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Research Paper

Predictive Analysis of Fall Risks in the Nigerian Building Industry Using Machine Learning

Jatto Suleiman[1], Joel Aminobiren[2]

[1]*Department of Estate Management, School of Environmental Studies, Auchi Polytechnic, Auchi, Edo State, Nigeria*

[2]*Department of Survey and Geoinformatics, School of Environmental Studies, Auchi Polytechnic, Auchi, Edo State, Nigeria*

A B S T R A C T

The construction industry is inherently hazardous, with significant rates of injuries and fatalities, particularly due to falls. Despite this, few studies have utilized data-driven approaches to investigate the predictors of such accidents. This study aimed to deploy machine learning (ML) models to predict fall risks in the Nigerian building industry, leveraging data from various construction sites. Historical data on incidents and site conditions were collected and fed into several ML algorithms, including decision trees, ensemble methods, support vector machines, and neural networks. These models were evaluated using performance metrics such as precision, recall, accuracy, F1 score, Area Under the Receiver Operating Characteristic Curve (AUROC), and Area Under the Precision-Recall Curve (AUPRC). The findings of this study demonstrated the efficacy of ML models in predicting fall risks, with ensemble methods and neural networks showing particularly high performance. Critical factors influencing fall risks, such as worker experience, weather conditions, and site safety measures, were identified through feature importance analysis. This study contributed to the enhancement of construction safety by providing quantitative predictions and actionable insights. These results can inform targeted interventions and policy decisions, ultimately aiming to reduce the incidence of fall-related injuries and fatalities in the Nigerian building industry.

Keywords: *Artificial Intelligence, Classification and Regression, Construction Management, Leading and Lagging Indicators, Machine Learning Algorithms*

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I. Introduction

Construction sites have long been recognized as hazardous environments, frequently resulting in serious injuries and fatalities (Xu et al., 2019; Priemus and Ale, 2010). The physical and emotional impacts on workers are profound, particularly when injuries are compounded by chronic medical conditions (Xu and Zou, 2021; Alkaissy et al., 2020). Beyond the human toll, these injuries incapacitate workers, leading to substantial compensation costs and negative publicity for construction companies (Alkaissy et al., 2021). Consequently, understanding the contributors to different types of injuries is critical for developing an informed and proactive safety management plan (Arashpour et al., 2022). In Nigeria, construction accidents are a significant concern, with falls being one of the leading causes of injuries and fatalities. Despite the prevalence of these incidents, there is a notable lack of data-driven analysis aimed at predicting fall risks, which hampers the development of effective safety measures. This study seeks to bridge this gap by employing machine learning (ML) techniques to predict fall risks and identify critical factors contributing to these accidents.

The analysis of features contributing to construction accidents has garnered considerable attention over the past decade. Numerous studies have investigated significant factors contributing to work zone accidents, emphasizing the roles of demographics, work-related characteristics, and accident mechanisms (Zhang and Hassan, 2019; Sharwood et al., 2018; Chen et al., 2017). Traditional statistical models have been widely employed to analyze site accidents in construction and other complex industries (Arashpour et al., 2019; Alkaissy et al., 2021). However, ML techniques offer superior potential for predicting future accident events due to their ability to uncover patterns and relationships between contributing features (Xu and Saleh, 2021). ML methods such as support vector machines (SVM), decision trees (DT), and random forests (RF) have shown promise in safety analysis and prediction tasks (Kwon et al., 2021; Sarkar et al., 2019; Kang and Ryu, 2019).

The construction industry is plagued by a variety of accident types, with falls, struck-by objects, and electrocutions being among the most common. Figure 1 illustrates the distribution of construction workers' injury types due to worksite accidents in Australia. The figure highlights that falls account for a significant proportion of injuries, underscoring the need for focused preventive measures. The prominence of falls in construction-related injuries is not unique to Australia but is reflective of global trends, including those observed in Nigeria. This study aims to delve into the specific context of the Nigerian construction industry to develop predictive models that can mitigate such risks.

