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Hidden in Plain Sight: A Data-Driven Approach to Safety Risk Management for Highway Traffic Officers

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Abstract: Highway traffic officers (HTOs) are often exposed to life-threatening workplace incidents while performing their duties. However, scant research has been undertaken to address these safety concerns. This research explores case study data from highway incident reports (held by National Highways, a UK government company) and employs deep neural network (DNN) in unearthing patterns which inform safety decision makers on pertinent safety challenges confronting HTOs. A mixed philosophical stance of positivism and interpretivism was adopted to synthesise the findings made. A four-phase sequential method was implemented to evaluate the validity of the research *viz.:* (i) architectural design; (ii) data exploration; (iii) predictive modelling; and (iv) performance evaluation. The DNN model's predictive performance is benchmarked against three other machine learning models, namely Support Vector Machines (SVM), Random Forest (RF), and Naïve Bayes (NB). The DNN model outperformed the other three models. Findings from the data exploration also show that most work operations undertaken by HTOs have a medium risk level with night shifts posing the greatest risk challenges. Carriageways and traffic management enclosures had the highest incident occurrence. This is the first study to uncover such hidden patterns and predict risk levels using a database specifically for HTOs. This study presents evidence-based information for proactive risk management for HTOs.

Keywords: health and safety; artificial intelligence; data exploration; risk prevention; predictive modelling

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1. Introduction

The UK's Health and Safety Executive (HSE) reported that the transportation sector had lost approximately two million working days to workplace illness and injuries, with workplace injuries, accounting for 21% and work-related illnesses for 79% of these absences [1]. On average, this translates to each worker losing approximately 1.4 working days, which is higher than the overall industry average of 1.1 days [1]. Highway Traffic Officers (HTOs) are employees in the transportation industry who play an integral role in ensuring the safe running and operation of road networks [2,3]. However, due to the nature of work undertaken by HTOs in preserving smooth transportation and road network operations, they are confronted with various risks and hazards themselves [4,5]. Modern industry has attempted to address such risks by the incorporation of advanced digital technologies under the umbrella of Industry 4.0 (IR 4.0) [6]. The applications of these IR 4.0 technologies are myriad and include the following: artificial intelligence (AI) to accurately model big datasets [5]; building information modelling (BIM) to create visualisations of geometric and semantic elements within buildings and infrastructures [7]; and blockchain to protect data security [8]. Despite the fundamental contributions HTOs make towards preserving road safety, research undertaken to assess the impact of these advanced digital transformations upon engendering a safer workspace remains scant [3].

Before addressing the safety risks faced by HTOs, a comprehensive understanding of existing vulnerabilities and hazards is required [9]. Therefore, organisational workplace health and safety teams must strive to proactively identify and tackle safety infractions on work sites before HTOs are deployed to their workstations [10]. Such a comprehensive understanding can be gained from analysing historical incident data through exploratory data analysis (EDA) to probe into the data and investigate patterns and trends uncovered [11]. AI predictive modelling of safety risk data could also be employed to analyse the data and forecast future outcomes based on past occurrences [12]. Applications of EDA and AI predictive modelling of incipient accidents depart from the current practice of using traditional statistical methods to mitigate safety risks after their occurrence [13]. Instead, they provide a proactive approach to risk prevention through their ability to analyse large volumes of data—where such is a major limitation of statistical methods [14]. Milo and Somech [15] espouse that although EDA and AI predictive modelling require a high level of analytical and domain skills, advancements in machine learning (ML) provide a better avenue for navigating the complexities EDA and predictive modelling presents. These inherent advantages of DNN and ML make them the preferred methods in this study [14,15]. By predicting high-risk situations using DNN, incident occurrences could be reduced, ultimately minimising lost work hours.

Based on a layered software architecture [16,17], this paper develops a proof of concept for a highway safety risk assessment model (HSAM). Such a model could help safety officers analyse incident data and gain a deeper understanding of the nature of existing risks, incident occurrences, safety gaps and vulnerabilities as well as forecasting incipient accidents before they lead to workplace injuries or lost work hours [18]. Safety officers can then tailor safety training to highlight existing safety vulnerabilities and educate HTOs on how to avert such risks [19]. An initial EDA is carried out using descriptive data analysis of a database owned and managed by National Highways (a UK government company which reports to the Department of Transport)—specifically, frequencies and distributions [20] were used to investigate the trends and patterns presented in the data. Furthermore, a feedforward Deep Neural Network (DNN) was used to predict risk levels involved in highway projects and operations [21]. DNN performance was then benchmarked against three other ML algorithms *viz.*: (i) Support Vector Machine (SVM); (ii) Random Forest (RF); and (iii) Naïve Bayes (NB). The associated objectives are as follows: (i) delineating the architectural design for the proposed HSAM; (ii) uncovering and understanding the trends and patterns present in the incident data analysed; (iii) classifying the severity of risks involved in highway operations using DNN and ML models; and (iv) evaluating model performance using metrics such as accuracy score, precision, recall, F1-score and Area Under the Receiving Operating Characteristic (AUROC).

The novelty of this research lies in the analysis and prediction of safety risks specifically associated with HTOs using DNN. While previous studies [22–24] have demonstrated the potential of using ML and DNN to improve managing and analysing traffic safety, they do not address safety risks faced by front-line workers (HTOs) in the transportation industry. For instance, Wang et al. [22] employed ML in optimising traffic flow, while Razi et al. [23] explored the use of DNN in traffic safety analysis for autonomous vehicles and human-operated vehicles. This research is therefore distinguished by its use of EDA and DNN to uncover hidden patterns in incident data, thereby allowing the prediction of risk levels before incidents occur.

2. Materials and Methods

A mixed philosophical paradigm consisting of positivism and interpretivism was adopted in this research [25–27]. While the data analysed are subjected to interpretivism, this research sought to pursue objectivity in deriving knowledge using empirical evidence [28]. Several studies [25,29,30] have employed this approach in preventing bias and providing assumptions backed by evidence. An inductive approach was applied whereby patterns in the data were analysed first and conclusions were drawn afterward [27]. The research follows a mixed-method approach, integrating qualitative and quantitative data [28]. The use of exploratory data analysis (EDA) and predictive modelling represents the quantitative aspect, while the interpretation of patterns and trends aligns with qualitative analysis [29].

