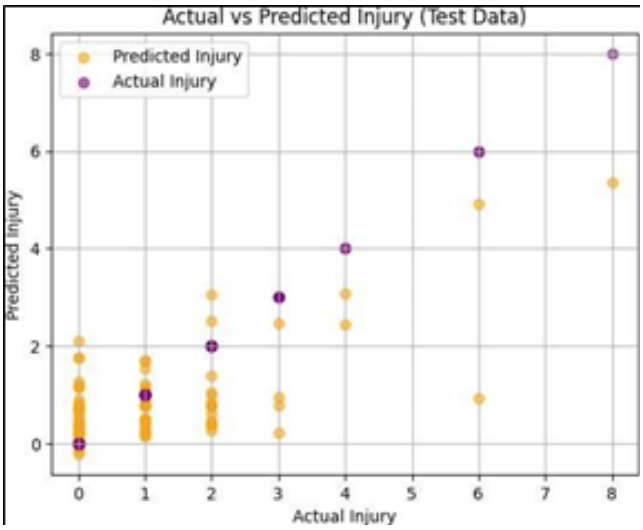


Figure 4. Actual vs. predicted injuries train- XG boost.

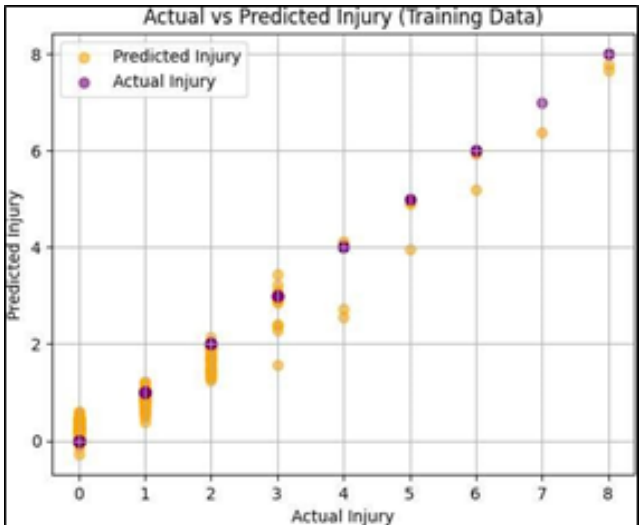


Figure 5. Actual vs. predicted injuries test – XG boost.

Bayesian Ridge and Ridge Regression perform similarly, with training R-squared values of 0.572 and 0.616 respectively. XG Boost has the highest test R-squared value (0.430), indicating better generalization. Random Forest and Decision Tree have moderate test R-squared values, suggesting they struggle with generalization. XG Boost has the smallest standard deviation (0.041), making it the most stable across bootstrapped samples. Its high mean R-squared from K-Fold cross-validation and bootstrapping performance makes it the top-performing model for this problem. Linear models like Ridge and Bayesian Ridge offer simpler alternatives with decent performance but may miss capturing more complex relationships in the data compared to XG Boost. Hyperparameter tuning of models like Random Forest and Decision Tree could improve their generalisation capabilities.

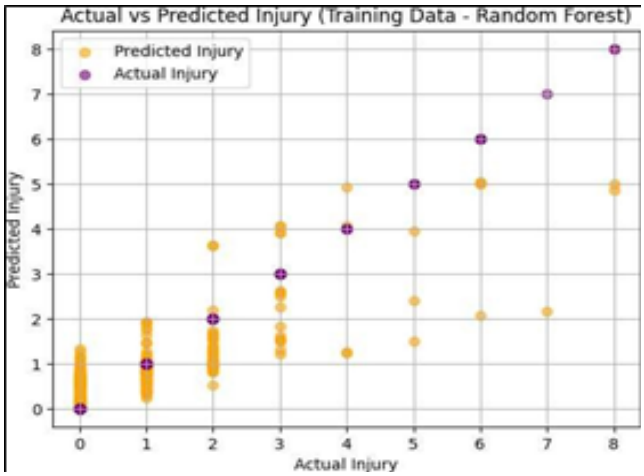


Figure 6. Actual vs. predicted injuries train-RF.

