**Master Thises**

**Title:**

# Comparative Analysis of Machine Learning Models for Predicting Workplace Accident Severity

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# **Comparative Analysis of Machine Learning Models for Predicting Workplace Accident Severity**

## **Abstract**

This thesis presents a comprehensive machine learning approach to predict workplace injury hospitalizations using data from the Occupational Safety and Health Administration (OSHA) Severe Injury Reports. By applying advanced preprocessing, feature engineering, and model optimization techniques, we developed a high-performance predictive system capable of identifying workplace incidents likely to result in hospitalization with over 92% accuracy. The XGBoost algorithm demonstrated superior performance compared to other machine learning models, achieving an AUC of 0.967 and F1-score of 0.953. Injury characteristics such as nature of injury and body part affected emerged as the strongest predictors, alongside geographical factors. This research provides a foundation for proactive workplace safety interventions and demonstrates the potential of machine learning to enhance occupational health outcomes.

## **Chapter 1: Introduction**

### **1.1 Background and Motivation**

Workplace injuries present significant challenges to employee well-being, organizational productivity, and healthcare systems. The U.S. Bureau of Labor Statistics reported approximately 2.7 million nonfatal workplace injuries and illnesses in private industry in 2020, with nearly one-third requiring days away from work (BLS, 2021). Beyond the immediate physical impact on workers, these injuries incur substantial economic costs, with estimates suggesting annual direct and indirect costs exceeding $170 billion nationwide (NSC, 2021).

Since 2015, the Occupational Safety and Health Administration (OSHA) has required employers to report all work-related hospitalizations, amputations, and losses of an eye within 24 hours. This reporting mandate has created a rich dataset of severe workplace injuries that provides an opportunity to identify patterns and develop predictive models to anticipate high-risk scenarios before they occur.

The ability to predict whether a workplace incident will result in hospitalization has far-reaching implications for occupational safety. Early identification of high-risk factors enables targeted preventative measures, more efficient resource allocation, and ultimately, a reduction in severe workplace injuries. This predictive capability is particularly valuable for industries with elevated injury rates, where strategic interventions based on data-driven insights could significantly improve worker safety.

### **1.2 Research Objectives**

This research aims to develop and evaluate machine learning models capable of accurately predicting whether a workplace incident will result in hospitalization based on incident characteristics. The specific objectives include:

1. Conduct thorough exploratory data analysis of OSHA Severe Injury Reports to identify patterns and relationships between incident features and hospitalization outcomes
2. Develop a comprehensive data preprocessing pipeline to handle categorical variables, missing values, and geographical data
3. Engineer relevant features to enhance model performance, including text analysis of incident narratives
4. Evaluate and compare multiple machine learning algorithms to identify the most effective approach for hospitalization prediction
5. Optimize the best-performing model to achieve maximum predictive accuracy
6. Interpret model results to identify the most significant predictors of hospitalization
7. Create a deployable model that can be integrated into safety management systems

### **1.3 Research Significance**

This research contributes to the field of occupational safety in several important ways:

1. **Data-Driven Prevention**: By identifying the strongest predictors of hospitalization, safety professionals can target high-risk areas with specific interventions
2. **Resource Optimization**: Prioritizing resources toward incident types with higher hospitalization probabilities enables more efficient safety management
3. **Early Intervention**: Predictive models allow for the identification of situations with elevated hospitalization risk before incidents occur
4. **Quantifiable Risk Assessment**: The probability scores generated by the model provide a quantitative basis for risk evaluations
5. **Methodological Innovation**: The application of advanced machine learning techniques to occupational safety data represents a novel approach to workplace injury prevention

The methodologies and findings presented in this thesis establish a framework for predictive analytics in occupational safety that can be adapted to various industries and contexts, potentially improving worker safety on a broad scale.

## **Chapter 2: Literature Review**

### **2.1 Workplace Injury Prediction and Prevention**

The field of workplace injury prediction has evolved substantially over the past decade. Early research relied heavily on statistical methods to identify risk factors associated with occupational injuries. Khanzode et al. (2012) provided a comprehensive review of occupational injury research, noting the transition from purely descriptive approaches to more sophisticated predictive methodologies. Traditional approaches focused primarily on industry-specific risk factors, with construction, manufacturing, and healthcare receiving particular attention due to their elevated injury rates (Asfaw et al., 2011).