This research is carried out in four phases using the sequential explanatory method [28] *viz.*: (i) architectural design; (ii) data exploration; (iii) predictive modelling; and (iv) performance evaluation—refer to Figure 1. The first phase delineates the architecture of the proposed highway safety risk prediction model (software) [31]. The model's functional and non-functional requirements are defined in this phase and communication between the system components (and the resources they share) are specified explicitly. The model's architecture defines the data sources and is evaluated using EDA and predictive modelling. Qualitative and quantitative secondary data were collected from a National Highways database (entitled highway accident report tool (HART)) and pre-processed using Jupyter notebooks, a web-based interactive development environment which presents an interface for coding and configuring workflows [30]. Missing data from either columns or rows of the dataset could weaken the representativeness of data and skew conclusions derived from it [11,15]. Therefore, columns which had less than 50% of the data required were dropped from the dataset to enhance the consistency of the dataset [11]. Missing data from rows were also filled in with data using information from the rows that have similar and corresponding features to prevent any biases [15].

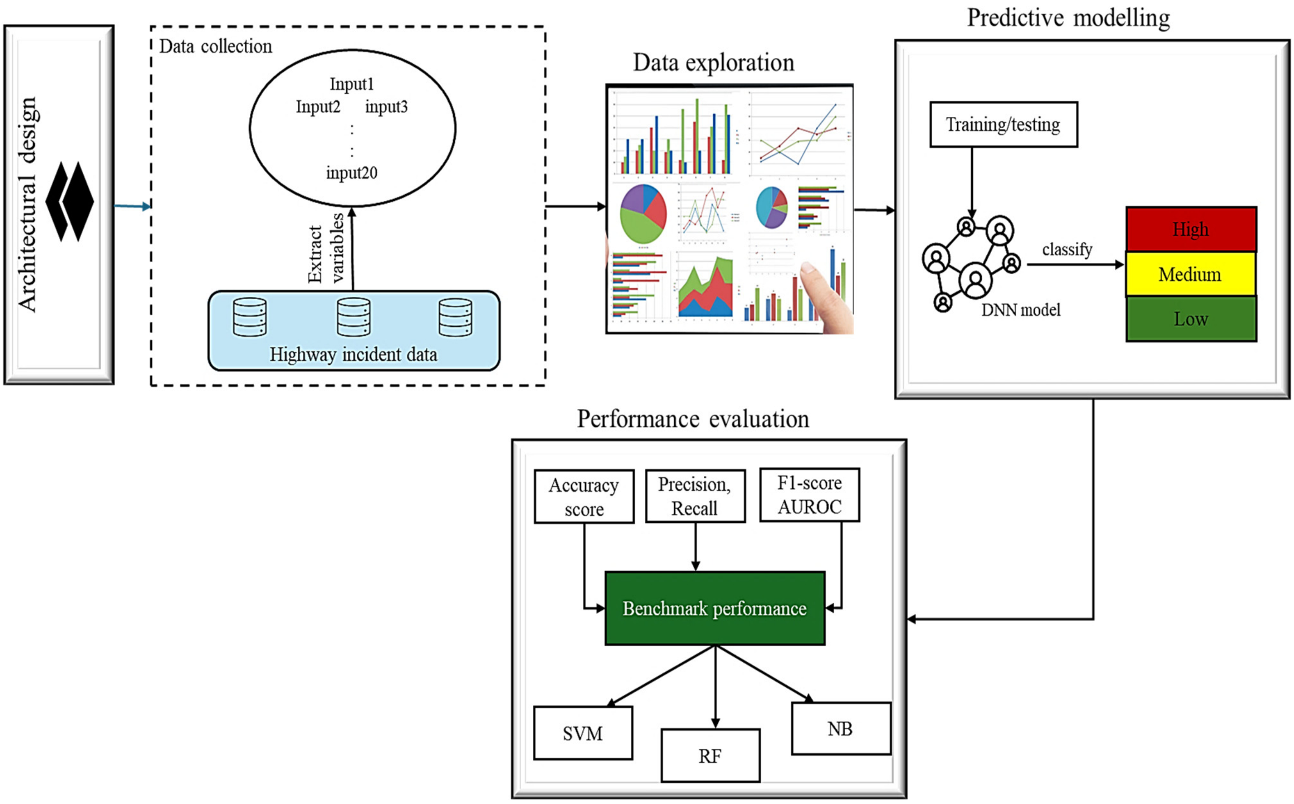


Figure 1. The methodology process.

The second phase of the study details the insights gained from data exploration through data visualisation and statistical analysis. An EDA is carried out to understand the data, identify patterns and trends, and prepare the data for further analysis [11].

Various pertinent tasks such as data cleaning, data visualisation and statistical analysis were performed during the data exploration stage to better understand the data and identify any issues or inconsistencies [32].

The third phase presents the predictive modelling of project risk levels and forecasts the severity of risks involved based on the model's input data. This phase involves initially training a feedforward DNN model using 70% of the input variables derived from the dataset and subsequently, testing the model with a 30% hold-out sample of the data for validation purposes. The two DNN models' performance (initial and hold-out sample) was then evaluated in phase four. The performance metrics utilised were as follows: accuracy score, precision, recall, f1-score, and the AUROC [33]. The performance of the DNN model is then benchmarked against three other ML models, namely SVM, RF and NB.

2.1. Data Collection

A total of 72,811 incident cases reported between 2017 and 2022 were selected from the HART database. The data comprise 21 features, signifying the characteristics and nature of incidents that have occurred on past highway projects. In total, 20 of these features are independent variables while one of these is the target variable (i.e., '*project risk level*' with three classes of high, medium and low risk) (refer to Table 1). The 'actual risk severity' column, which ranges from 1 to 25, is used to compute and classify the project risk level into high (20–25), medium (10–19), and low (1–9) based on National Highways GG104 requirement (an internal control guidance document) for safety risk assessment [34]. The class distribution for the target variable is noted to be imbalanced, which can result in biassed classifications if not handled. Table 1 shows the variables used in building the prediction model in this study and indicates the independent and dependent variables, respectively.