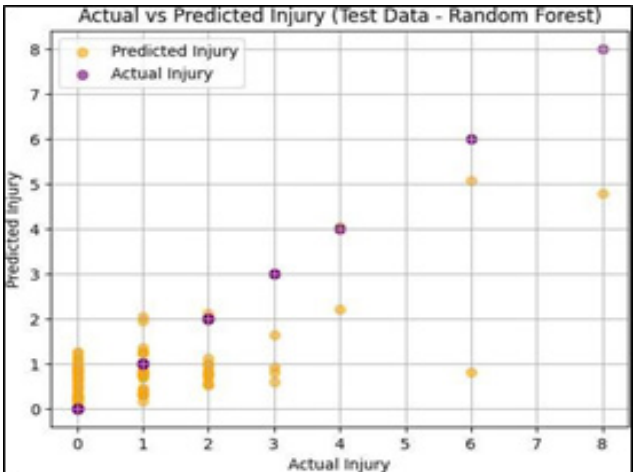


Figure 7. Actual vs. predicted injuries test-RF.

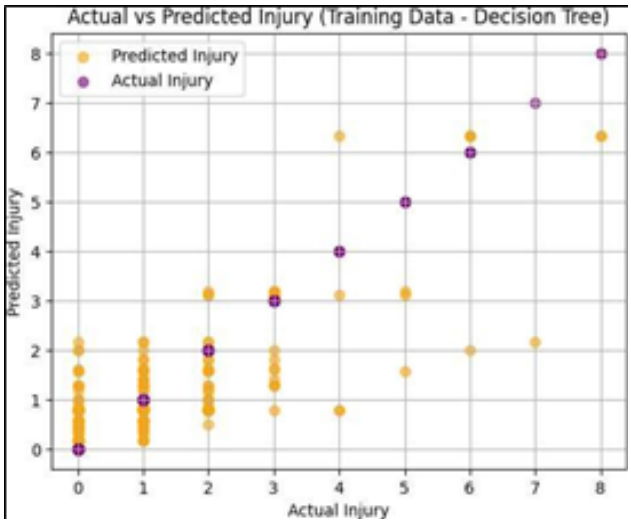


Figure 8. Actual vs. predicted injuries train- DTR.

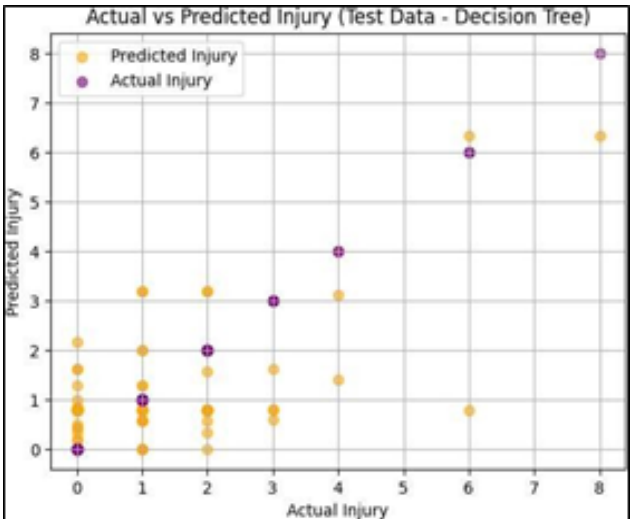


Figure 5. Actual vs. predicted injuries test -DTR.

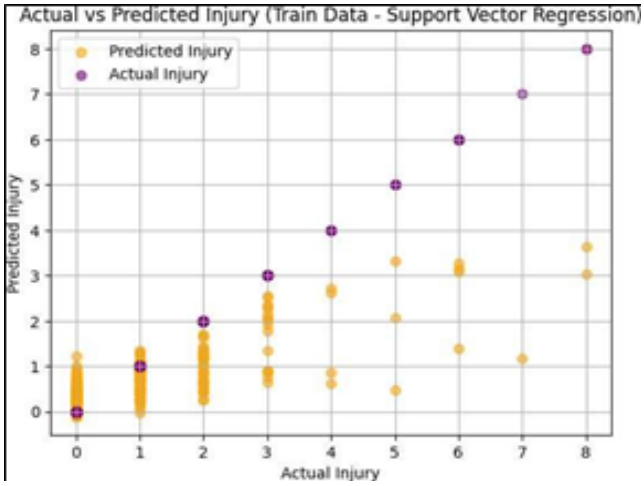


Figure 10. Actual vs. predicted injuries train SVM.

