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Research Article

The Anatomy of Harm: A Machine Learning Smart Shield for Predicting Highway Worker Injuries

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Abstract

Despite growing interest in the application of machine learning (ML) for accident prediction and safety analysis, limited research has explored its use in predicting anatomical injury risk among highway workers. This study addresses this gap by developing a predictive model capable of classifying body parts most susceptible to injury in highway-related incidents. Positivism and interpretivism set the theoretical foundations for this study. The sequential exploratory mixed method adopted involved the preprocessing of accident datasets, feature selection and model evaluation using established performance metrics. A Support Vector Machine (SVM) algorithm was employed as the primary classifier, with its performance benchmarked against three comparative models: Naïve Bayes (NB), Random Forest (RF) and a Recurrent Neural Network (RNN). Analysis results showed that variables such as 'region', 'site/project', 'event type', 'vehicles involved' and 'location' were very significant in predicting bodily injuries. Moreover, the findings also indicate that the SVM model, when optimally tuned, yields competitive classification accuracy, with RF and RNN models showing promising supplementary performance. This study introduces a novel framework for body-part injury classification within high-risk highway environments tailored for highway workers. This is the first study to use real life datasets specifically collected from highway worker injuries and departs from previous studies which have focused on drivers, pedestrians and the road only.

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Highlights

- Proposed an ML framework for anatomical injury risk classification in highway workers.
- Identified region, event type, site, vehicle involvement, and location as key predictors.
- Optimised SVM achieved competitive accuracy versus RF and RNN benchmark models.

1 Introduction

Project sites and locations for highway operations normally present hazardous elements which could be detrimental to the safety of highway workers (Eseonu et al., 2018). However, there is the probability that exposure to such hazardous elements could engender body part injuries (e.g. arms, head, legs or torso) which could impact the overall health and wellbeing of workers (Alkaissy et al., 2023). In several instances, injury occurrences on highway project locations have rendered victims incapacitated hence, exposing employers to cost of compensation claims and a significant dent in organisational reputation (Zhang et al., 2023). Such negative consequences present a need for drawing insights from factors that contribute to injury occurrences and proffering tailored solutions to proactively prevent such incidents (Abukhashabah et al., 2020; Bortey et al., 2024a). In a survey conducted by Headway (2020), head injuries accounted for 20% of all workplace injuries. According to Eurostat (2023) injuries to the upper limbs (shoulders, arms and hands) accounted for 38.3% of the total number of non-fatal accidents at work while the lower limbs (hips, legs and feet) recorded 29.1% of body parts affected in injuries.

Incident data from the highway accident reporting tool (HART) database in the UK (administered by National Highways – A UK government company) presents a number of reported injury events with the associated body parts that were affected during the injury (Bortey et al., 2024b). Analysing these injuries cases could provide an understanding of the most frequent body part affected, which could in turn present an indication of the type of work or activity that causes such body parts to be inflicted (Lo et al., 2020). Furthermore, the body part affected could give insight to which injuries were more likely to be fatal and has the potential of resulting in more grievous consequences (Parra-Dominguez et al., 2015). For example, an injury to the head could result in a more fatal outcome as compared to an injury to leg (Dumrak et al., 2013). Such knowledge presents an important opportunity for safety managers to devise suitable control measures to reduce risks posed (Sarvari et al., 2024).

Although a few studies have sought to uncover the determinants of injuries affecting various body parts (cf. Dumrak et al., 2013; Lo et al., 2021), an insufficiency of data and absence of detailed comprehension of the relationships that exist between these factors have impeded the development of accurate predictive models that could classify these injuries into body parts likely to be affected (Kashani et al., 2022). In cases where data could be accessed, the quality of existing data is sub-optimal (Xu & Zou, 2021). However, data is crucial in the development of both stochastic and deterministic predictive models (Bortey et al., 2022).

Understanding significant factors that are essential to injury occurrences and developing predictive models which could identify underlying patterns and trends prior to an injury occurring is a significant step towards enhancing safety risk management (Amini et al., 2022). Such a model would enable evidence-based decision making and contribute to prioritising and maximising the utility of available resources (Alawad et al., 2019). Machine learning (ML) has been utilised in many industries to predict injury including construction, manufacturing and logistics. However, the literature (Eseonu et al., 2018b; Bortey et al., 2024) reveals that the application of ML for enhancing safety in highway operations (particularly for highway traffic officers (HTOs)) has been scant. For example, Alshboul et al. (2024) used artificial intelligence (AI) and ML to empirically explore predictive maintenance in concrete manufacturing. Similarly, Kang & Ryu (2019) employed a random forest (RF) algorithm to identify key determinants of construction accident types, uncovering that human factors, lack of supervision and insufficient protective equipment were major contributors. In another study, Ekanem (2025) used ML to forecast the severity of road traffic accidents and significant insights that could be derived from them. In a highway setting, Bortey et al., (2024a) and Ajayi et al., (2020) predicted the risk levels involved in highway operations and identified relevant features that contributes to increasing safety risk challenges. Collectively, these studies reveal the potential of applying ML in accident prediction and analysis, and the significance of identifying and choosing pertinent features that could positively impact and prediction model developed. However, there remains a research gap in using ML to determine which body regions are most at risk during highway operations. A gap that this present research addresses and contributes to knowledge.

This paper therefore aims to develop a predictive model capable of classifying body part injuries using a support vector machine (SVM) algorithm. Three ML algorithms were used to compare and benchmark the performance of the SVM algorithm viz.: naïve bayes (NB); RF, an ensemble learning algorithm that employs all three ML algorithms; and a deep neural network (DNN) model known as recurrent neural network (RNN). Associated research objectives are to identify the most efficient ML algorithm and the most suitable parameters for body part injury classification. This study also uses statistical tests such as chi-square test to investigate significant relationships between the target variable (i.e. body-part affected) and the independent variables sourced from extant literature (e.g. weather, experience, age, etc.) to determine the most pertinent variables which influence the classification of body part injuries. Research questions framed to guide this work are i) what are the most important predictors of body parts likely to be affected in an injury?; and ii) what ML model can be effective for classifying body parts likely to be affected in an injury? The research presented in this seminal paper is not a fully developed and deployed safety prediction model but instead focuses on developing a proof-of-concept ML model for risk assessment in highway operations.