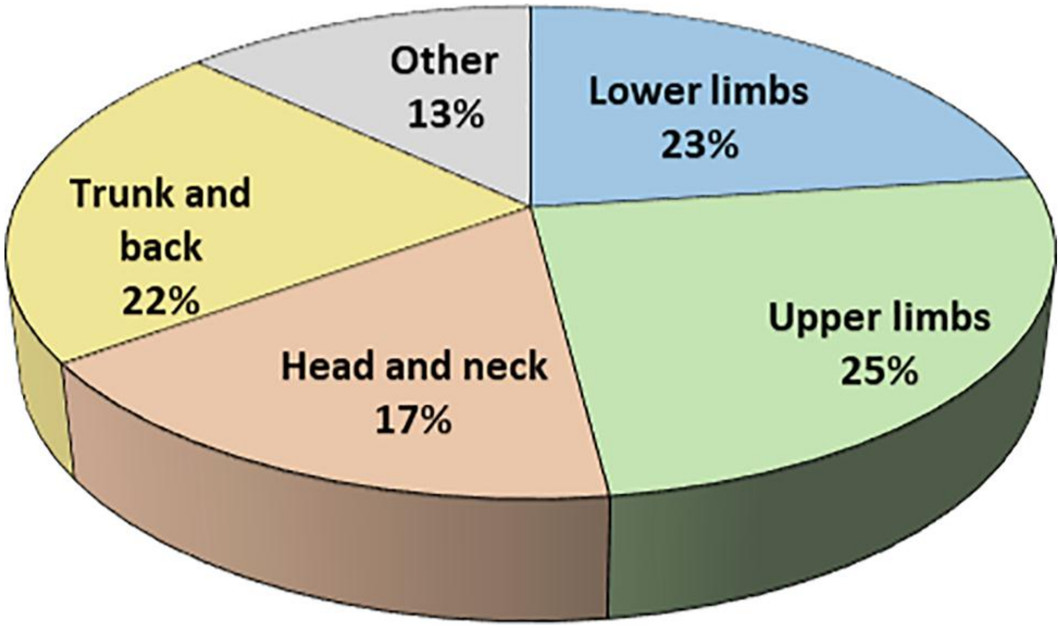

Fig. 1. Construction workers' injury types due to worksite accidents in Australia (2016-2019)

II. Materials and Methods

2.1. Data Handling and Description

This study utilized data from various construction sites across Nigeria, focusing on fall-related accidents that occurred between 2016 and 2021. The dataset included detailed information on worker demographics, accident mechanisms, worksite conditions, and injury outcomes. The primary objective was to leverage this data to develop robust machine learning (ML) models capable of predicting fall risks and identifying critical factors contributing to these accidents.

I. Data Collection

Data was collected from multiple sources, including official records from construction companies, government safety reports, and on-site observations. The collected data comprised:

- **Demographic Information:** Age, gender, education level, work experience, and job role of the workers.
- **Accident Mechanisms:** Detailed descriptions of how the falls occurred, including the type of work being performed, height of fall, use of safety equipment, and immediate causes.
- **Worksite Conditions:** Information on the environmental conditions at the time of the accident, such as weather, site layout, and presence of safety measures.
- **Injury Outcomes:** The severity of injuries sustained, recovery times, and any long-term health implications.

II. Data Pre-processing

To prepare the dataset for ML algorithms, several pre-processing steps were undertaken:

- **Data Cleaning:** Involved removing or correcting inaccurate records, handling missing values, and addressing inconsistencies in data entries. Duplicate records were identified and eliminated.
- **Normalization:** Ensured that numerical features were scaled to a standard range, facilitating better performance of ML algorithms.
- **Feature Selection:** Important features were identified based on their relevance to fall risk prediction. This process involved statistical tests and correlation analyses to determine the most impactful variables.