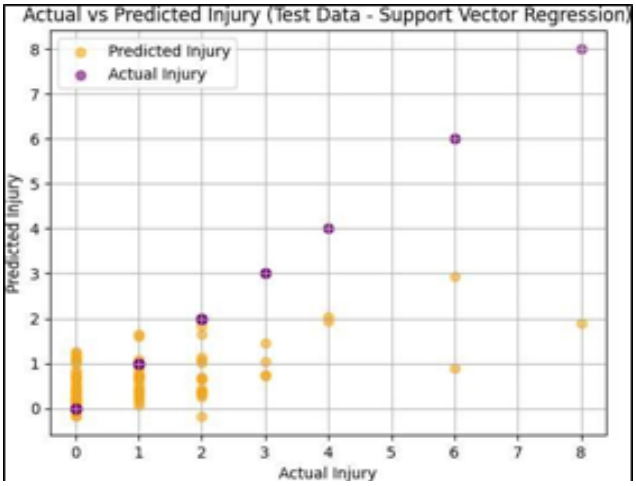


Figure 11. Actual vs. predicted injuries test-SVM.

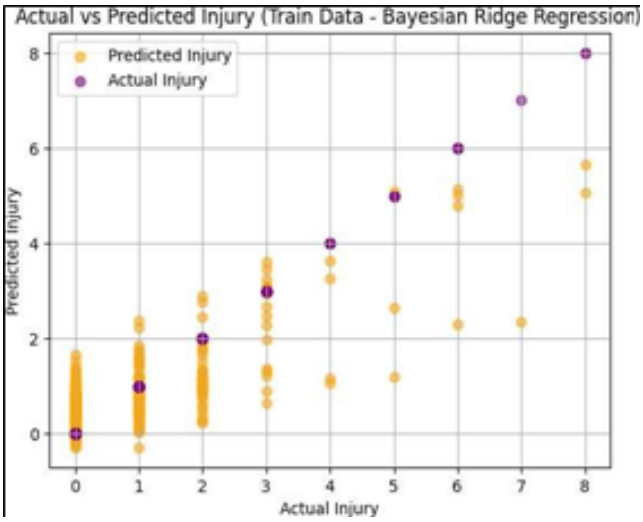


Figure 12. Actual vs. predicted injuries train –BRR.

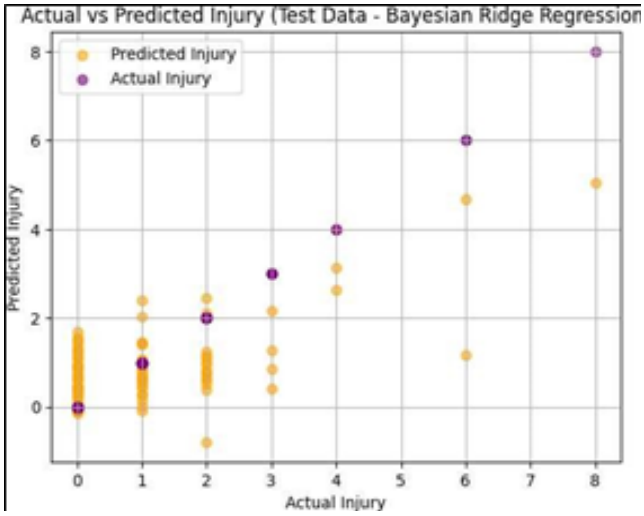


Figure 13. Actual vs. predicted injuries test -BRR.

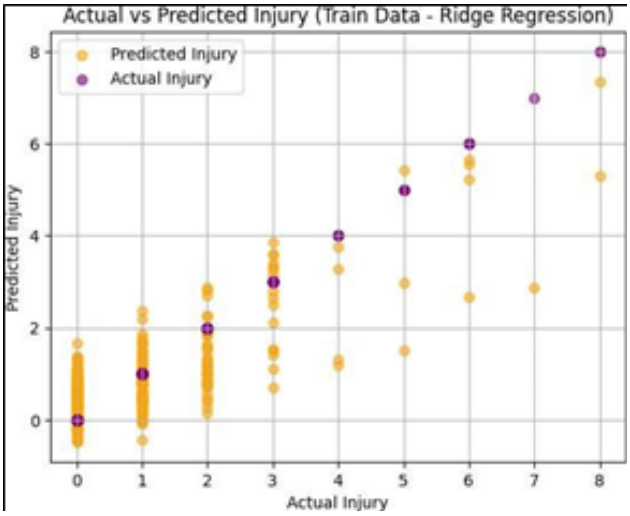


Figure 14. Actual vs. predicted injuries train –RR.