Table 1. Description of variables used in modelling.

Independent Variable	Data Type	Meaning	References
Region	Categorical	The region where the project is based.	[35]
Site/project	Categorical	The site where the project is based.	[36]
Vehicles involved?	Categorical	Are there vehicles involved in the project (yes/no)?	[37]
Type of person	Categorical	The status of the individual's employment or visit (employee, contractor, member of the public, customer).	[38]
Location	Categorical	The location of the project site.	[18]
Did this event occur on the SRN (strategic road network)?	Categorical	Is the incident a strategic road network related? (Yes/No).	[39]
Experience in current role	Integer	The number of years the worker has been working in that position.	[40]
Age range	Integer	The age of the worker.	[40]
Weather/visibility	Categorical	The visibility at the time of the incident (rainy, stormy, clear, windy).	[41]
Potential severity rating	Integer	What the possible impact of the incident could be (1–25).	[35]
Actual severity rating	Integer	What the actual impact was (1–25).	[18]
Month	Integer	The month of the incident.	[31]
Season	Categorical	The season of the incident (winter, summer, spring and autumn).	[31]
Type_of_work	Categorical	The type of work being undertaken (traffic management, highway operation, not applicable).	[41]

Table 1. *Cont.*

Independent Variable	Data Type	Meaning	References
'Injury type'	Categorical	The types of injury that could occur (cut/laceration/sprain/strain, bruising, amputation. Musculoskeletal, abrasion).	[18]
Day_of_week	Categorical	The day of the week the incident happened (Monday-Sunday).	[42]
Time_of_day	Categorical	The time of the day (morning, afternoon, evening and night).	[43]
Event	categorical	The type of incident likely to occur	[35]
'Injury occurrence'	Categorical	The likelihood of an injury occurring (True/False).	[18]
Dependent variables			
'Project risk level'	Categorical	The likely severity of project risk (high, medium, low).	[40]

2.2. Modelling

The models (i.e., DNN, SVM, NB and RF) were initialised and assigned significant parameters to optimise their performance. The synthetic minority oversampling technique (SMOTE) was employed to handle the issue of data imbalance by generating artificial samples of the minority [44]. A stratified K-fold cross validation technique [45] was then used to split the data into 10 folds while preserving the class distribution. The training and validation datasets were extracted for each fold and stored. The AUROC scores for each class of the target variable were computed separately and averaged to empirically evaluate classification models [46]. The mean AUROC curves are then computed across folds for each model.

The DNN Architecture

A DNN functions like the human brain by mapping an input vector to an output vector [47,48]. For instance, a DNN model trained to identify the features of a particular gender (say a female) will study the attributes associated with being female and estimate the probability that a given classification task will produce a female based on the given features [48]. Results can be reviewed to choose which likelihoods the network should present and produce the proposed class. Neurons, weights, synapses, functions and biases make up the components of a DNN [49]. The multiple number of layers, nodes and the depth of a DNN make it complex hence the term 'deep' [50]. Due to its predictive power, deep neural networks have been successfully applied in intelligent transportation systems [51]; segmentation of images [52]; and facial recognition [53]. In the field of risk prediction, deep neural networks have been used to forecast risk with electronic health records [38] and predict accidents [38,41], hence, justifying the usage of a DNN in this present study.

DNN is empirically represented as follows:

Given H hidden layers.

$$\text{Let } h \in (1 \ldots H) \tag{1}$$

$$\text{Let } V^h = vector\ of\ input\ into\ the\ layer\ h \tag{2}$$

$$j^h = vector\ of\ output\ from\ the\ layer\ h \tag{3}$$

$$j^0 = x\ \rightarrow input \tag{4}$$

For a standard NN, the feedforward task for its hidden layers $h \in (1 \ldots H)$ and any hidden layer (i) where the weighted matrix is W^h and the bias is b^h can be expressed as follows:

$$v_i^{(i+1)} = W_i^{(i+1)} j^h + b_i^{(i+1)} \tag{5}$$

$$j_i^{(i+1)} = f\left(v_i^{(i+1)}\right) \tag{6}$$

where f is the activation function employed to add non-linearity between the input and output [50]. A tan function is represented as $f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$ or a rectified linear unit function most commonly referred to as the ReLu function is expressed as [50]:

$$f(x) = \max(0, x) \tag{7}$$

In this study, the DNN architecture is constructed using the Graphviz framework, which is a Python library that aids in drawing computational graphs [54]. The architectural network (refer to Figure 2) shows the input and output variables, and the hyperparameters employed in the structure. The network consists of 6 layers in total, namely the (i) input layer; (ii) first dense layer with 128 neurons (ReLU activation); (iii) first dropout layer with a dropout rate of 0.5; (iv) second dense layer with 64 neurons (ReLU activation); (v) second dropout layer with a dropout rate of 0.5; and (vi) output layer with three neurons (Softmax activation). However, in the computation, core neural layers comprise four layers (the two dense layers and the two dropout layers), including the final output layer. The feedforward DNN employed in this study allows data to move from the input layer to the output layer via hidden layers and back again in a single direction [50]. The gradient descent and backpropagation are key learning techniques which form the foundation of the DNN's learning process [53]. Therefore, during training, backpropagation was used to compute the error between the expected and actual outputs. Also, to minimise errors, weights and biases were adjusted by propagating the error backward through the network. Gradient descent is then used to iteratively update the weights of the DNN in a way that minimises the loss function, or the difference between the actual and anticipated values. The DNN modifies the weights to minimise the total error by calculating the gradient of the loss function [52].