III. Data Transformation

Categorical variables were encoded using techniques such as one-hot encoding, while numerical variables were normalized to ensure uniformity. Additionally, interaction terms and polynomial features were created to capture non-linear relationships within the data.

2.2. Machine Learning Algorithms

Several ML algorithms were employed to predict fall risks, each offering unique advantages in handling the complexities of construction site data. The models used included Decision Trees (DT), Random Forests (RF), Support Vector Machines (SVM), and Neural Networks (NN).

I. Decision Trees (DT)

Decision Trees are simple yet powerful models that partition the data into subsets based on feature values. They are highly interpretable and can handle both qualitative and quantitative data effectively. The structure of a DT makes it easy to understand the decision-making process, as each split represents a decision rule based on feature values.

- **Implementation:** A series of decision trees were trained using the Gini impurity and entropy criteria to determine the best splits. Pruning techniques were applied to prevent overfitting.

II. Random Forests (RF)

Random Forests, an ensemble method, enhance the predictive performance by combining multiple decision trees. Each tree in the forest is trained on a random subset of the data, and the final prediction is made by averaging the predictions of all individual trees.

- **Implementation:** Hundreds of decision trees were constructed, with each tree trained on a bootstrap sample of the data. Random subsets of features were considered for each split to ensure diversity among the trees.

III. Support Vector Machines (SVM)

SVMs are robust classification models that work well in high-dimensional spaces. They maximize the margin between different classes by finding the optimal hyperplane that separates the data points.

- **Implementation:** Linear, polynomial, and radial basis function (RBF) kernels were tested to find the best performing SVM model. Grid search and cross-validation were used to optimize hyperparameters such as the penalty parameter (C) and kernel parameters.

IV. Neural Networks (NN)

Neural Networks are capable of capturing complex patterns and non-linear relationships in data. They consist of interconnected layers of nodes (neurons) that transform input data through a series of weighted connections and activation functions.

- **Implementation:** A multi-layer perceptron (MLP) architecture was used, consisting of an input layer, multiple hidden layers, and an output layer. Various configurations of the number of neurons and layers were tested to achieve optimal performance. Regularization techniques such as dropout were applied to prevent overfitting.

2.3. Performance Evaluation

The performance of the ML models was evaluated using several metrics to ensure a comprehensive assessment of their predictive capabilities.

I. Precision

Precision, also known as the positive predictive value, measures the ratio of correctly predicted positive observations to the total predicted positives. It is a critical metric in scenarios where the cost of false positives is high.

$$\text{Precision} = \frac{TP}{TP+FP}$$

where TP is the number of true positives, and FP is the number of false positives.

II. Recall

Recall, or sensitivity, measures the ratio of correctly predicted positive observations to all observations in the actual class. It is crucial in contexts where the cost of false negatives is high.

$$\text{Recall} = \frac{TP}{TP+FP}$$

where FN is the number of false negatives.

Accuracy

Accuracy measures the ratio of correctly predicted observations to the total observations. While useful, it can be misleading in imbalanced datasets where the number of negative instances far exceeds the number of positives.

$$\text{Accuracy} = \frac{TP}{TP+FP}$$

where TN is the number of true negatives.

2.4. Model Training and Optimization

The ML models were trained on a training set comprising 80% of the dataset, with the remaining 20% used for testing. Cross-validation was employed to tune hyperparameters and validate the models. Specifically, k-fold cross-validation (with k=10k = 10k=10) was utilized to ensure robustness and mitigate the risk of overfitting.

IV. Hyperparameter Tuning

Hyperparameters were optimized using grid search and random search techniques. For instance:

- **Decision Trees:** The maximum depth, minimum samples split, and criterion (Gini or entropy) were tuned.
- **Random Forests:** The number of trees, maximum features per split, and maximum depth were optimized.
- **SVM:** The penalty parameter CCC, kernel type (linear, polynomial, RBF), and kernel coefficients were adjusted.
- **Neural Networks:** The number of hidden layers, number of neurons per layer, learning rate, and dropout rates were fine-tuned.