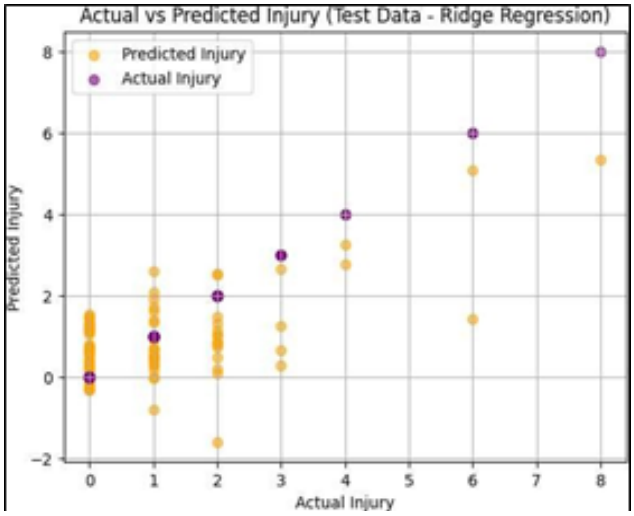


Figure 15. Actual vs. predicted injuries test –RR.

4.0 Conclusions

This study evaluates the injuries, personal and occupational factors of contractual workers in an opencast limestone mine using Python coding and AI/ ML techniques. Minor injuries are common, while severe injuries are rare. The mean injury value is 0.90 per instance, suggesting moderate frequency. Fatalities are rare, but their impact can be significant. Focusing on minimising near-misses could greatly increase workplace safety because they can act as a crucial early warning indicators for possible future injuries. According to the descriptive statistics, there is no significant correlation between age, experience and the incidence of injuries. The workforce is mostly middle-aged (average age: 43.12 years) and experienced (average experience: 13.81 years), which usually corresponds to fewer accidents. P-value < 0.05 indicates statistical significance, while higher F-values suggest stronger effects. Significant factors (P< 0.05) are fire, experiences (years), skill level, severity level, positive attitude towards safety, medical facilities, working conditions of the site, and available equipment with safety features. Age and experience do not show a strong direct relationship with injury occurrence, suggesting they might not be the

primary drivers of injury rates. Uniform work conditions, such as duty hours, attendance, and leave entitlement, limit variability and make it harder to identify individual behavioural patterns influencing safety outcomes. Wages (T-0.07, P-0.95) and skill levels (T-5.08) show moderate variability, which could potentially be linked to different injury outcomes. Demographic influence is not significant, and consistency of work conditions may mask specific factors leading to higher injury or near misses. The report offers practical advice on workplace safety is important safety drivers are competent and experienced employees. Equipment (T-1.41) that has been properly maintained and has safety measures, favourable working circumstances and attitudes toward safety. Access to healthcare facilities for timely treatment. Areas of focus for improvement include a focus on skill development via training initiatives, improving working conditions offering equipment that complies with safety regulations, and encouraging a positive and safety-conscious work environment. Future points to remember, the reasons why some characteristics, such as environment (T-0.06) and salary (T-0.07), were not important may be examined in more detail. Overall, individual, occupational, and systemic factors all play important roles in the multifactorial safety outcomes. By addressing these issues, workplace productivity and safety can significantly increase. The study compares six models for injury prediction XG Boost, Random Forest, Decision Tree, SVR, Bayesian Ridge Regression, and Ridge Regression. XG Boost scored the highest training R-squared, explaining 95% of the variance in training data. XG Boost performed best fit in this study because of algorithm optimized the performance for better generalisation, robust demonstration capability, consistent prediction, balance between training and testing data set, scalability the efficiency, and shapely additive explanations as the injuries often depend on multiple interacting factors, complexity, heterogeneous, involves diverse features likes, personal characteristics, physical condition, environmental influences, occupational, health factor.

5.0 Acknowledgments

The authors acknowledge the case study mines for supporting the research work.