Recent studies have increasingly incorporated machine learning techniques to enhance predictive capabilities. Sarkar et al. (2019) applied classification algorithms to construction safety data, achieving promising results in identifying high-risk scenarios. Their work demonstrated that random forest algorithms could predict certain types of construction accidents with accuracy rates exceeding 85%. Similarly, Tixier et al. (2016) utilized natural language processing techniques to analyze injury reports and extract predictive features from unstructured text descriptions.

Despite these advances, a significant gap exists in the literature regarding the prediction of hospitalization outcomes specifically. Most existing studies focus on predicting injury occurrence rather than severity or resulting hospitalization, which represents a distinct prediction problem with different feature importance patterns (Bevilacqua et al., 2018).

### **2.2 Machine Learning in Occupational Safety**

The application of machine learning to occupational safety has gained momentum as data availability and computational capabilities have expanded. Hegde and Rokseth (2020) surveyed the landscape of machine learning applications in safety, noting particular success in anomaly detection and risk assessment. Their review highlighted the potential of supervised learning approaches for classification of safety-critical events.

Several machine learning paradigms have demonstrated utility in safety applications. Decision tree-based methods have proven particularly effective, with random forests and gradient boosting machines frequently outperforming other approaches (Crown et al., 2018). Gradient boosting frameworks such as XGBoost have shown exceptional performance in predicting occupational accidents, as demonstrated by Ayhan and Tokdemir (2020), who achieved 91% accuracy in predicting construction site accidents.

Deep learning approaches have also been explored, particularly for complex data types. Ding et al. (2019) utilized convolutional neural networks to analyze workplace images for safety violations, while Kim and Chi (2019) employed recurrent neural networks to predict temporal patterns in accident occurrence. Despite their potential, these methods often require larger datasets than are typically available in occupational safety contexts.

The relative performance of various machine learning approaches for safety applications remains an active area of research. Comparisons by Delen et al. (2020) suggest that ensemble methods generally outperform single classifiers for safety prediction tasks, though the optimal approach varies based on dataset characteristics and specific prediction targets.

### **2.3 OSHA Data Analysis and Applications**

The OSHA Severe Injury Reports database has been utilized in several research contexts since its inception in 2015. Descriptive analyses by Nighswonger (2018) highlighted industry-specific patterns in severe injuries, noting particularly high rates in manufacturing, construction, and transportation. Subsequent work by Marsh et al. (2020) expanded this analysis to examine geographical variations in reporting rates, finding significant regional differences that suggested potential underreporting in certain areas.

From an analytical perspective, OSHA data presents several challenges that have been addressed in the literature. Missing values, coding inconsistencies, and unstructured narrative elements require specialized preprocessing approaches, as detailed by Williams et al. (2020). Their work developed standardized methods for cleaning and preparing OSHA data for statistical analysis, providing a valuable methodological foundation.

The application of machine learning to OSHA data specifically remains relatively limited in the published literature. Notable exceptions include work by Zhang and Fang (2022), who used OSHA citation data to predict safety violations, and research by Rahmani et al. (2021) exploring the prediction of amputation injuries using OSHA reports. However, comprehensive machine learning approaches to hospitalization prediction using the full spectrum of available OSHA features have not been thoroughly explored.

### **2.4 Gaps in the Literature**

This literature review reveals several important gaps that the present research addresses:

1. **Hospitalization Prediction**: While injury occurrence prediction has been studied extensively, specific prediction of hospitalization outcomes from workplace incidents represents an underexplored area with significant practical implications
2. **Comprehensive Feature Utilization**: Most existing studies utilize only a subset of available features, whereas this research leverages the full spectrum of OSHA data elements, including geographical, temporal, and categorical variables
3. **Model Comparison and Optimization**: Systematic comparison of multiple machine learning approaches for this specific prediction task, followed by hyperparameter optimization, has not been comprehensively reported in the literature
4. **Deployment Frameworks**: Practical implementations of machine learning models for workplace safety applications remain limited, with few studies addressing the challenges of model deployment in real-world safety management systems

By addressing these gaps, this research contributes both methodologically and practically to the field of occupational safety prediction.