2.3. Performance Evaluation

The confusion matrix is crucial for assessing a model's classification performance [33]. True positives (TPs), true negatives (TNs), false positives (FPs) and false negatives (FNs) are the four classification outcomes in the widely used two-class confusion matrix [55]. Five metrics for accuracy, sensitivity (recall), specificity, precision and F1-score were proposed based on the four outcomes [56]. These five metrics were used for performance evaluation [55] are as follows:

Precision: measures the number of correctly predicted positive instances.

$$precision = \frac{TP}{TP + FP} \tag{8}$$

Recall: evaluates the predictive ability of the model for positive samples. It is the proportion of positive samples to total positive cases that were correctly categorised as positive.

$$recall = \frac{TP}{TP + FN} \tag{9}$$

Specificity: measures the number of actual negative instances correctly predicted as negative.

$$specificity = \frac{TN}{TN + FP} \tag{10}$$

F1-score: it is the harmonic mean of recall and precision. It offers a balanced evaluation of precision and recall, which is particularly valuable when classes are imbalanced.

$$F1 - score = \frac{2(precision * recall)}{precision + recall} \tag{11}$$

Accuracy score: measures the total accurate predictions (both true positives and true negatives) out of all instances.

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{12}$$

Figure 2. The DNN architecture.

Area Under the Receiving Operating Characteristic

The AUROC is a performance metric adopted in model evaluation to empirically evaluate classification models [46,57]. It is also known as a performance metric for 'discrimination' because it exhibits the ability of a model to discriminate between events (positive cases) and non-events (negative cases) [58]. For example, for a safety risk prediction model, an AUROC can help determine the probability that a randomly selected worker on a particular project has a higher chance of experiencing an incident event than another worker on the same project or another project. Having an AUROC of ≥ 0.7 indicates the strength of a model's discriminatory ability [41,46,57]. This means that, for 70% of the time, the model will accurately determine the class of an event [41].

3. Results

To provide a blueprint which details the various components of the HSAM, a system architecture is proposed (refer to Figure 3) to define the functional and non-functional requirements of the model [59]. Providing an architecture which specifies the system components and the interactions between them helps to enhance the system's performance. The assessments to be carried out by the HSAM are as follows: EDA to provide insights and report on trends and patterns that exist in the data; and predictive analysis to predict project risk levels associated with particular highway tasks based on specified input variables such as time, age, experience, etc.

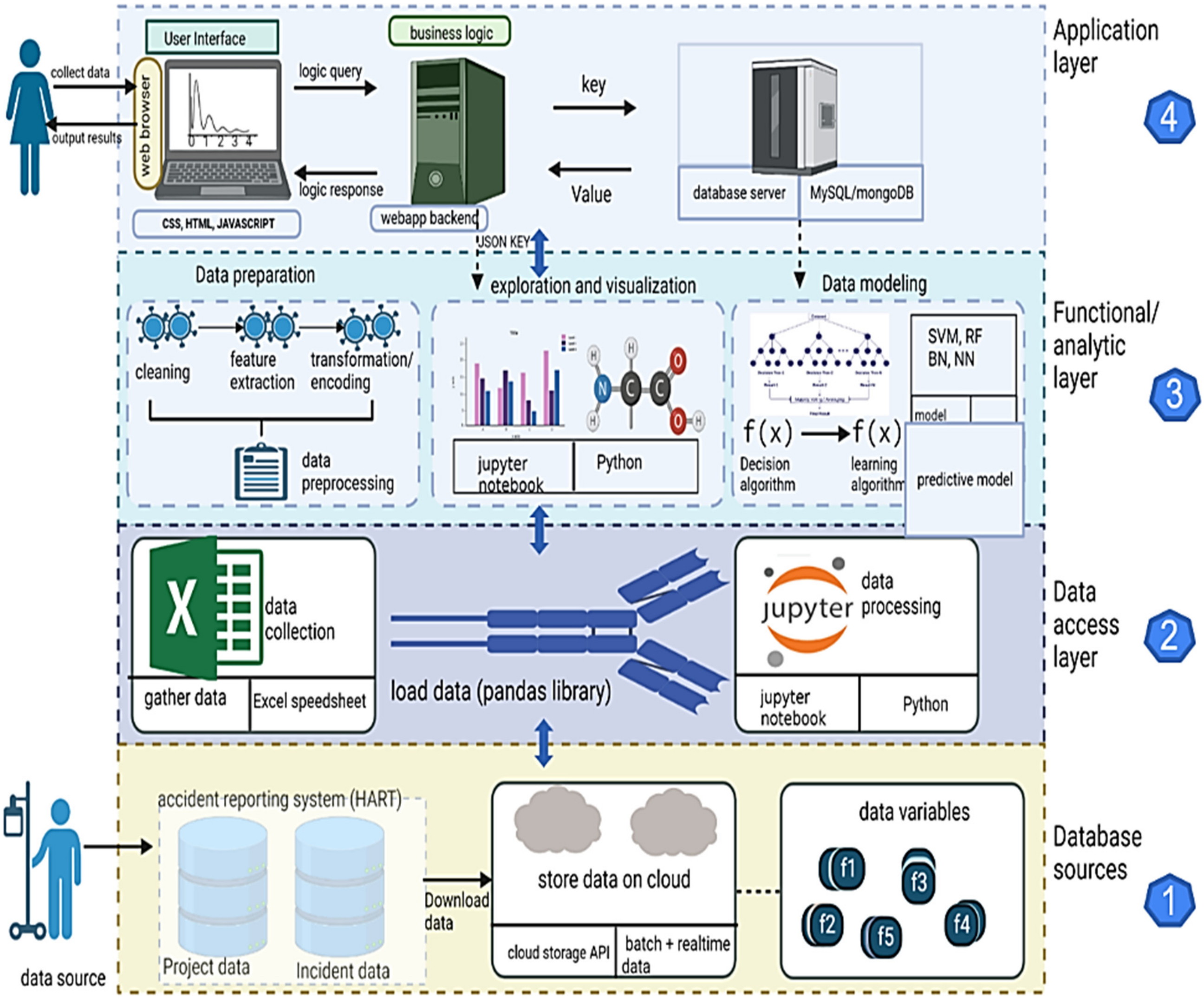


Figure 3. Proposed HSAM architecture.