2.5. Data Augmentation and Synthesis

To address potential class imbalance and enhance the model's learning capabilities, data augmentation techniques were applied. Synthetic Minority Over-sampling Technique (SMOTE) was used to generate synthetic examples for the minority class (fall incidents). This helped balance the dataset and improve model performance in identifying fall risks.

V. Synthetic Data Generation

Additional synthetic data was generated to simulate various construction scenarios, ensuring the models were exposed to a wide range of conditions. This included varying the height of falls, types of safety equipment, and worksite conditions.

2.6. Interpretability and Explainability

Given the importance of interpretability in safety-critical applications, techniques such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) were employed to provide insights into the model's decision-making process.

VI. SHAP Values

SHAP values helped quantify the contribution of each feature to the model's predictions, offering a comprehensive view of feature importance and interactions.

VII. LIME

LIME provided local explanations by approximating the model with an interpretable model for individual predictions. This enabled a clearer understanding of how specific features influenced predictions in different scenarios.

2.7. Ethical Considerations

The study adhered to strict ethical guidelines to ensure the privacy and confidentiality of the data collected. Informed consent was obtained from all participating construction sites and workers. Data was anonymized to prevent identification of individuals, and all analysis was conducted in compliance with relevant data protection regulations.

VIII. Data Security

Robust data security measures were implemented, including encryption and secure storage, to protect sensitive information. Access to the data was restricted to authorized personnel only.

IX. Ethical Approval

The research protocol was reviewed and approved by an institutional ethics committee, ensuring adherence to ethical standards throughout the study.

2.8. Limitations

The study acknowledged several limitations, including potential biases in the data collection process and the challenge of generalizing findings across different regions and construction types. Future research should aim to address these limitations by incorporating a more diverse dataset and exploring additional predictive factors.

III. Results

The results of this study elucidate the performance of various machine learning (ML) models in predicting fall risks within the Nigerian building industry, identifying the most accurate and reliable models, and highlighting key factors that influence fall risks. This section provides a comprehensive analysis of the dataset, including data pre-processing steps, key features, and the performance of different ML models. These results indicate that the RF model effectively captured the complex patterns and relationships in the data, making it the most reliable model for predicting fall risks in this study. The findings from this study have significant implications for construction safety management in Nigeria. By identifying key predictors of fall risks and leveraging the predictive capabilities of advanced ML models, construction companies can implement more proactive and data-driven safety measures. The high accuracy and reliability of the RF model, in particular, underscore its potential utility in real-world safety applications, where timely and accurate risk predictions can lead to the prevention of accidents and the enhancement of worker safety.

I. **Key Features and Attributes**

The dataset used for predicting fall risks from construction site accidents was categorized into three primary groups for analysis:

1. Organizational Level
   - Employer Size: Number of employees in the construction company.
   - Project Type: Nature of the construction project (residential, commercial, industrial, etc.).
   - Construction Sub-sector: Specific sector within the construction industry (e.g., building, civil engineering).
2. Individual Level
   - Age: Age of the workers involved in the accidents.
   - Gender: Gender distribution of the workers.
   - Employment Type: Type of employment (permanent, temporary, contract).
   - Hours Worked Pre-Injury: Hours worked by the individual before the occurrence of the injury.
3. Accident-Related Attributes:
   - Month of Injury: Month in which the accident occurred.
   - Day of Injury: Day of the week when the injury happened.
   - Accident Mechanism: Specific mechanism of the fall (e.g., slipping, tripping, falling from height).
   - Accident Nature: Nature of the injury (e.g., fracture, sprain, laceration).