## **Chapter 3: Methodology**

### **3.1 Data Source and Description**

This study utilized data from the OSHA Severe Injury Reports database, which contains records of workplace incidents resulting in hospitalizations, amputations, or loss of an eye reported to OSHA since January 2015. The dataset includes detailed information about each incident, including:

* Event date and location (state, latitude, longitude)
* Industry information (NAICS code)
* Injury characteristics (nature, part of body affected, event type)
* Source of injury and secondary source
* Narrative description of the incident
* Hospitalization status (target variable)

The complete dataset contained 93,011 records, with hospitalization present in 80.8% of cases and absent in 19.2%, representing a moderately imbalanced classification problem. The data included both structured categorical fields (often using numeric codes for categorization) and unstructured text in the narrative descriptions.

#### **3.1.1 Data and Code Availability**

The OSHA Severe Injury Reports dataset used in this study is publicly available and can be accessed at:<https://www.osha.gov/severeinjury/>

The complete code implementation for this research, including data preprocessing, model development, evaluation, and deployment, is available in the following link:https://colab.research.google.com/drive/1oUCbflz7sxrVbg0qtEZJIvnFf35ghOST?usp=sharing

This repository contains all necessary scripts to reproduce the analysis, as well as documentation for deploying the optimized model. By making both the data source and implementation code publicly available, this research supports reproducibility and enables further extension by other researchers and safety professionals.

## **3.1.2 OSHA Code Quick Reference Guide**

### **Body Part Codes (likely examples in your data)**

* **4422**: Fingers, fingertips
* **4429**: Multiple fingers, hand-finger combinations
* **4420**: Hand(s), except finger(s)
* **341**: Chest, including ribs, internal organs
* **510**: Leg(s), upper leg, thigh, femur
* **111**: Brain, cranial region
* **899**: Multiple body parts (combinations of regions)
* **6**: Neck, cervical vertebrae
* **52**: Shoulder, including clavicle, scapula
* **9999**: Unspecified body parts

### **Nature of Injury Codes**

* **1311**: Fractures (likely a specific type, possibly compound or multiple)
* **111**: Simple fracture
* **1220/1221**: Cuts, lacerations, punctures
* **1522**: Heat burns, thermal burns (second degree)
* **195**: Amputations
* **4XXX**: Various strains, sprains, tears
* **5XXX**: Bruises, contusions
* **1XXX**: Traumatic injuries

### **Event Type Codes (what caused the injury)**

* **4330**: Fall to lower level (from height)
* **4331**: Fall down stairs or steps
* **6411**: Assault, violent act by person(s)
* **6412**: Struck by person accidentally
* **422**: Struck by falling object or equipment
* **642**: Struck by moving object
* **640**: Struck by object or equipment
* **6311**: Assault by weapon (knife, cutting instrument)
* **531**: Caught in running equipment or machinery

### **Source of Injury Codes**

* **5721**: Co-worker, former co-worker
* **7261**: Welding, cutting, and blow torches
* **5772**: Inmate or detainee in custody
* **8XXX**: Tools, instruments, and equipment
* **3XXX**: Parts and materials
* **0XXX**: Chemicals and chemical products
* **9XXX**: Other sources

### **3.2 Data Preprocessing**

A comprehensive preprocessing pipeline was developed to prepare the raw data for modeling. This pipeline addressed several data challenges:

#### **3.2.1 Temporal Feature Extraction**

Event dates were converted to datetime format and decomposed into multiple temporal features:

* Day of month
* Month
* Year
* Day of week
* Weekend indicator (binary variable indicating weekend events)

This decomposition allowed the models to capture seasonal and weekly patterns in hospitalization rates.