3.1. Architecture of Proposed Highway Safety Risk Assessment Model

The proposed architecture for the HSAM is based on a layered architecture [59,60] which organises components and parts of a system that possess similar functionalities into horizontal layers [59]. Therefore, individual layers within the system have particular roles they perform within the application (such as data storage) and promote partitioning points of concerns (where the latter allows easy updates to the system and promotes unproblematic division of workload among teams) [61]. The view of a layered architecture provides an abstraction of a complete system because it stipulates details, characteristics, features and responsibilities of each layer and how they interact with each other [31]. The layers of the HSAM architecture include the (i) application layer; (ii) functional and analytics model layer; (iii) data access layer; and (iv) data storage layer (database sources).

3.1.1. Database Sources (the Data Storage Layer)

This layer represents data sources (project data and incident data) which are required to effectively build and run the HSAM and perform EDA for creating descriptive analytical models for organisational purposes [11]. Data consists of information such as project region, project type, project location, and the exact project or site. Incident data also contains historical information about any event that occurred that either resulted in an accident or could have resulted in an undesired event such as event type, injury type, the potential and actual severity of the event and the part of the body affected. The diverse nature of data stored in this layer has been presented in a graphical user interface (GUI) on the HART system for easy accessibility.

3.1.2. The Data Access Layer

A data access layer presents an opportunity for computer programmes to have simplified access to data stored in an obstinate database such as an entity-relational database [62]. This layer can return rows of fields from a database table or a reference to an object furnished with its features when dealing with object-oriented programming [63]. A detailed presentation of components to be created is therefore enabled. Abstraction of this kind seeks to mask the complexity of the nature of data storage beneath it [62]. This layer also provides a common data format for exchanges in the entire system data through data provisioning and exchange formatting [64]. The application layer which is at the topmost end of the architecture can also have access to the databases through the data provisioning functionality [65]. The experimental setup (prototyping) in this study uses the Pandas library to upload the dataset from an Excel spreadsheet onto cloud storage into a data frame well suited for referencing and manipulating the data. However, in production environments, tools and frameworks that provide automation, scalability, security, and efficiency (such as MYSQL or MongoDB for database queries), Apache airflow for data extraction, transformation and loading (ETL) operations, Google cloud dataflow for large-scale data integration tasks, etc. can be used as alternatives [66].

3.1.3. The Functional/Analytic Layer (FAL)

FAL provides programming that controls services responsible for returning data when a query is made and is also known as the business logic layer [67]. FAL also provides access to services which enable the display of data or to query a business process. There is also an additional independent business logic in the application layer which manages the interaction between the end user interface and the databases by transforming messages to name-value pairs (JSON) for processing [68]. Health and safety data are characterised by their high volume and complexity [41]; therefore, it is imperative that they possess the ability to efficiently analyse and swiftly act when queried.

In this present study, this layer consists of one functional model responsible for H&S data pre-processing and three analytical processes—namely the exploratory, descriptive and predictive analytical process all of which make up the HSAM system. For this research, python libraries, such as sklearn, matplotlib, NumPy and pandas, were used to build the analytical and exploratory models in the Jupyter notebooks. However, as mentioned, H&S model building is highly data-driven; therefore, in future models where the data volumes require higher computation capacity, Apache spark engine and pySpark [66] can be configured in the Jupyter notebooks to increase its in-memory storage capacity to efficiently handle high volumes of data and for effective computation.

For data exploration: EDA forms a critical part of the ML workflow because it provides insight into the data being worked with and an opportunity to make sense of the data before modelling it [11]. EDA recognises patterns that exist within the data, enables an understanding of relationships between data variables, and identifies probable outliers and missing values within the data. NumPy and pandas' libraries [41], provide data structures and analytical tools which enables effortless extract-transform-load (ETL) processes, such as data cleansing. Pandas provides useful functions for column and row operations and data transformation. The pandas' library also provides certain functions that could otherwise be accessed using SQL, such as join, merge, etc. Also, other libraries, such as matplotlib and sklearn, provide useful functions for visualisations [42]. Being able to visualise H&S data offers the potential to improve the knowledge and understanding of non-technical decision making, and stakeholders in the H&S domain (such as site supervisors and foremen).

For predictive modelling: Python provides libraries for predictive models, such as sklearn which has methods like the RandomForestClassier, SVM and the Tensorflow library which has the DNNClassifier method for DNN [69]. These methods provide direct access to creating models with data [66]. The cleaner the data, the more effective the models are, thus, leading to an increase in their prediction ability [11].

3.1.4. The Application Layer

The application layer provides an abstraction which stipulates the communication between the user interface and the databases [70]. This 'shell' employs a graphic user interface (GUI) to communicate the system's functions to the end user [70]. It ensures that information from the other layers passes through communication protocols which makes it readable to end users and the application layer of other systems [71]. Powerful application programming interfaces (APIs) can be accessed in building this layer. The end users for this tool include workers, safety officers, site managers, and supervisors employed by National Highways. The descriptive variables for a highway project are input into the system through the user interface provided and loaded onto a file system and a database through an intermediary business logic. The input data then trigger the analytic pipeline to predict the level of risk involved in an operation, prior to a worker going to a project site. These proactive predictions are then communicated through the interface to the end user for effective decision making before work commences on the project.

3.2. Exploratory Data Analysis

Knowing how frequently a particular event occurs or is likely to occur is an essential feature of EDA [15]. This is because the measure of frequency can be used to represent personal information variables or variables that have discrete values (i.e., there are various categories that could be represented in the variable) [32]. Such a representation could give details about and insights into any hidden information about the variable(s). This section explores the distribution of some of the variables used in the risk prediction model to uncover pertinent insights from the incident data.