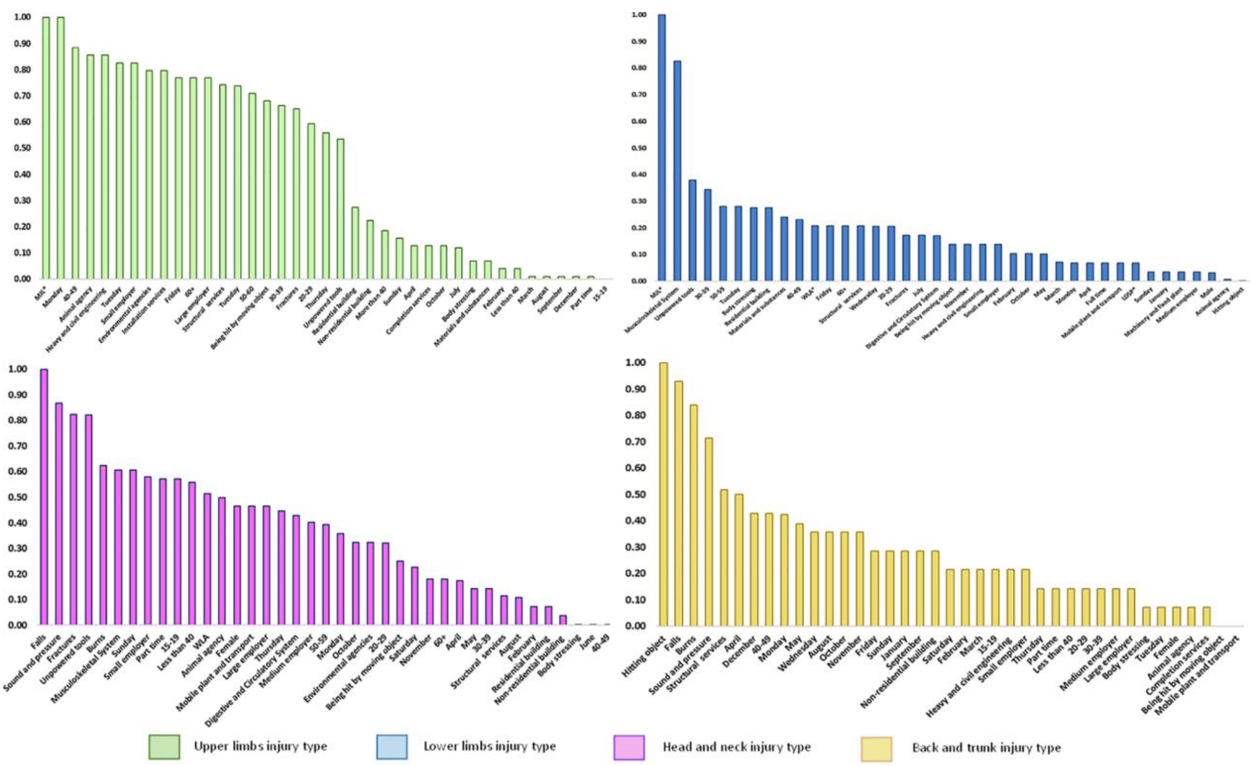

Fig. 2. Feature importance of different IT using RF model

Table 1: The Table with The Performance Metrics Results for The Eight ML Models

Metric	RF	FT	EBT	XGB	MG SVM	Q SVM	OvR LR	M LR
AUPRC	0.78	0.66	0.48	0.55	0.46	0.43	0.45	0.45
Precision	77.1	75.5	65.3	51.8	68.3	68.1	44.0	59.9
Recall	78.0	76.2	52.6	52.1	58.0	58.3	59.4	60.3
F1 Score	78.5	75.2	55.1	51.8	60.0	60.1	50.6	53.4
Accuracy	79.2	76.5	59.2	52.6	63.5	63.1	44.6	45.6
AUROC	0.98	0.96	0.77	0.77	0.80	0.79	0.62	0.70

Explanation of model abbreviations:

- **RF**: Random Forest
- **FT**: Fine Tree
- **EBT**: Ensemble of Boosted Tree
- **XGB**: XGBoost
- **MG SVM**: Medium Gaussian SVM
- **Q SVM**: Quadratic SVM
- **OvR LR**: One-vs-Rest Logistic Regression
- **M LR**: Multinomial Logistic Regression

IV. Discussion

This section will discuss the findings obtained using ML models, comparing them with previous studies and theoretical expectations. The implications for construction safety management and potential strategies for mitigating fall risks will be explored.