#### **3.2.2 Missing Value Handling**

Missing values were present in several fields, requiring appropriate imputation strategies:

* Categorical variables: Missing values were imputed with "Unknown" for text fields or -1 for numeric codes
* Numerical variables: Median imputation was employed during the modeling pipeline
* Narrative text: Empty narratives were replaced with blank strings

#### **3.2.3 Target Variable Preparation**

The hospitalization field was converted to a binary classification target:

* Original values ranging from 0-6 (indicating number of hospitalizations)
* Transformed to binary (0 = no hospitalizations, 1 = one or more hospitalizations)

#### **3.2.4 Text Preprocessing**

Narrative descriptions underwent specific text preprocessing:

* Conversion to lowercase
* Removal of special characters and numbers
* Removal of extra whitespace
* Stopword elimination using NLTK's English stopword list

#### **3.2.5 Geographical Clustering**

To capture regional patterns beyond state boundaries, a K-means clustering approach was applied to valid latitude and longitude coordinates:

* Invalid coordinates were handled by imputation
* K-means with k=5 was applied to group incidents into geographical clusters
* Resulting cluster assignments were added as a new feature

### **3.3 Feature Engineering**

#### **3.3.1 Feature Selection**

From the preprocessed data, multiple feature sets were defined:

**Categorical Features**:

* State
* Nature of injury
* Part of body affected
* Event type
* Source of injury
* Secondary source
* NAICS sector (first two digits of NAICS code)
* Geographical cluster

**Numerical Features**:

* Day of month
* Month
* Year
* Day of week
* Latitude
* Longitude

**Text Features**:

* Processed narrative descriptions

#### **3.3.2 Text Feature Extraction**

Term Frequency-Inverse Document Frequency (TF-IDF) vectorization was applied to extract features from narrative descriptions:

* Maximum of 100 features
* Minimum document frequency of 5 to filter rare terms
* Resulting TF-IDF features were appended to the numerical feature set

### **3.4 Model Development**

#### **3.4.1 Training and Test Split**

The data was split into training (80%) and test (20%) sets using stratified sampling to maintain the class distribution:

* Training set: 74,408 records
* Test set: 18,603 records

#### **3.4.2 Preprocessing Pipeline**

A scikit-learn preprocessing pipeline was constructed to ensure consistent transformation of both training and test data:

**For numerical features**:

* Median imputation for missing values
* Standardization (zero mean, unit variance)

**For categorical features**:

* Most frequent value imputation for missing values
* One-hot encoding with handling of unknown categories

#### **3.4.3 Model Selection and Implementation**

Four machine learning algorithms were implemented and evaluated:

1. **Logistic Regression**: A linear model with L2 regularization
2. **Decision Tree**: A non-linear model capable of capturing complex interactions
3. **Random Forest**: An ensemble of decision trees to reduce overfitting
4. **XGBoost**: A gradient boosting framework known for performance and efficiency

Each model was integrated into the preprocessing pipeline to ensure proper feature transformation during both training and prediction.

### **3.5 Model Evaluation**

#### **3.5.1 Performance Metrics**

Multiple evaluation metrics were used to assess model performance:

* **Accuracy**: Overall prediction correctness
* **Precision**: Proportion of positive identifications that were correct
* **Recall**: Proportion of actual positives that were identified
* **F1 Score**: Harmonic mean of precision and recall
* **ROC AUC**: Area under the Receiver Operating Characteristic curve
* **Classification Report**: Detailed metrics by class

#### **3.5.2 Feature Importance Analysis**

For tree-based models (Decision Tree, Random Forest, XGBoost), feature importance analysis was conducted to identify the most influential predictors of hospitalization:

* Feature importances were extracted from trained models
* Importances were normalized and ranked
* Top 15 features were visualized for interpretation

### **3.6 Hyperparameter Optimization**

Grid search with 5-fold cross-validation was employed to optimize hyperparameters for each model:

**Logistic Regression**:

* Regularization strength (C): [0.01, 0.1, 1.0, 10.0]
* Solver: ['liblinear', 'saga']

**Decision Tree**:

* Maximum depth: [None, 5, 10, 15]
* Minimum samples for split: [2, 5, 10]

**Random Forest**:

* Number of estimators: [50, 100]
* Maximum depth: [None, 10, 20]
* Minimum samples for split: [2, 5]

**XGBoost**:

* Number of estimators: [50, 100]
* Maximum depth: [3, 5, 7]
* Learning rate: [0.01, 0.1]

F1 score was used as the optimization metric to balance precision and recall, given the moderate class imbalance in the dataset.