3.2.1. The Distribution of the Types of Events (Incidents) Likely to Occur

The events (incidents) that often occur in the highway industry have been categorised into nine unique values, namely utility strike (frequency (f) = 280 or 0.43%); security (f = 344 or 0.53%); structural safety (f = 344 or 0.53%); environmental (f = 448 or 0.69%); facility/site (f = 681 or 1.05%); incursion/IPV strike (f = 1028 or 1.58%); infrastructure/asset (f = 1460 or 2.25%); personal illness or injury (f = 1656 or 2.55%); and undesired circumstances/near miss (f = 48,671 or 74.55%). Figure 4 shows the percentage of how frequently each of these incidents occurs individually. From the diagram, it is noted that the distribution of undesired circumstances/near misses occurs most among the incidents recorded. Workers are 74.55% more likely to encounter an undesired circumstance/near miss in a typical highway project than any other incident. Moreover, apart from an undesired circumstance/near miss, personal illness/injuries are also more likely to occur than other incidents, while utility strikes are the least likely occurring incident. This type of insight gives an understanding of the distribution of incidents when prioritising probable incidents on a highway project and making decisions on possible measures to control the likelihood of an event occurring.

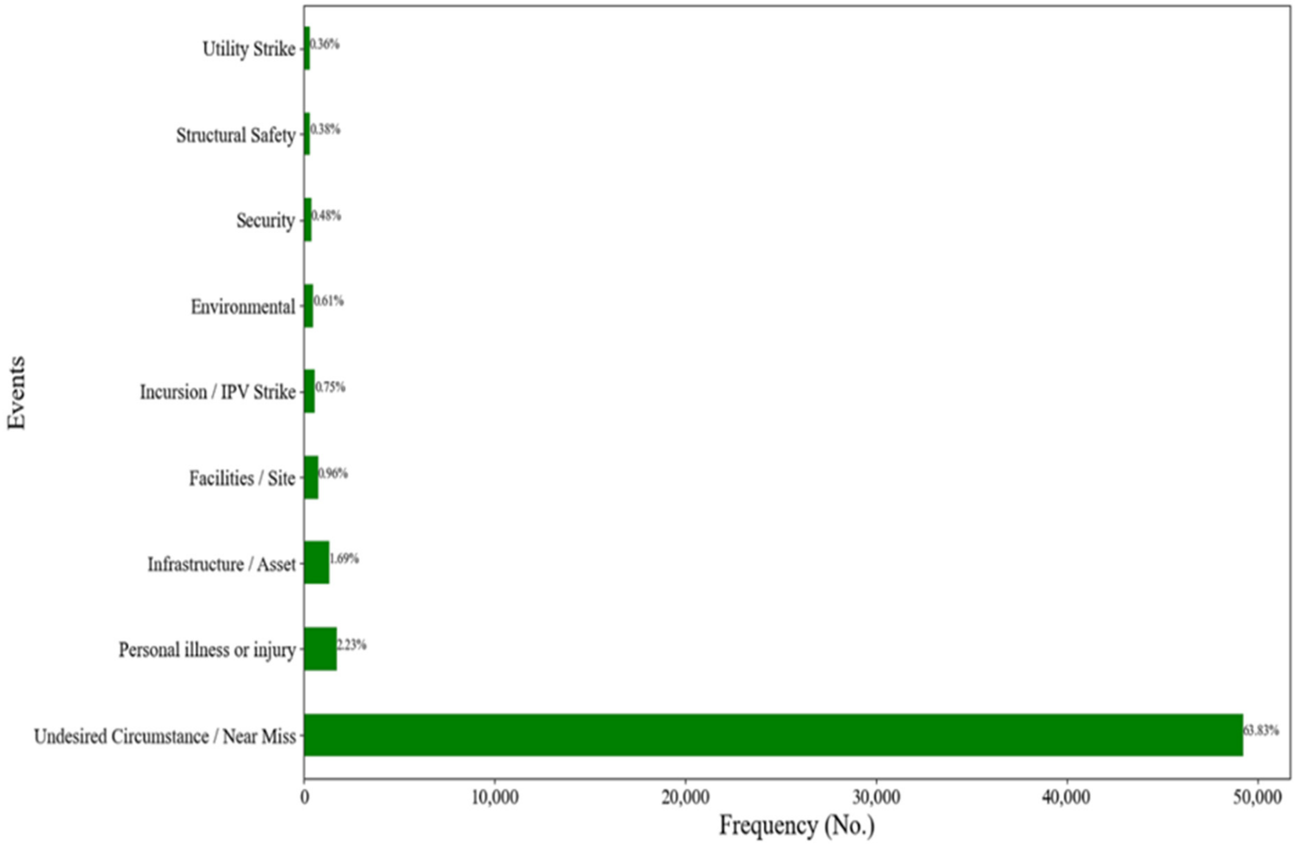


Figure 4. Categorisation of event occurrence.

3.2.2. The Distribution of Project Risk Levels

The highway incident data present severity ratings for incidents which are further classified as high, medium, and low-risk incidents (refer to Figure 5). This is examined to gain valuable insights into the level of risk HTOs are usually exposed to and the detrimental impacts of project risk levels on HTOs. Considering the different levels of risk associated with highway operations undertaken by HTOs, it is crucial to assess the severity of the risk associated with incidents when they occur [42].

Figure 5 shows that the vast majority (f = 50,966 or 92%) of the operations undertaken by HTOs have a medium risk level, followed by high risk and low risk, respectively, with little difference between the frequency of high-risk and low-risk operations. This finding is consistent with Sharaf and Abdelwahab's [72], who using Egypt as a case study, found that the overall risk in the highway projects is considered medium level.