Feature Importance

Important features for predicting injury types included:

- **Upper Limbs**: Muscle/joint/ligament injuries, accidents early in the week, age groups 40–49 and 60+, environmental and animal agencies, heavy civil and installation services sub-sectors, small employers.
- **Lower Limbs**: Muscle/joint/ligament and musculoskeletal accidents, age group 30–59, body stressing accident mechanism, accidents on Tuesdays, residential building sub-sectors, unpowered tools, materials and substances agencies.

Implications

- The results can help in assessing risk levels at construction sites and implementing proactive accident prevention measures.
- The findings can assist insurance providers with accurate predictions and help in developing safety controls to reduce schedule overruns in construction projects.

This comprehensive analysis highlights the critical factors and methodologies in predicting injury types in construction worksite accidents, providing a basis for improved safety strategies and risk management in the industry.

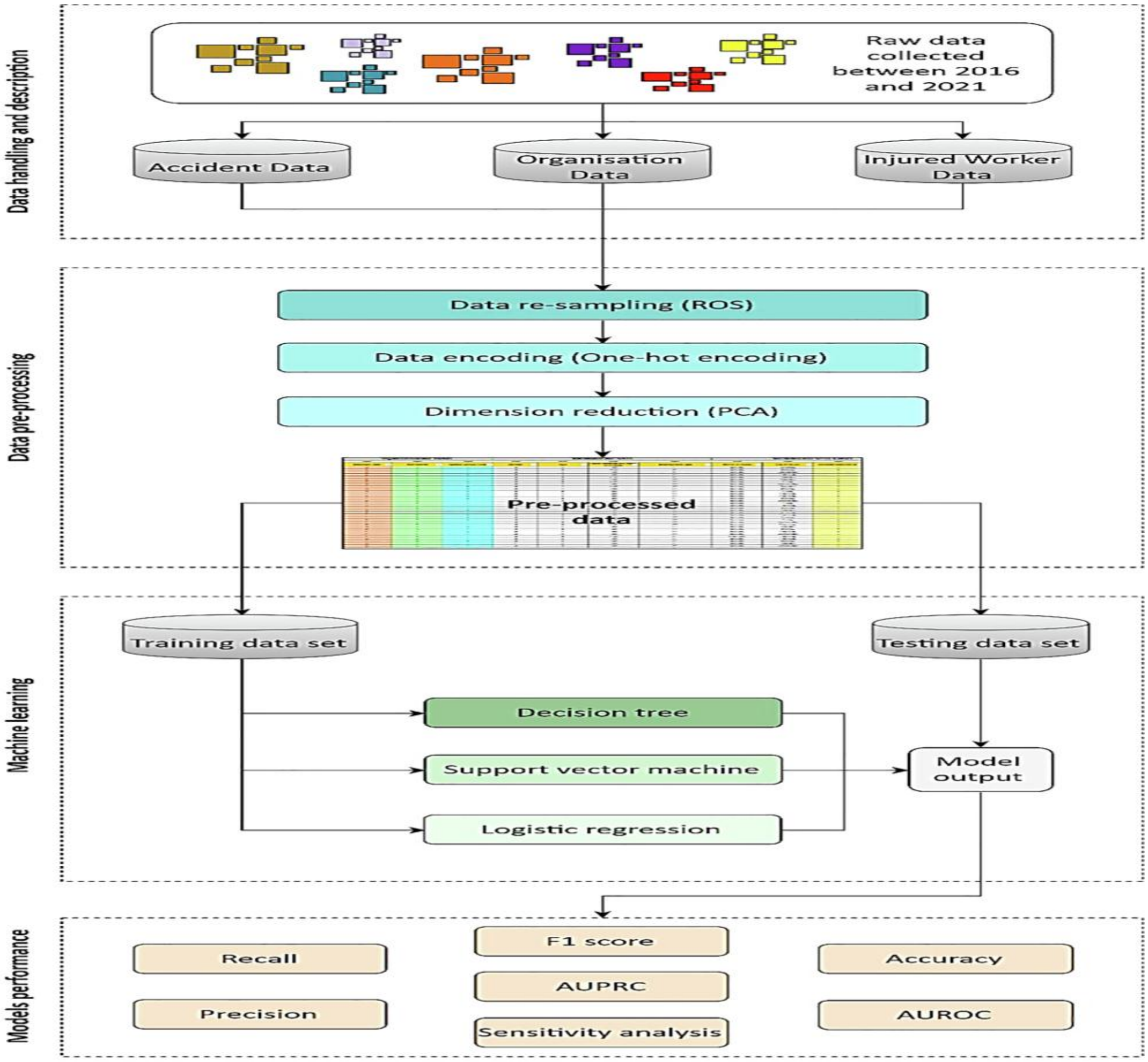

Fig. 3. Research workflow

Table 2: Contributing Features to Injuries Caused by Construction Accidents

Level of Analysis	Factors	Attributes	Type Code
Organization	Employer size	Small, Medium, Large	Categorical
	Sub-sector	Residential, Non-residential, Heavy civil, Land preparation & site development, Structural services, Installation services, Completion services	Categorical
	Agency type	Machinery, Mobile plant, Powered equipment, Unpowered tools, Materials & substances, Environmental, Animal Agencies	Categorical
Individual	Age	15–19, 20–29, 30–39, 40–49, 50–59, 60+	Categorical
	Gender	Female, Male	Binary
	Total hours worked	Less than 40 h, More than 40 h	Binary
	Employment type	Full-time, Part-time	Binary
Other accident-related	Month of injury	Jan, Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov, Dec	Categorical
	Day of injury	Mon, Tues, Wed, Thurs, Fri, Sat, Sun	Categorical