### **3.7 Model Deployment**

The best-performing model was prepared for deployment through several steps:

1. **Model Persistence**: Saving the trained model using both pickle and joblib serialization
2. **Feature Documentation**: Creating comprehensive documentation of required features
3. **Inference Script**: Developing a Python script for making predictions with new data
4. **API Development**: Implementing a Flask-based REST API for prediction requests
5. **Deployment Testing**: Validating the deployed model with test cases

This methodology ensures reproducibility and provides a practical framework for integrating the predictive model into occupational safety management systems.

## **Chapter 4: Results**

### **4.1 Exploratory Data Analysis**

#### **4.1.1 Target Distribution**

The analysis of the target variable revealed a moderately imbalanced dataset:

* Hospitalized cases (1): 75,120 records (80.8%)
* Non-hospitalized cases (0): 17,891 records (19.2%)

This imbalance reflects the nature of the OSHA Severe Injury Reports database, which primarily captures serious workplace incidents.

#### **4.1.2 Feature Distributions**

**Geographical Distribution**:

* States with highest incident counts: Texas (15,207), Florida (10,109), and Pennsylvania (7,421)
* Latitude range: -34.92 to 70.34
* Longitude range: -170.71 to 166.64

**Categorical Variables**:

* Nature of injury: Categories 111 (28,394 cases), 1311 (23,446), and 1972 (6,512) were most common
* Body part affected: Categories 4422 (10,507), 4429 (8,964), and 4420 (6,821) were predominant
* Event types: Categories 6412 (6,694), 4330 (5,903), and 6411 (5,296) occurred most frequently

These distributions highlight the concentrated nature of workplace injuries in certain categories and regions.

### **4.2 Model Performance Comparison**

#### **4.2.1 Initial Model Performance**

All four models demonstrated strong performance on the test set:

Model | Accuracy | Precision | Recall | F1 Score | ROC AUC |

Logistic Regression | 0.9245 | 0.9828 | 0.9223 | 0.9516 | 0.9648 |

Decision Tree | 0.9064 | 0.9473 | 0.9356 | 0.9415 | 0.8610 |

Random Forest | 0.9201 | 0.9699 | 0.9295 | 0.9493 | 0.9628 |

XGBoost | 0.9248 | 0.9825 | 0.9229 | 0.9518 | 0.9669 |

**XGBoost achieved the highest accuracy, F1 score, and ROC AUC, marginally outperforming Logistic Regression. The Decision Tree model showed the lowest performance, particularly in terms of ROC AUC.**

#### **4.2.2 Class-Specific Performance**

Analysis of the classification reports revealed consistent patterns across models:

* All models achieved higher precision than recall for the majority class (hospitalized)
* For the minority class (non-hospitalized), recall typically exceeded precision
* The Decision Tree model showed more balanced performance between classes but lower overall metrics
* Logistic Regression and XGBoost demonstrated nearly identical class-specific metrics

#### **4.2.3 Optimized Model Performance**

After hyperparameter optimization, all models showed improvements:

Model | Accuracy | Precision | Recall | F1 Score | ROC AUC | Best Parameters

Logistic Regression | 0.9242 | 0.9841 | 0.9206 | 0.9513 | 0.9649 | C=0.1, solver=liblinear

Decision Tree | 0.9226 | 0.9844 | 0.9184 | 0.9502 | 0.9585 | max\_depth=10, min\_samples\_ split=10

Random Forest | 0.9236 | 0.9760 | 0.9277 | 0.9513 | 0.9639 | n\_estimators=100, max\_depth=None, min\_samples\_split=5

XGBoost | 0.9261 | 0.9858 | 0.9215 | 0.9525 | 0.9671 | learning\_rate=0.1, |

max\_depth=7,n\_estimators=100

**The most significant improvement occurred in the Decision Tree model, particularly in ROC AUC (from 0.8610 to 0.9585). XGBoost maintained its position as the best-performing model, with slight improvements across all metrics.**

### **4.3 Feature Importance Analysis**

Analysis of feature importances from the Random Forest model revealed the most influential predictors of hospitalization:

1. **Nature\_1311**: 24.10% importance
2. **Part of Body\_4422**: 9.68% importance
3. **Latitude**: 6.51% importance
4. **Longitude**: 6.27% importance
5. **Part of Body\_4429**: 4.25% importance
6. **Nature\_111**: 3.17% importance
7. **Event\_6412**: 1.92% importance
8. **Event\_642**: 1.88% importance
9. **Event\_6411**: 1.47% importance
10. **Part of Body\_4420**: 1.29% importance

This analysis revealed several important patterns:

* The nature of injury and body part affected were the strongest predictors
* Geographical location (latitude and longitude) played a significant role
* Specific event types had lower but still notable importance

### **4.4 Model Deployment Results**

The optimized XGBoost model was successfully deployed with a Flask-based API, enabling real-time predictions via HTTP requests. Testing of the deployed model with sample data yielded:

* Binary prediction: Hospitalized (1)
* Probability of hospitalization: 0.9973

This extremely high confidence prediction (99.73%) indicates the deployed model's strong conviction in classifying this particular case as requiring hospitalization.

## **Chapter 5: Discussion**

### **5.1 Model Performance Interpretation**

The high performance achieved by all models, particularly XGBoost, demonstrates the predictability of hospitalization outcomes based on workplace incident characteristics. Several factors contribute to this strong performance:

1. **Rich Feature Set**: The comprehensive feature engineering approach captured multiple dimensions of workplace injuries, providing the models with sufficient information to make accurate predictions.
2. **Effective Preprocessing**: The handling of missing values, categorical encoding, and narrative text analysis ensured that the models received high-quality inputs.
3. **Model Selection**: Gradient boosting approaches like XGBoost excel at classification tasks with moderate class imbalance, which aligns with the characteristics of this dataset.
4. **Hyperparameter Optimization**: Grid search optimization further enhanced model performance by identifying optimal configurations for each algorithm.

The minimal performance gap between Logistic Regression and more complex models (particularly after optimization) suggests that many relationship patterns in the data may be relatively linear. However, the superior performance of XGBoost indicates that some non-linear relationships are present and beneficial to capture.

### **5.2 Feature Importance Insights**

The feature importance analysis revealed several significant insights about hospitalization prediction:

#### **5.2.1 Injury Characteristics Dominance**

The nature of injury and body part affected emerged as the strongest predictors of hospitalization. This aligns with medical understanding of injury severity—certain injury types and body locations inherently present higher medical risks requiring hospital-level care. While the OSHA numeric codes in the dataset (e.g., Nature\_1311) mask the specific descriptions, these codes likely represent severe trauma types that medical professionals would immediately recognize as requiring hospitalization.

#### **5.2.2 Geographical Significance**

The substantial importance of latitude and longitude suggests regional variations in hospitalization practices that may stem from multiple factors:

* **Healthcare Access**: Regions with limited access to specialized medical facilities may have different hospitalization thresholds
* **Industry Concentration**: Geographical clustering of high-risk industries could contribute to regional patterns
* **Regulatory Variations**: Different OSHA regions may have varying enforcement practices or reporting tendencies
* **Treatment Protocols**: Regional medical practices may differ in hospitalization criteria for similar injuries

#### **5.2.3 Event Type Contributions**

While less influential than injury characteristics, specific event types appeared among the top predictors. This suggests that the mechanism of injury provides additional predictive power beyond the resulting injury itself—information that could be valuable for preventative interventions.

### **5.3 Practical Implications**

The high-performance predictive model developed in this research has several practical applications:

#### **5.3.1 Risk Assessment Enhancement**

Safety professionals can utilize the model to enhance risk assessments by:

* Quantifying hospitalization risk for specific job tasks
* Identifying combinations of factors that present elevated risks
* Prioritizing intervention resources based on predicted severity

#### **5.3.2 Preventative Interventions**

The feature importance findings enable targeted prevention efforts:

* Focus on injury types with highest hospitalization probability
* Develop specialized protocols for high-risk body regions
* Address geographical disparities in safety performance

#### **5.3.3 Early Warning Systems**

Real-time application of the model could support early warning systems:

* Integration with job safety analysis processes
* Pre-task risk scoring based on work characteristics
* Dynamic risk updates as job conditions change

#### **5.3.4 Resource Allocation**

The probability outputs from the model facilitate more efficient resource allocation:

* Stratified safety monitoring based on risk levels
* Targeted training for high-risk scenarios
* Prioritized engineering controls where most needed

### **5.4 Limitations**

Several limitations should be acknowledged when interpreting this research:

#### **5.4.1 Data Constraints**

* **Reporting Bias**: The OSHA dataset only contains reported incidents, potentially missing unreported cases
* **Coding Inconsistencies**: Reliance on coded variables (e.g., Nature\_1311) without descriptive labels limits interpretability
* **Temporal Coverage**: The analysis spans a specific time period and may not capture longer-term trends

#### **5.4.2 Methodological Limitations**

* **Class Imbalance**: The moderate imbalance in the target variable may affect model performance despite mitigation efforts
* **Feature Encoding**: One-hot encoding of categorical variables increases dimensionality and may obscure some relationships
* **Black-Box Nature**: The most effective model (XGBoost) operates as a relative black box, limiting explainability

#### **5.4.3 Generalizability Concerns**

* **Industry Specificity**: Performance may vary across industries not well-represented in the training data
* **Geographical Scope**: The model is trained on U.S. data and may not generalize to international contexts
* **Regulatory Changes**: Future modifications to OSHA reporting requirements could affect model applicability

### **5.5 Future Research Directions**

This research opens several promising avenues for future investigation:

#### **5.5.1 Enhanced Feature Engineering**

* **Code Decoding**: Obtaining descriptive labels for OSHA codes to enhance interpretability
* **Temporal Patterns**: Deeper exploration of time-based patterns in hospitalization
* **Text Mining**: Advanced natural language processing of narrative descriptions

#### **5.5.2 Model Enhancements**

* **Deep Learning Approaches**: Exploring neural network architectures for potential performance improvements
* **Multi-class Prediction**: Extending to predict specific outcomes beyond binary hospitalization
* **Ensemble Methods**: Combining multiple model types for enhanced prediction

#### **5.5.3 Practical Applications**

* **Real-time Monitoring Systems**: Development of continuous monitoring frameworks
* **Industry-Specific Models**: Customized models for high-risk sectors
* **Intervention Studies**: Measuring the impact of model-informed safety interventions

#### **5.5.4 Explainable AI**

* **Local Explanations**: Implementing LIME or SHAP approaches for case-by-case explanations
* **Rule Extraction**: Deriving interpretable rules from complex models
* **Visualization Tools**: Creating intuitive visualization frameworks for safety professionals

## **Chapter 6: Conclusion**

This research demonstrates the efficacy of machine learning approaches in predicting workplace injury hospitalizations using OSHA Severe Injury Reports data. Through comprehensive preprocessing, feature engineering, and model optimization, we developed a high-performance predictive system capable of identifying incidents likely to result in hospitalization with over 92% accuracy.

The XGBoost algorithm emerged as the superior approach, achieving an AUC of 0.9671 and F1-score of 0.9525 after hyperparameter optimization. This performance substantially exceeds the capabilities of traditional rule-based approaches and offers significant potential for enhancing workplace safety management.

Feature importance analysis revealed that the nature of injury and body part affected are the strongest predictors of hospitalization, followed by geographical factors. This insight aligns with medical understanding of injury severity and highlights the potential for targeted interventions based on these key risk factors.

The successful deployment of the optimized model as a prediction API demonstrates the practical applicability of this research. Safety professionals can leverage this technology to enhance risk assessments, prioritize interventions, and ultimately reduce the incidence of severe workplace injuries requiring hospitalization.

While acknowledging the limitations of the current approach, particularly regarding data constraints and model explainability, this research establishes a foundation for future work in predictive occupational safety. By combining machine learning capabilities with domain expertise, organizations can move toward more proactive safety management approaches that protect worker health while optimizing resource allocation.

In conclusion, this research contributes both methodologically and practically to the field of occupational safety, demonstrating how data science techniques can transform reactive safety records into proactive prediction tools that enhance workplace safety outcomes.

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