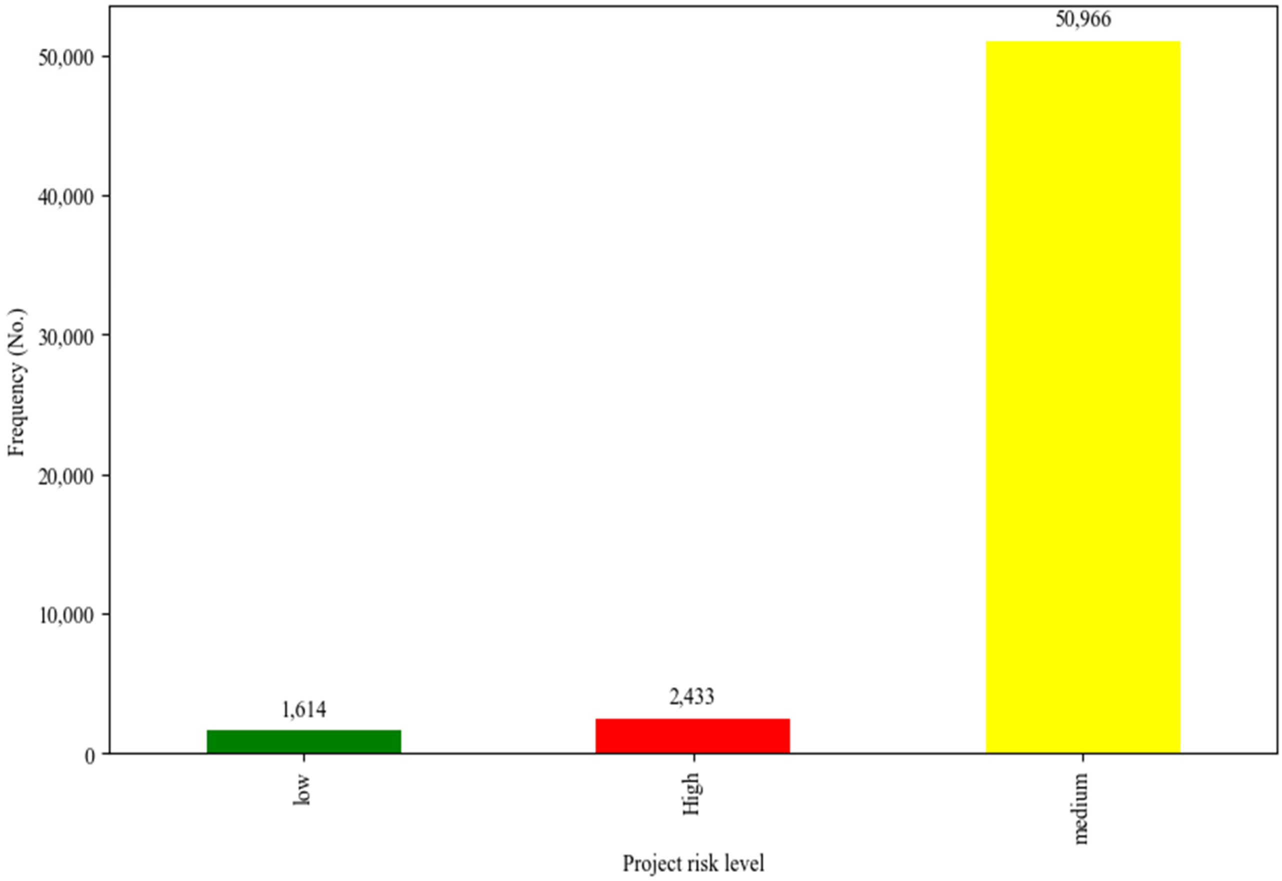


Figure 5. Visualisation of project risk levels.

3.2.3. The Distribution of Project Risk Level per Time of Day

The time of incident occurrences was divided into four periods, i.e., morning (7:00–11:59 a.m.), afternoon (12:00–15:59 p.m.), evening (16:00–20:59 p.m.), and night (21:00 p.m.–6:59 a.m.) to capture the different traffic patterns and levels of activity on the highways. Figure 6 presents the project risk levels for individual times of the day. For each time of the day, it is observed that the most prevalent risk level was the medium risk level, followed by the high-risk level and low-risk level, respectively. Furthermore, it is notable that the 'night' category presented a major challenge in terms of risk, followed by morning, afternoon and evening, respectively. This finding is consistent with the claims made by Thokala et al. [73] that most accidents occur during the nighttime. Moreover, Simončič [74] found that accidents which occur on the road at nighttime were more serious than those which occurred during the day or other times. This could be due to the vehicle driver of HTO fatigue (due to a disrupted circadian rhythm) [75] or the handover of projects to the HTOs (as part of shift work) where risks have changed between shifts or new risks are posed [74]. Also, the intensity of light at night is less than at other times of the day; therefore, it becomes more difficult for drivers to see road workers or road markings [73]. It is also difficult for HTOs to see incoming vehicles and other dangerous objects such as animals, falling debris, moving objects or equipment, etc., leading to being struck by accidents, slips and falls, or even severe vehicle crashes [76].