	Accident mechanism	Falls, Hitting objects, Being hit by moving object, Sound & pressure, Body stressing	Categorical
	Accident nature	Fracture, Wounds & lacerations, Muscle/joint/ligament injury, Musculoskeletal system, Digestive and Circulatory system, Burns	Categorical

This table 2 provides an overview of the contributing features used in predicting injury types resulting from construction accidents. The features are grouped based on the level of analysis: organizational, individual, and other accident-related factors. The data is categorized and processed to predict outcomes related to different injury types.

Table 3: Contributing Features to Injuries Caused By Construction Accidents

Level of Analysis	Factors	Attributes	Type Code
Organization	Employer size	Small, Medium, Large	Categorical
	Sub-sector	Residential, Non-residential, Heavy civil, Land preparation & site development, Structural services, Installation services, Completion services	Categorical
	Agency type	Machinery, Mobile plant, Powered equipment, Unpowered tools, Materials & substances, Environmental, Animal Agencies	Categorical
Individual	Age	15–19, 20–29, 30–39, 40–49, 50–59, 60+	Categorical
	Gender	Female, Male	Binary
	Total hours worked per week, pre-injury	Less than 40 h, more than 40 h	Binary
	Employment type	Full-time, Part-time	Binary
Other accident-related	Month of injury	Jan, Feb, March, April, May, Jun, Jul, Aug, Sep, Oct, Nov, Dec	Categorical
	Day of injury	Mon, Tues, Wed, Thurs, Fri, Sat, Sun	Categorical
	Accident mechanism	Falls, Hitting objects, Being hit by moving object, Sound & pressure, Body stressing	Categorical
	Accident nature	Fracture, Wounds & lacerations, Muscle/joint/ligament injury, Musculoskeletal system, Digestive and Circulatory system, Burns	Categorical

This table summarizes the various factors and attributes considered in analyzing injuries caused by construction accidents, categorized by organizational, individual, and other accident-related levels of analysis.