2 Methodology

This study follows the methodological steps detailed by Saunder *et al.* (2016) to develop a proof-of-concept predictive model capable of forecasting body parts likely to be affected in injurious incidents. An overarching epistemological framework, combining positivism and interpretivism, served as the philosophical foundation for this research (Alharahsheh & Pius, 2020). Deductive and inductive reasoning (Edwards *et al.,* 2020) was employed to first explore the relationships between variables and obtain insights from the data before training and testing ML algorithms to ascertain the best performing model. Using incident data obtained, a sequential exploratory mixed method approach (Roberts *et al.,* 2021) was adopted to gain understanding of the trends and patterns presented by the qualitative data. Insights from this initial phase informed the subsequent quantitative phase, where the variables are coded and used to build a ML prediction model. A case study strategy was then employed to provide contextual depth and real-world relevance to the analysis *(*Bayramova *et al.,* 2023). Such a strategy allowed for a focused examination of safety and incident patterns in highway environments. A retrospective time horizon was adopted for this study because all data points were acquired from historical data contained within the case studies analysed (Kiyatkin *et al.,* 2023). The data was pre-processed using python programming tools to handle missing data and clean out duplicates. Methodological steps adopted are elaborated in Figure 1 while techniques and procedures (adopted in each of the key stages *viz.*: data collection; data pre-processing; training and testing; the modelling process; and performance and testing) are detailed in the subsequent subsections.

2.1 Data collection

A comprehensive dataset comprising 72,811 recorded highway incident cases from 2017 to 2022 was obtained to investigate the contributing factors to injuries sustained during past highway operations conducted by highway workers. The dataset includes 23 variables, of which 22 are independent features and one is the target variable (body part affected)**,** categorised into 13 distinct classes**.** Independent variables used (refer to Table 1) represent diverse organisational, environmental, temporal and demographic characteristics. These include factors such as region, project site, date and time of event, weather and visibility conditions, experience in current role, type of work and project risk level. Independent variables were selected based on their relevance to previous research in occupational incident analysis (Bortey *et al.et al.*, 2024a) and the strategic objective of identifying patterns that may enhance predictive accuracy in safety risk modelling for highway operations.

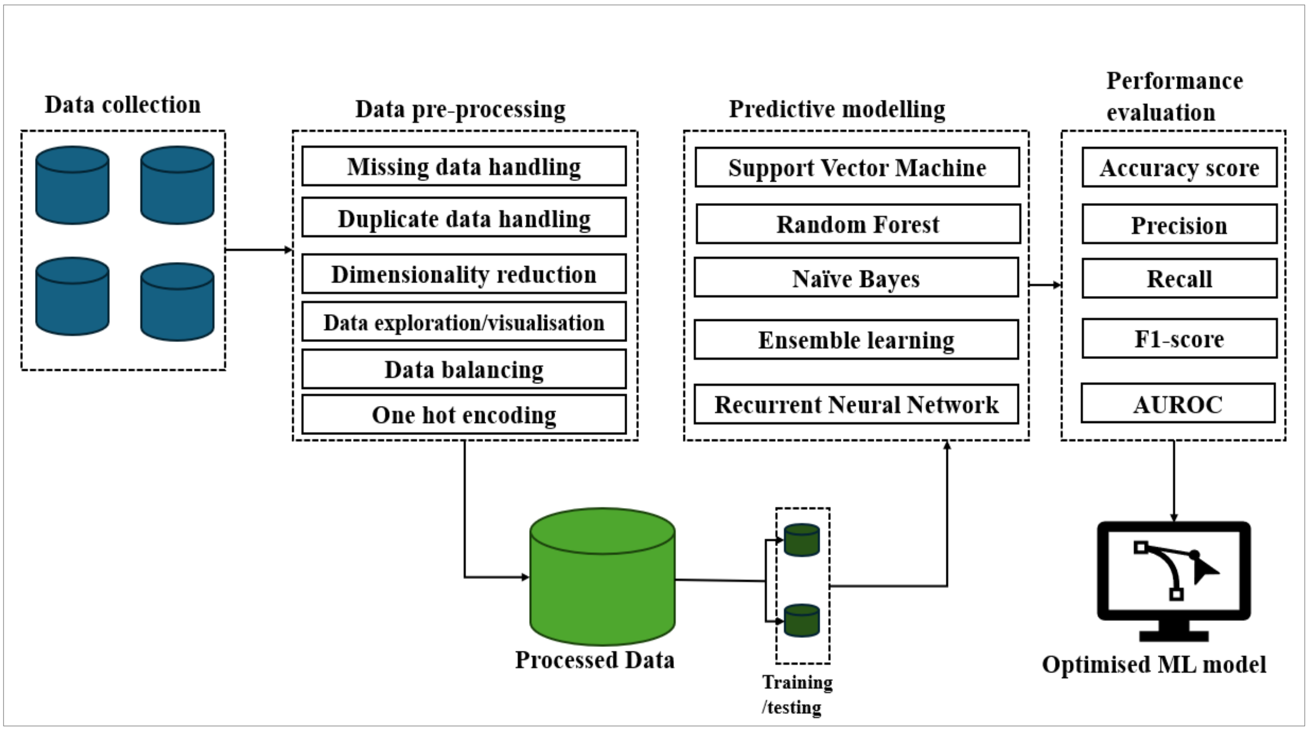

Figure 1: Methodological process.

Table 1: Variables in dataset.

Independent Variable	Data Type	Meaning	References
PublishedRecordId	Int	ID number for data point	(Ebrahimvandi et al., 2022)
Region	Categorical	The region where project is based	(Chandar et al., 2020)
Site/Project'	Categorical	The site where project is based	(Huang et al., 2020)
Date and Time of Event	Datetime	The date and time incident occurred	(Bai et al., 2021)
vehicles involved?	Categorical	Are there vehicles involved in the project (yes/no)	(Alozi and Hussein, 2022)
Type of Person	Categorical	The status of the individual's employment or visit (employee, contractor, member of public, customer)	(Rajini et al., 2018)
Location	Categorical	The location of the project site	(Huang et al., 2020)
Did this event occur on the SRN (strategic road network)?	Categorical	Is incident a strategic road network related? (Yes/No)	(Bortey et al., 2024a)
Experience in Current Role	Integer	The number of years worker has been working in that position	(García-Rois et al., 2021)
Age Range	Integer	The age of the worker	(Bortey et al., 2024a)
Weather / Visibility	Categorical	The visibility at time of incident (rainy, stormy, clear, windy)	(Abohassan et al., 2022)
Potential Severity Rating	Integer	What the possible impact of incident could be (1-25)	(Kashani et al., 2022)
Actual Severity Rating	Integer	What the actual impact was (1-25)	(Amini et al., 2022)
Month	Integer	The month of incident	(Hale et al., 2018)
Season	Categorical	The season of the incident (winter, summer, spring, and autumn)	(Ajayi et al., 2020)
Type_of_work	Categorical	The type of work being undertaken (traffic management, highway operation, not applicable)	(Choi et al., 2020)
Year	Categorical	Year of incident	
Day_of_week	Categorical	The day of the week incident happened (Monday-Sunday)	(Al-Kasasbeh et al., 2021)