6.0 References

1. Ajith MM, Ghosh AK, Jansz J. Contributing effects of individual characteristics, behavioural and job-related factors on the occurrence of mining-related injuries: A systematic review. Work. 2022; 71(1):87-117. https://doi.org/10.3233/WOR-205227 PMid:34924421.
2. Ajith MM, Ghosh AK, Jansz J. Risk factors for the number of sustained injuries in artisanal and small-scale mining operation. Safety and Health at Work. 2020; 11(1):50-60. https://doi.org/10.1016/j.shaw.2020.01.001 PMid:32206374 PMCid: PMC7078527.
3. Ganson GA. Assessing the effectiveness of health and safety practices at AngloGold Ashanti Company, Obuasi Mine. (Doctoral dissertation); 2014.
4. BETH AA. Assessment of occupational safety compliance in small-scale gold mines in Siaya county, Kenya. (Doctoral dissertation, University of Nairobi); 2017
5. Debela MB, Azage M, Begosaw AM. Prevalence of occupational injury among workers in the construction, manufacturing, and mining industries in Africa: A systematic review and meta-analysis. J Occup Health Epidemiol. 2021; 10(2):113-126. https://doi.org/10.21203/rs.3.rs-538186/v1
6. Doyle K. The safety and sustainability of mining at diverse scales: Placing health and safety at the core of responsibility; 2023.
7. Fabiano B, Currò F, Reverberi AP, Pastorino R. A statistical study on temporary work and occupational accidents: Specific risk factors and risk management strategies. Safety Science. 2008; 46(3):535-544. https://doi.org/10.1016/j.ssci.2007.05.004
8. Ghosh AK, Bhattacharjee A, Chau N. Relationships of working conditions and individual characteristics to occupational injuries: a case-control study in coal miners. J Occup Health. 2004; 46(6):470-480. https://doi.org/10.1539/joh.46.470 PMid:15613770.
9. Hatami SE, Ravandi MR, Hatami ST, Khanjani N. Epidemiology of work-related injuries among insured construction workers in Iran. Electron Physician. 2017; 9(11):5841. https://doi.org/10.19082/5841 PMid:29403628 PMCid:PMC5783137.
10. Khanzode VV, Maiti J, Ray PK. Injury count model for quantification of risk of occupational injury. Int J Inj Contr Saf Promot. 2011; 18(2):151-162. https://doi.org/10.1080/17457300.2010.540332 PMid:21432706.
11. Kunar BM, Bhattacharjee A, Chau N. Relationships of job hazards, lack of knowledge, alcohol use, health

status and risk-taking behaviour to work injury of coal miners: a case-control study in India. J Occup Health. 2008; 50(3):236-244. https://doi.org/10.1539/joh.L7054 PMid:18431033.

12. Namumba E. The impact of occupational health hazards and injuries on livelihoods of affected workers: A case of Kitwe district. (Doctoral dissertation, Mulungushi University); 2018.
13. Ricci F, Nucci M. Safety Integrated Model-training (SIM-t) and its evaluation: A safety training proposal for mechanical companies. Saf Sci. 2022; 146:105538. https://doi.org/10.1016/j.ssci.2021.105538
14. Salve UR, Paul A. Ergonomics in mining: Current status and future challenges. In Medical geology in mining: Health hazards due to metal toxicity. Cham: Springer International Publishing; 2022. p. 253-271. https://doi.org/10.1007/978-3-030-99495-2_11
15. Senapati A, Bhattacharjee A, Chatterjee S. Causal relationship of some personal and impersonal variates to occupational injuries at continuous miner worksites in underground coal mines. Saf Sci. 2022; 146:105562. https://doi.org/10.1016/j.ssci.2021.105562
16. Shaikh AM, Mandal BB, Mangalavalli SM. Causative and risk factors of musculoskeletal disorders among mine workers: A systematic review and meta-analysis. Saf Sci. 2022; 155:105868. https://doi.org/10.1016/j.ssci.2022.105868
17. Tripathi G, Tanksale AN, Verma M. Optimal location of accident relief facilities in a railway network. Saf Sci. 2022; 146:105560. https://doi.org/10.1016/j.ssci.2021.105560
18. Underhill E, Quinlan M. How precarious employment affects health and safety at work: the case of temporary agency workers. Relations Industrielles. 2011; 66 (3):397-421. https://doi.org/10.7202/1006345ar
19. Xu X, Zou PX. Discovery of new safety knowledge from mining large injury datasets in construction. Saf Sci. 2021; 144:105481. https://doi.org/10.1016/j.ssci.2021.105481