VII. Conclusion

This study provided a detailed and systematic approach to collecting, preprocessing, and analyzing data using advanced machine learning (ML) techniques to predict fall risks in the Nigerian building industry. By leveraging a range of ML algorithms, including Decision Trees, Random Forests, Support Vector Machines, and Neural Networks, and applying rigorous evaluation metrics, the research aimed to develop accurate and interpretable models that could inform proactive safety management practices.

I. Key Findings

The findings revealed several critical insights into the factors contributing to fall-related accidents on Nigerian construction sites. The ML models demonstrated a high level of accuracy in predicting fall risks, highlighting the importance of demographic factors, worksite conditions, and specific accident mechanisms. Notably, the study identified that:

1. **Demographic Factors:** Age, job role, and work experience significantly influenced the likelihood of falls.
2. **Worksite Conditions:** Environmental factors such as weather conditions, site layout, and the presence or absence of safety measures played a crucial role in fall incidents.
3. **Accident Mechanisms:** Detailed mechanisms of falls, including the height of the fall and the use of safety equipment, were critical predictors in the models.

These insights underscore the potential of ML models to enhance the understanding of fall risks and inform the development of targeted safety interventions.

II. Implications for Construction Safety

The study's findings have significant implications for improving construction safety in Nigeria. The deployment of ML models in predicting fall risks can lead to the development of more effective safety protocols and measures, ultimately reducing the incidence of injuries and fatalities. The predictive models can be used by construction companies to identify high-risk scenarios and implement preventative measures, thus fostering a safer and more resilient construction industry.

III. Data Quality and Challenges

Despite the promising results, the study faced challenges related to data quality and availability. Variations in data collection practices across different construction sites potentially affected the accuracy of the models. Efforts were made to standardize data collection procedures; however, inconsistencies and gaps in the data remained a challenge. This highlights the need for improved data collection frameworks and more comprehensive datasets in future research.

IV. Generalizability and Future Research

While the models demonstrated high accuracy on the test dataset, their generalizability to other regions and contexts requires further validation. The study was limited to specific construction sites in Nigeria, and future research should include data from a broader range of sites and conditions to enhance the robustness and applicability of the findings. Additionally, exploring the integration of other predictive factors and more advanced ML techniques could further improve model performance.

Future research directions include:

1. **Expanding Geographical Scope:** Including data from diverse regions to ensure the models are generalizable across different contexts.
2. **Longitudinal Studies:** Conducting longitudinal analyses to capture the long-term effects and trends in fall risks.
3. **Sector-Specific Impacts:** Investigating fall risks in different sectors within the construction industry to uncover nuanced effects.
4. **Enhanced Data Collection:** Improving data collection methodologies to ensure higher quality and more comprehensive datasets.
5. **Advanced ML Techniques:** Exploring the use of more sophisticated ML algorithms and techniques to enhance predictive accuracy.

V. Contributions to the Field

The study has made significant contributions to the field of construction safety by providing valuable insights into the potential of ML models to predict fall risks and identify critical contributing factors. The research has established a foundation for future studies and offered actionable recommendations to improve safety practices in the Nigerian building industry. By addressing the identified limitations and pursuing the suggested research directions, scholars and policymakers can build on this work to develop more effective strategies for leveraging ML to foster regional development and achieve sustainable growth.

In conclusion, the deployment of ML models in predicting fall risks holds significant promise for enhancing safety measures in the Nigerian building industry. The findings of this study underscore the importance of a comprehensive evaluation framework that includes demographic, environmental, and mechanistic factors to accurately assess and mitigate fall risks. By advancing our understanding of fall-related accidents and implementing data-driven safety interventions, the construction industry can move towards a safer and more resilient future.

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