Time_of_day	Categorical	The time of the day (morning, afternoon, evening, and night)	(Al-Fedaghi, 2020)
'Injury occurrence	Categorical	The likelihood of an injury occurring (True/ False)	(Amini et al., 2022)
'Injury Type'	Categorical	The types of injury that could occur (cut/laceration/ sprain/strain, bruising, amputation. Musculoskeletal, abrasion)	(Baker et al., 2020)
Project risk level'	Categorical	The likely severity of project risk (high, medium, low)	(Amini et al., 2022)
Event Type'	Categorical	The kind of incident likely to occur (Personal illness/injury, undesirable circumstance, security, environment, infrastructure)	(Bortey et al., 2024b)
Dependent variable			
'Part of Body Affected',	Categorical	The part of the body likely to be affected (head, hand, waist, leg etc.)	((Ajayi et al., 2020)

2.2 Data Pre-Processing

Several preprocessing techniques were applied to enhance the efficiency and facilitate the modelling process. Initially, to address missing values, the '*SimpleImputer'* class from scikit-learn library (Hussain *et al.et al.,* 2024) provided a strategy parameter, which enabled the specification of variables to impute missing categorical values with the mode (i.e. most frequently occurring number). This method significantly improved the predictive power of the final models despite its computational demands. The simple imputation method has been used by several studies to fill in missing data in ML tasks (Abd Halim *et al.,* 2020; Hussain *et al.,* 2024).

The values in the 'body part affected' column in Table 1 had duplicate entries which posed challenges for data analysis and interpretation. For example, entries such as 'back/spine', 'lower arm, hip, hand, back/spine', 'hip' were observed. In this example, the values 'back/spine' and 'hip' can be seen to have been duplicated leading to an inaccurate representation of the true count of unique values. To address duplicate entries, the first four letters of each entry was examined, and the same value was assigned to entries with identical prefixes. The observation made by examining the first four letters of the duplicate entries was that they possessed common prefixes. Therefore, by focusing on the first four letters, the commonalities were effectively captured and consolidated. Hence, the unique values were reduced from 179 to 13 unique entries. Assigning the same value to entries sharing a common prefix resulted in the reduction of the unique values in the 'body part affected' column without any loss of essential information conveyed by the original values. Merging the duplicate entries improved the clarity and interpretability of the data, hence facilitating meaningful insights and promoting reliable analysis of results.

Additionally, if two features were found to have a high p-value (Alozi & Hussein, 2022) one of the features was dropped in a process known as dimensionality reduction (Jia *et al.,* 2022). This is because, the model's complexity increases with a high dimensional feature set (Huang *et al.,* 2018). Also, some of the variables may be redundant and might exhibit multicollinearity, thereby undermining the statistical significance of the independent variables (Hasan & Abdulazeez, 2021).

2.3 Training and Testing

After the data was pre-processed, the dataset was split into two sets at random: 1) the training set, which was used to train the model and rank the significance of the variables for the feature selection process); and 2) the test dataset, which was used to verify the performance of the prediction model. This strategy sought to reduce any variance that might be produced by performing a simple train test split (Bichri *et al.,* 2024). The 70-30 split was chosen to ensure that the model has sufficient data to learn from while reserving a significant portion for an unbiased evaluation (c.f. Naseer *et al.*, 2020). To optimise the performance of the models, the values of the parameters for each of the algorithms were controlled by suitably chosen grids detailed in the modelling process.

2.4 Modelling Process

An SVM model was created and fit to the training data in the model experiment. The kernel applied was the polynomial kernel, the probability was set to 'true' with a random state of '42'. Different experiments were also conducted for three other ML models namely, RF, NB and the ensemble learning method to compare their performance against that of SVM model. A DL model was also used to perform classification to ascertain whether a neural network would have a better performance on the data as compared to ML models. The models were then validated using a technique called k-fold cross-validation (Malakouti *et al.,* 2023) that involved using the procedure in k number of tests and randomly dividing the data into k folds. The value of k in this experiment was randomly chosen as ten. The performance of each model was then compared, and the top performing model was identified.

The algorithmic modelling steps are:

Input: Pre-processed dataset D

Set Parameters:

kernel ← poly

probability ← True

random_state ← 42

k ← 10 for k-fold cross-validation

Initialise Models:

M_1 ← SVM_Model ← Support Vector Machine with above parameters

M_2 ← RF_Model ← Random Forest

M_3 ← NB_Model ← Naive Bayes

M_4 ← Ensemble_Model ← Chosen ensemble learning method

M_5 ← RNN_Model ← Recurrent Neural Network for classification

Create k-Folds:

For i from 1 to k:

Use fold Fi as validation set;

Use remaining k-1 folds as training set;

Train the model on training set;

Evaluate performance on validation set;

Store performance metric (e.g. accuracy, F1-score); and

Compute average performance metric over k folds;

Mathematically, this is represented as:

Splitting the dataset D into k equally sized folds $F_1, F_2, \dots, F_k$; and

For each model $M \in \{ M_1, M_2, M_3, M_4, M_5\}$.

For $i = 1\ to\ k$:

Let $V = F_{i\ (validation\ set)}$ V;

Let $T = D/F_{i\ (training\ set)}$;

Train M on T;

Evaluate M on V;

Store evaluation metric E_i; and

Compute average performance over k folds: $\bar{E} = \frac{1}{k}\sum_{i=1}^{k} E_i$.

Compare the average performance of all models on the average metric $\bar{E}$

$$M^* = \arg {}^{max}_{M} \bar{E}(M)$$

Select and report the model with the highest average performance

Output: Best-performing model based on cross-validation results M^*

2.5 Performance Evaluation

To identify the best performing model among the set of ML models utilised, a comprehensive set of classification metrics was adopted to evaluate the performance of each model. The most commonly used metric for evaluating ML models is the accuracy score (Agarwal *et al.,* 2021). However, in cases where the data shows instances of class imbalance, accuracy score alone can be misleading (Fernández *et al.,* 2018). Therefore, in addition to the accuracy score metric, other metrices viz; precision, recall, F1-score and Area Under the Receiver Operating Characteristic Curve (AUROC) were employed to give a more detailed indication of the models' performance.

Accuracy score presents a general sense of overall model performance by evaluating the ratio of correctly predicted cases out of the total predictions (equation 1).

$$accuracy = \frac{TP+TN}{TP+TP+FP+FN} \quad (1)$$

Precision gives an indication of how reliable the positive classifications are. Therefore, it examines the ratio of true positive predictions out of all the positive predictions made by the model (equation 2).

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

Recall measures how effective the model is in capturing the relevant instances. Hence, it evaluates the model's ability to correctly identify all the positive cases which are actually positive (equation 3).

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

The F1-score provides a balance between the precision and the recall and is otherwise known as the harmonic mean of the precision and recall (Yacouby & Axman, 2020). It is very useful when seeking a trade-off between false positives and negatives (equation 4).

$$F1 - score = \frac{2(precision*recall)}{precision+recall} \quad (4)$$

The AUROC helps to assess the model's ability to differentiate between the distinct classes across various classification thresholds (Amini *et al.*, 2022). The higher the AUROC value, the better its ability to distinguish. This is known as the discriminative performance of the model (Anagnostakis *et al.*, 2024). Due to the multi-class nature of the classification task in this study, the use of the AUROC metric is essential in objectively evaluating the performance of each model.

3 Results – Key Findings

Data for the target variable was explored and visualised to aid in obtaining a better understanding of its structure and nature. Visualisation also sought to help uncover an trends and patterns that may be hidden in the data. Figure 2 presents the distribution of body part affected from various personal illness and injury incidents. The category 'not applicable' represents incidents which did not lead to injuries were the most occurring. However, for incidents which injuries had ensued, the most frequently reported body part affected on highway project site/locations was the leg/knee (*f*=338 or 17.2%). This was followed by: lower arm including wrist and hand (*f*=275 or 14%); head (*f*=207 or 10.5%); ankle/foot (*f*=204 or 10.3%); finger/thumb (*f*=198 or 10.1%); mental/psychological (*f*=163 or 8.3%); back/spine (*f*=156 or 7.9%); neck/shoulder (*f*=126 or 6.4%); upper arm including elbow (*f*=97 or 4.9%);, chest/stomach (*f*=74 or 3.8%); eye/ear (*f*=58 or 2.9%); hip (*f*=21 or 1.1%); and lungs/throat (by chemical) (*f*=16 or 0.8%). Evidently, the chest/stomach area, eye/ear, hips and lungs/throat were the least recorded body part involved in injuries.

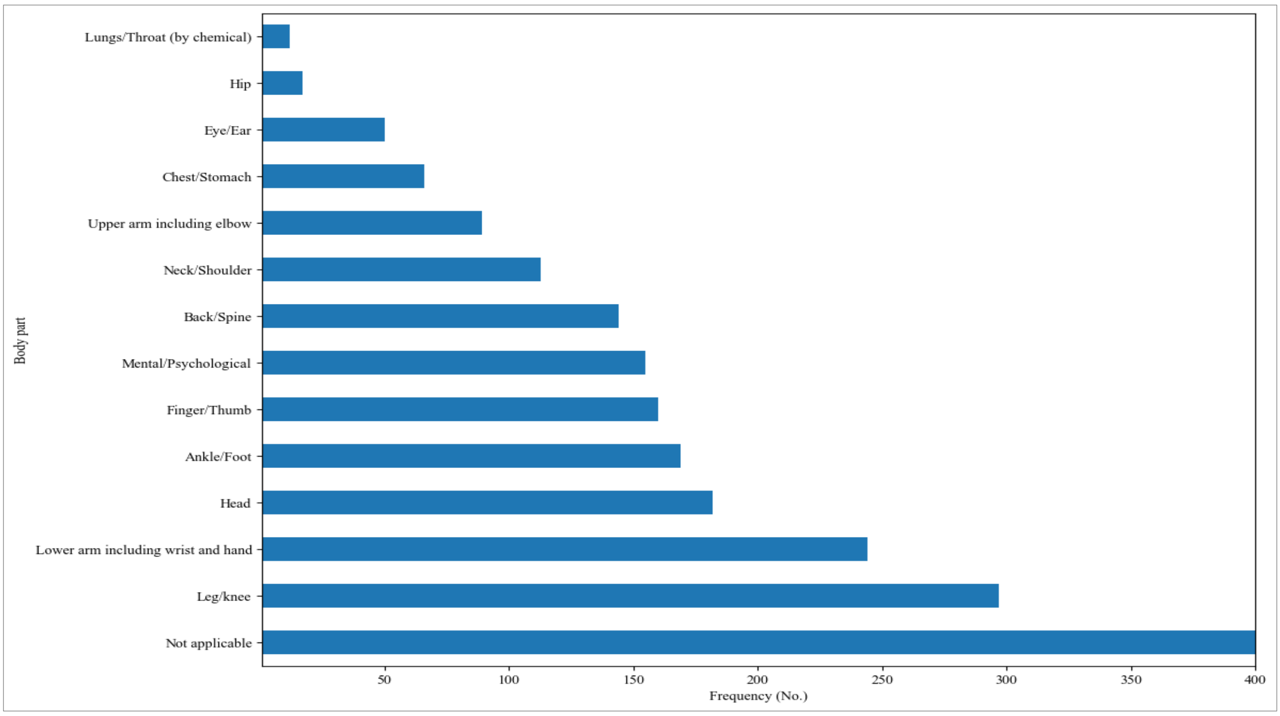

Figure 2: Distribution of body parts affected by injuries.

3.1 Feature Importance and Dimensionality Reduction (Chi-square test)

Table 2 presents the independent variables and their associated chi-square statistic and p-value. The chi-square statistic measures the difference between the observed frequencies and the expected frequencies if two categorical variables were deemed associated. The greater the difference between observed and expected frequencies, the greater the values of the chi-square statistic. Therefore, a high chi-square value indicates an association between the variables while a low value indicates independence. In contrast, the smaller the *p*-value (i.e. <0.05), the greater the chance of an association between the variables, hence rejecting the null hypothesis of independence.

Table 2: Chi-square table.

Variables	Chi-square (CS)	P-value (PV)
Region	2197.618813	5.218114e-259
Site/project	15773.829953	0.000000e+00
Event type	51244.164903	0.000000e+00

Vehicles involved	1093.540835	1.392244e-225
Type of person	34.574609	6.718692e-01
Location	2774.114106	0.000000e+00
Did this event occur on the SRN?	179.344500	2.308856e-31
Injury type	114009.334610	0.000000e+00
Weather/visibility	248.317880	3.150706e-23
Season	39.119176	4.645261e-01
Type_of_work	34.574609	1.211591e-01
Injury occurrence	50650.254417	0.000000e+00
Project risk level	35544.383540	0.000000e+00
Day_of_week	77.599370	4.915031e-01
Time_of_day	77.518971	1.241510e-02

Two separate heatmaps (refer to Figure 3a and 3b) were created for the chi-square statistics and the p-values with each heatmap displaying the values for each variable, with annotations showing the numerical values. A cool warm colour map was used to represent the values, with blue colours indicating lower values and red colours indicating higher values.

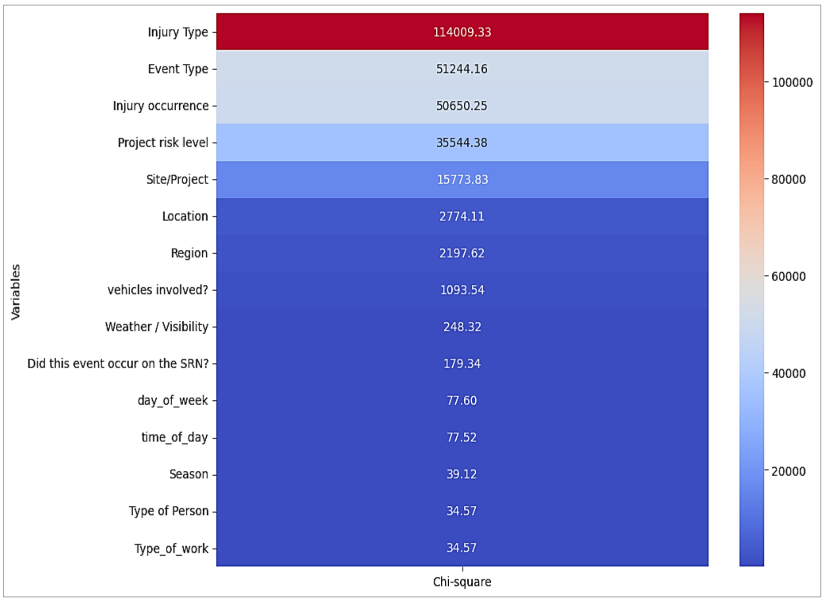

Figure 3a: Chi-square statistics for categorical variables.

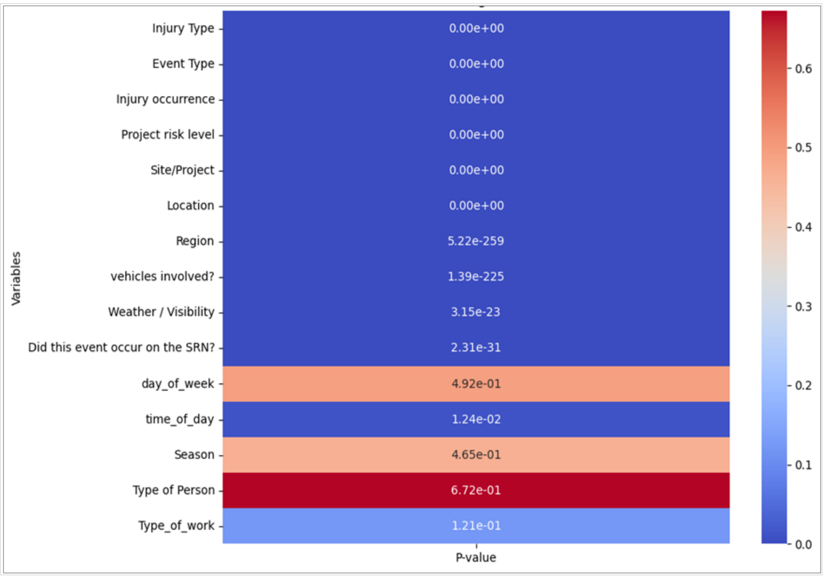

Figure 3b: P-value for categorical variables.

The variables ‘type of person (*PV*=0.67)’; ‘day of week (*PV*=0.49)’; ‘season (*PV*=0.46); ‘type of work (*PV*=0.12)’ had *p*-values > the significant level of 0.05. Similarly, the variables with higher p-values, also had relatively very small chi-square statistic value indicating that there is no statistically significant association between the ‘type of person’, ‘season’, ‘day of week’ and ‘type of work’ variables and the target variable (body part affected). Therefore, the null hypothesis of non-association is not rejected. However, the variables, ‘region’, ‘site/project’, ‘event type’, ‘vehicles involved?’, ‘location’, ‘did this event occur on the SRN?’, ‘injury type’, ‘weather / visibility’, ‘season’, ‘injury occurrence’ and ‘project risk level’ had large chi-square statistics which indicates a substantial discrepancy between the observed and expected frequencies, and a very low *p*-value which suggests that this association is highly unlikely to be due to chance alone. Therefore, the null hypothesis of non-association is rejected. These variables were then adopted as input variables in the modelling process.

3.2 Model Performance

Table 3 presents the performance metrics, including precision, accuracy, recall, F1-score and AUROC, for each of the different ML models used to classify the part of body likely to be affected in the event of an injury occurrence. The performance of the models was evaluated using the 10-fold cross-validation (Malakouti *et al.*, 2023). In each of the ten iterations, the dataset was randomly partitioned into ten equal subsets or “folds”, one-fold was set aside as the validation set and the model was trained on the remaining nine folds. This process was repeated such that each fold served once as the validation set, ensuring all data points were used for both training and validation across the iterations. The results showed that SVM outperformed all the other models in terms of accuracy.

Table 3. Classification results

Model	Accuracy score (%)	Precision (%)	Recall (%)	F1-score (%)	AUROC (%)
SVM	99	98	97	97	98
RF	96	94	94	94	95
NB	91	92	91	92	91
EL	98	97	98	98	97
RNN	95	94	92	94	94

Based on the overall performance of the models presented in Table 3, SVM is the best performing model in terms of accuracy (99%), AUROC (99%), indicating an almost precise level of consistency in classification. Ensemble learning had the second highest performance with an accuracy (98%) and AUROC (97%). RF ranked third with an accuracy (96%), AUROC (95%), followed by RNN, with accuracy (95%), AUROC (94%). NB was the least performing model with accuracy (91%) and AUROC (91%).

3.2.1 Performance of Each Class Using ROC Curve

Figure 4 presents the ROC curve which describes how well each class of the target variable performed in the experiment for the best performing algorithm which was the SVM algorithm. Using the one-vs-rest multi-class algorithm, the results show that, each class of the target variable had near perfect prediction for body part likely to be affected. This shows, the accuracy of 99% for the SVM was not influenced by biased prediction of the majority class but rather has a balanced high prediction ability across each of the classes. Such high AUC scores suggest that the model is highly effective at multi-class classification and is capable of distinguishing between categories with minimal overlap. The tight clustering of all curves near the top-left corner of the plot also implies low false positive rates and high true positive rates across board.

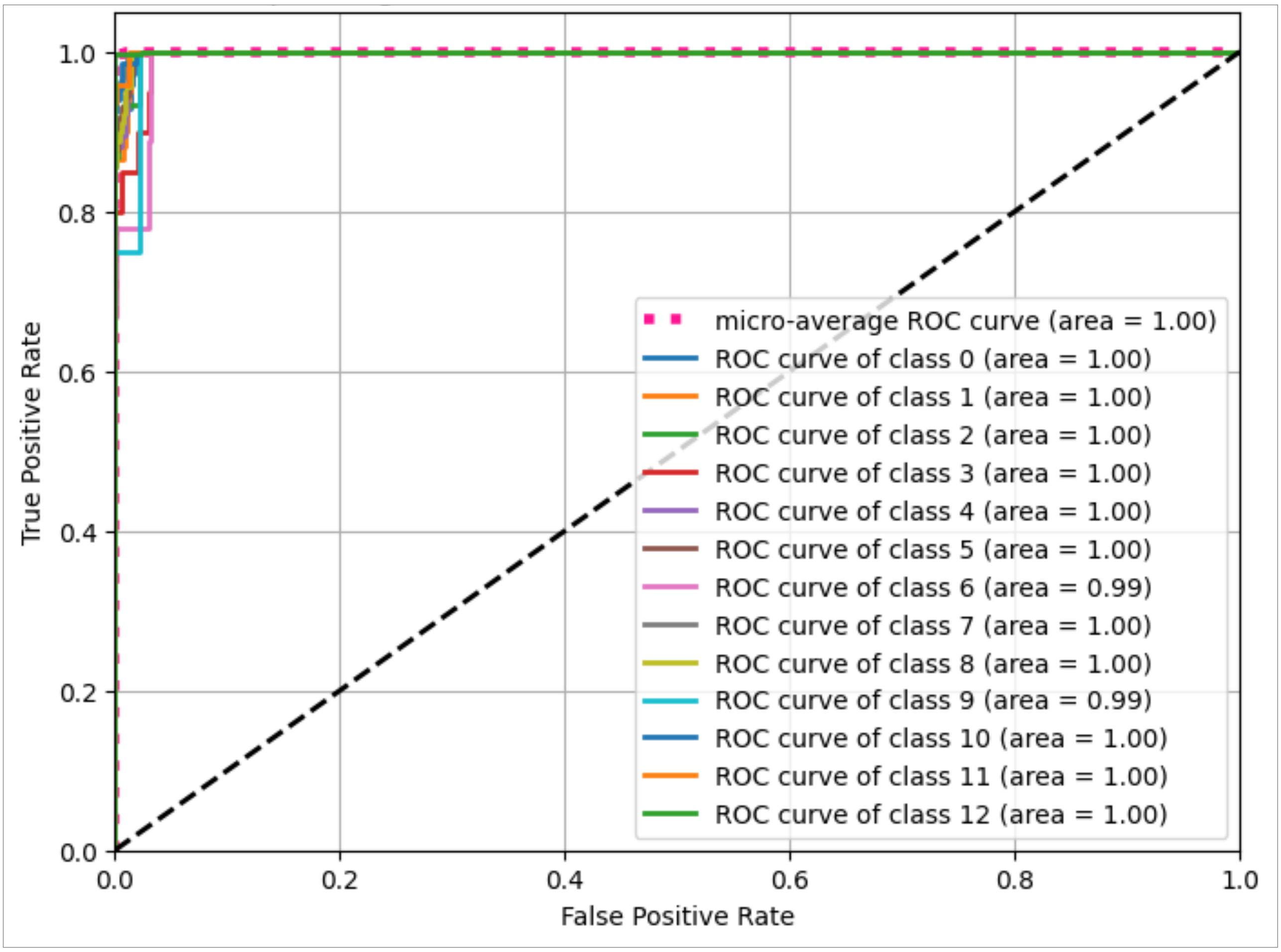

Figure 4: ROC curve for body part affected.

4 Discussion

An exploration of the target variable presented the top five body parts usually impacted in an injury as: i) leg/knee; ii) lower arm including wrist and hand; iii) head; iv) ankle/foot; and v) finger/thumb. This could give an indication of the type of activities or incidents that must be carefully considered, prioritised and evaluated during highway operations. The type of incident or activity that leads to an injury can be inferred from the body part affected (Oyedele *et al.*, 2021). Injury prevention resources must be prioritised for these areas to proactively pre-empt these injuries (cf.). Table 4 provides details of such incidents which could affect the body part stated.

Abukhashabah *et al.*, (2020) found that falling equipment caused 27% of head injuries at the workplace hence, the provision and use of appropriate PPEs was pertinent to reducing such injuries. However, it is far better to eliminate the risk of falling equipment altogether under the hierarchy of control theoretical concept (Almaskati *et al.*, 2024). Ahuja *et al.* (2024) also recognised that heavy objects falling on the foot, or heavy machinery running over the foot could be some examples of incidents that could cause injuries to the ankle or the foot with severe damages to the muscle or tissues. Alessa *et al.* (2020) found that handling equipment and climbing scaffolds are activities which could contribute to finger/thumb injuries. These studies support the postulations of incidents likely to be the causes of body part injuries in this study.

Table 4: Inferred incidents from body parts injured.

Body part	Incident/activity	References
Leg/Knee	Slips, falls or trips on uneven surfaces. Falls from heights.	(Xie *et al.*, 2021; Ishimaru *et al.*, 2024)

	Struck by falling objects. Twisting or hyperextension during physical activities. Overuse injuries from repetitive motions.	
Lower arm including wrist and hand	Accidents involving machinery or tools. Impact injuries from heavy objects. Repetitive strain injuries from typing or manual labour. Cuts or lacerations from sharp objects. Fractures or sprains from falls or collisions.	(Choi *et al.,* 2020; Edwards *et al.,* 2020)
Head	Falls from heights or slips. Struck by moving objects or equipment. Vehicle accidents. Impact injuries from falling debris and equipment.	(Hayes *et al.,* 2025)
Ankle/foot	Twisting or rolling the ankle on uneven ground. Falls or slips on slippery surfaces. Dropping heavy objects on the foot. Crushing injuries from machinery or equipment. Sprains or strains from sudden movements.	(Ahuja *et al.,* 2024; Lee *et al.,* 2025)
Finger/thumb	Pinching injuries from closing doors or machinery. Cuts or lacerations from sharp objects. Crush injuries from heavy objects or equipment. Impact injuries from striking objects. Fractures or dislocations from accidents or falls. Climbing scaffolds/ladder.	(Alessa *et al.,* 2020)

Analysis of association conducted using the chi-square test of association showed that, the independent variables 'region', 'site/project', 'event type', 'vehicles involved', 'location', 'did this event occur on the SRN', 'injury type', 'weather / visibility', 'season', 'injury occurrence' and 'project risk level' were the most significant variable in predicting a body part likely to be affected by an injury. This finding answers the research question '*what the most important predictor of body parts are likely to be affected in an injury*?' The finding is in congruence with findings of other studies that showed that 'project type', 'location', 'experience', 'day' and 'season' were influential to predicting body part injuries (Ajayi *et al.*, 2019; Oyedele *et al.*, 2021). Applying ML to predict body part injuries and the incidents that cause them presents an innovative opportunity to tackling health and safety risks, particularly in high-risk environments such as highway construction and maintenance. By analysing historical injury records and associating specific types of incidents like slips, falls or machinery accidents with injuries to particular body parts, ML models such as SVM, RF and RNN can detect significant patterns and correlations within the dataset. A nuanced understanding of the root causes of injuries could be a significant step to unearthing pertinent insights. Insights obtained could also help to identify combinations of risk factors such as location, project type, season and equipment used that increase the probability of injury occurrences for individual operations. For instance, if the model identifies a strong link between poor visibility and increased incidence of ankle injuries during winter roadworks, targeted adjustments such as better lighting and traction footwear can be introduced to reduce risks. Moreover, the costs for this investment can be justified by comparing the benefits to be accrued from control measures implemented when compared to the tangible and intangible costs incurred by an incident. Such costs can be considerable and for a fatality, this can run into several millions.

The results for model development indicate that SVM achieved the highest accuracy score of 99%, followed closely by Ensemble Learning (EL) with 98%. RF and RNN attained accuracy scores of 96% and 95%, respectively, while NB achieved an accuracy score of 91%. Across precision, recall and F1-score metrics, SVM consistently demonstrated strong performance, maintaining precision, recall and F1-score values above 97%. RF, EL and RNN also exhibited competitive performance across these metrics, with precision, recall, and F1-score values ranging from 94% to 98%. NB, while slightly lower in performance compared to other models, still demonstrated reasonable precision, recall, and F1-score values of around 91% to 92%. These results suggest that SVM is the most reliable classifier for this task, providing both high accuracy and balanced performance across multiple evaluation metrics. The strong performance of RF, EL and RNN indicates that these models are also suitable alternatives, while NB may be less optimal for fine-grained injury classification. The high performance across all models demonstrates the predictive value of the selected variables, specifically, the incident and site features as presented in the results.

The SVM outperforming all other models could be due to its ability to effectively model linear decision boundaries and handle high-dimensional feature spaces (Park *et al.*, 2020). In this thesis, SVM could have utilised the intrinsic linear separability of the data, resulting in robust predictions (Guan *et al.*, 2022). EL, which combined multiple models (SVM, RF, NB) to improve performance, also demonstrated a strong performance by making use of the diverse strengths the of individual models to enhance prediction accuracy (Mienye *et al.*, 2020). RF and RNN, while slightly lower in accuracy compared to SVM and Ensemble Learning, still exhibited competitive performance, indicating their capability to capture complex patterns in the data (Jung *et al.*, 2020). This could also be attributed to SVM having fewer hyperparameters to tune as compared to RNN and ensemble learning, which can simplify the model selection and tuning process. In the experiment, the hyperparameters of SVM were well-optimised for the data by exploring different combinations of hyperparameters to demonstrate which combination was most effective. The superior performance of SVM compared to RNN and Ensemble learning, could therefore be attributed to the optimal hyperparameter utilised as RNN and ensemble learning are more sensitive to hyperparameter settings (Farsi, 2021; Mohammed & Kora, 2023).

The predictive model developed has broad applicability beyond highway projects. Fields such as manufacturing, mining, healthcare and logistics where workers are exposed to physical hazards can adopt this model and tailor it with industry variables and characteristics to forecast injury patterns and design safer workflows. As organisations embrace such digital transformations, using ML to pre-emptively manage occupational risks could become a cornerstone of modern workplace safety strategies. Due to the safety-critical nature of highway operations, issues of model interpretability, transparency and ethical use are essential considerations (Jung *et al.*, 2020). As this study focuses on predictive feasibility the use of models such as SVM and RF enables post-hoc interpretability through feature importance analysis and decision boundary inspection (Oyedele *et al.*, 2021). Future work will incorporate formal explainable AI techniques (e.g. SHAP or LIME) alongside ethical validation frameworks (Mohammed and Kora, 2023) to support fairness, accountability and responsible adoption in safety-critical environments.

4.1 Practical Implications and Proposed User Interface

In highway operations, accurate prediction of body parts which could potentially be injured is a significant measure for a learning organisation (Oyedele *et al.*, 2022). Such a prediction will invariably influence the implementation of preventive measures and could be pertinent in developing tailored interventions to reduce highway safety injuries. The high accuracy of the ML models presents robust and effective decision-making tools which will enable safety managers prioritise resources and implement safety protocol which will significantly minimise injurious incidents. Using ML to analyse body part injuries in a predictive model could offer insights into the relationship between certain variables such as environmental, demographic, traffic patterns or location and specific types of injuries such as spine/back injuries, head trauma etc. A detailed understanding of such relationships enables proactive measures which facilitate the prevention of such injuries.

By identifying the factors that are most predictive of body-part injuries, the model can help support the development of targeted safety policies and interventions for highway workers. For example, agencies could prioritise safety training, equipment allocation and site supervision in locations or conditions identified as high risk. While these policy recommendations are conceptual at this stage, they illustrate how predictive insights can contribute to evidence-based occupational safety planning. They can also inform broader health and safety regulations in high-risk highway environments.

In the highway industry, contractors and subcontractors are often engaged by highway agencies (e.g. National Highways) to undertake various projects, yet they operate independently of direct oversight by these agencies (Kshraf *et al.*, 2022; Bortey *et al.*, 2025). Consequently, ensuring consistent safety standards across all contracted entities poses a challenge, as each contractor may adhere to varying safety policies and practices (Mbachu, 2008). Nonetheless, insights gained from body part injury prediction endeavours can be disseminated to contractors, serving as foundational knowledge for the development of principal safety guidelines applicable to all contractor companies. Relevant information such as anonymised injury prediction data and best practices could be obtained and can enhance collaboration between highway industry stakeholders by sharing insights derived from the data in the bid to improve safety efforts (Deep *et al.*, 2022). Figure 5 gives a representation of the proposed user interface for the body part prediction.

This representation presents an example of how the user interface of the body part prediction tool would be designed. As a proof-of-concept, this prediction tool will accept input variables (such as location, worker profile, weather conditions etc.) through the user interface. The ML algorithm will process the information and predict the injuries type, specifically, the body parts most likely to be affected in an injury. A core feature of the user interface is the integration of predictive analytics using a human body visualisation. This feature will emphasise the vulnerable body parts (e.g., hands, knees, wrists) based on the modelled risk profile. The tool also offers a descriptive analytics dashboard, which analyses the data and provides insights into injury distribution across seasons, types of incidents recorded within a given month, work activity proportions and accident frequency rates (AFR) over time. Future developments could include the input of leading indicators (Bayramova *et al.,* 2023) to measure the likelihood (probability) of incidents occurring under various given scenarios and perhaps more importantly, derived control measures that could be implemented to control the risk(s) posed. The adoption and use of such as system will enable proactive safety management (Bortey *et al.*, 2024b). Consequently, the system will provide safety managers (especially non-technical users) data-driven evidence that inform training, operation scheduling and the deployment of appropriate personal protective equipment (PPE) (Huang *et al.*, 2018).

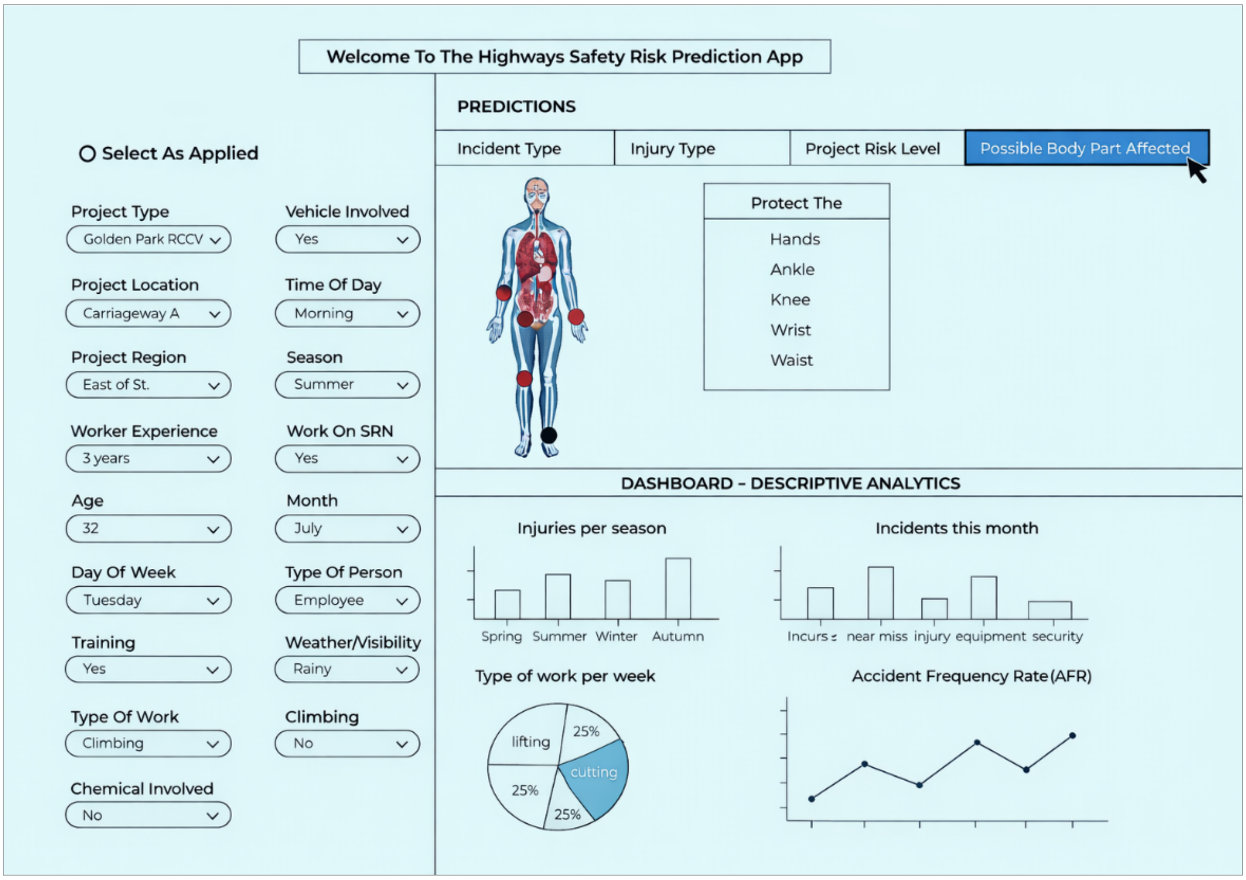

Figure 5: Proposed user interface for the body part prediction.

5 Conclusions

In contemporary times, ML has become an indispensable technique and has proved to be of utmost significance in curtailing injuries in various fields of occupational health and safety. This paper proposes a novel computational and ML model for determining body parts likely to be affected in an injurious incident. Five different algorithms (namely, SVM, RF, NB, EL, RNN) were employed to classify the body parts. The performance of each model was evaluated and compared based on five metrices (viz. accuracy score, precision, recall, F1-score and AUROC). The data is balanced using the SMOTE algorithm to prevent the models from being biased towards the majority class, which can affect performance accuracy. The parameters of each model are tuned to optimise their performance and evaluated with a train test split technique which reserves 30% of the data for testing purposes. The experimental results show that, SVM performed better than the three other ML algorithms i.e. RF, NB and EL. EL however had a slight advantage over RF and NB because it leveraged the strengths of both models to achieve a slightly better performance. This study acknowledges overfitting and data leakage as potential risks. Despite the precautions taken to mitigate such risk, the structured nature of the dataset and the consolidation of body-part labels may contribute to high accuracy scores. Therefore, these results should be interpreted as indicative of the model's feasibility rather than definitive evidence of deployment readiness.

Consequently, the RNN model although had a competitive performance, was the least performing algorithm. This was because RNN compared to the other algorithms, is more sensitive to hyperparameter settings (Farsi, 2021). A limitation of this work is that other different hyperparameters could have performed better for RNN which were not explored. Future work will explore these other hyperparameters to ascertain their effectiveness on the model. With the advent of large language models (LLM), a key limitation of this study is that it did not explore the use LLM for analysing the incident data. While the study focused on traditional ML techniques for safety risk prediction, LLMs could enhance the analysis of incidents by extracting deeper insights from unstructured text.

A significant quantity of safety-related data is available in unstructured formats, including incident reports, maintenance logs and employee feedback however, the traditional ML models used for safety prediction often rely on structured data. Future research will therefore explore the use of LLMs to analyse the vast amounts of historical safety reports, identifying key risk factors, trends, and correlations that may not be immediately evident through traditional statistical methods. It is also worthy to note that while the proposed framework demonstrates strong predictive capability using real-world data, it is presented as a proof-of-concept study. This framework is not yet intended for direct operational deployment. It would require further validation, system integration and stakeholder-led testing before practical implementation.

A practical implication of accurately predicting body parts which potentially could be injured is the significant milestone of transforming an organisation into a learning organisation (Oyedele et al., 2022). Such predictions could influence the implementation of preventive measures and could be pertinent in developing tailored interventions to reduce highway safety injuries. Future work will further investigate the performance of the models by validating the model using a stratified k-fold cross validation technique (Prusty et al., 2022). This will further strengthen the reliability of the model making it more robust. Moreover, the prediction tool will be tested in practice working in partnership with National Highways on real life highways projects. Such work will allow new real-life data collected continuously as incidents occur to further train and refine the prediction tool iteratively but also benchmark health and safety performance within the organisation. Lessons learnt will not only help the organisation but also members of their support chain who can benefit from this digital innovation.

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Data is subject to a non-disclosure agreement and is not available for wider dissemination or sharing.

Conflicts of Interest
The authors declare no conflict of interest.

AI Declaration
The authors confirm that no generative AI tools, including language models such as ChatGPT or other artificial intelligence systems, were used in the preparation, writing, analysis or review of this manuscript. All content; analysis and interpretations were produced solely by the authors.

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