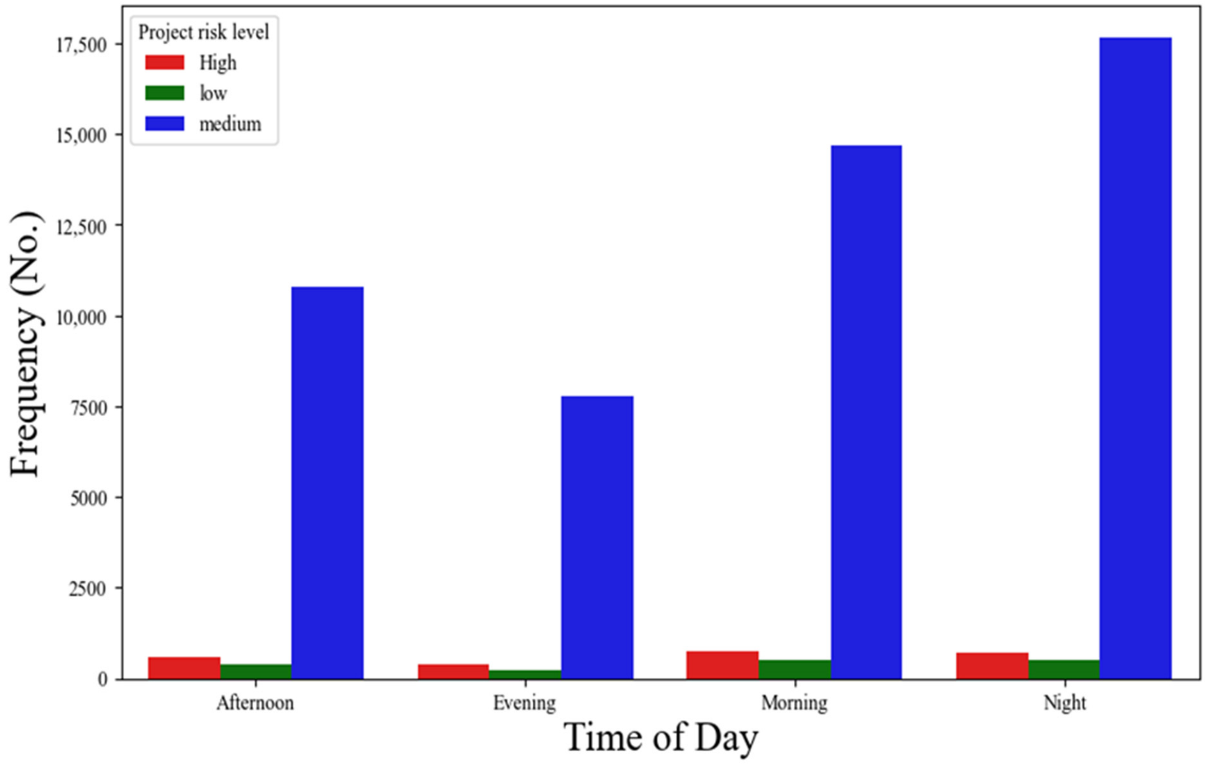


Figure 6. Project risk level at various times.

3.2.4. The Distribution of Events by Location

The location of a highway project or task could give an indication of the level of safety risk event likely to transpire based on how frequently incident have occurred at that location in the past. Previous incident locations for on-road HTOs were analysed and considered. In total, 20 locations were realised from the dataset where incidents often transpired. From the distribution—refer to Figure 7, the number of events that occurred at the location provides a basis to rank the top 10 locations with the most event occurrences as the following: carriageway A (f = 198 or **24.36%**); traffic management enclosure (f = 119 or 14.64%); carriageway B (f = 119 or 14.64%); within works area/safety zone (adjacent to a live carriageway) (f = 84 or 10.33%); off network, e.g., local authority road, footpath, marine (f = 46 or 5.66%); carriageway slip road J (f = 27 or 3.32%); outside works area—adjacent environment (f = 26 or **3.20%**); works area/safety zone access or exit point (f = 24 or 2.96%); working on SRN (f = 21 or **2.58%**); and carriageway hard shoulder (f = 19 or 2.34%).

3.3. Predictive Model Evaluation

The performance of the DNN model is benchmarked against various ML models employed and evaluated using the AUROC, the confusion matrix, and a classification report of each of the target variables according to their precision, recall, and F1-score.

3.3.1. AUROC

Figure 8a–d present the ROC curve for each ML model employed in the experiment. The AUROC's average performance for the individual classes of the dependent variable is detailed in Table 2 and indicates that the resultant models are effective and they are generalisable. This means, the model can be applied to similar unseen data and the predictions made will still be reliable.

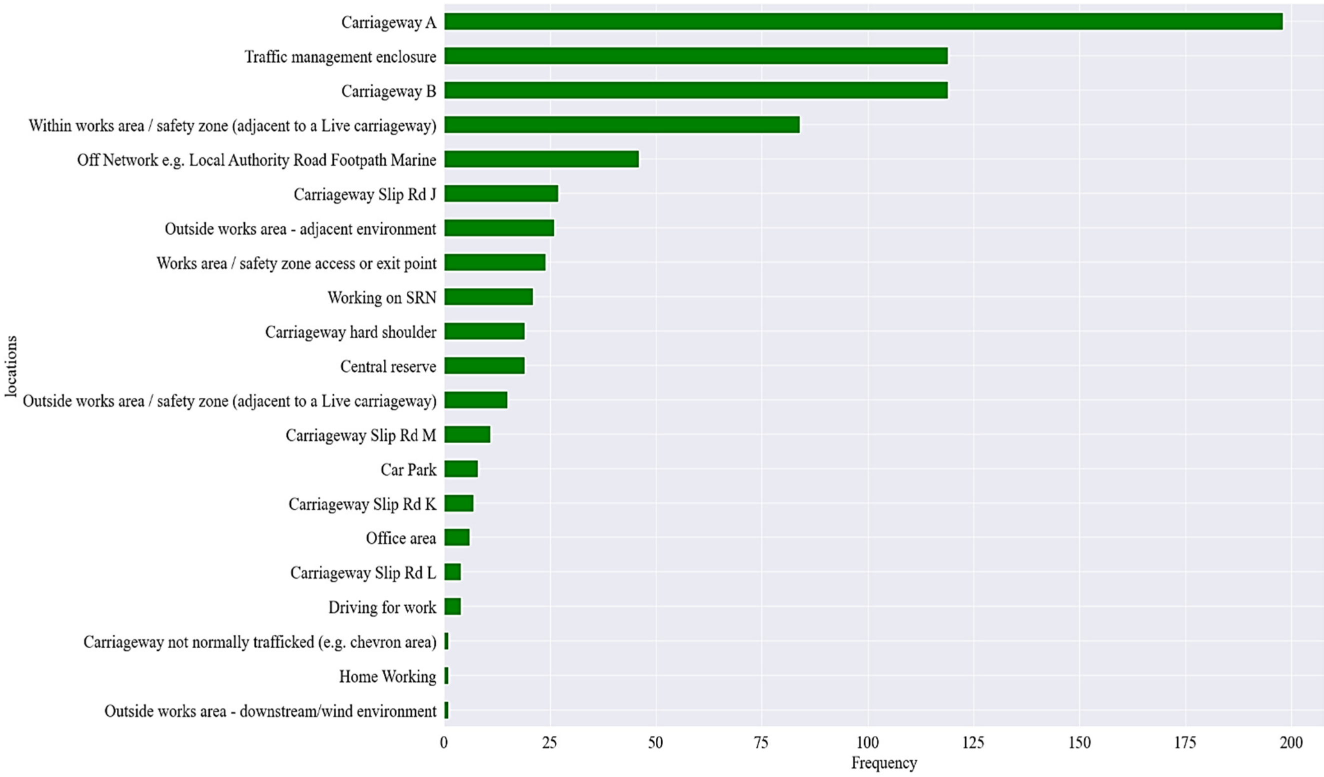


Figure 7. Events by location.

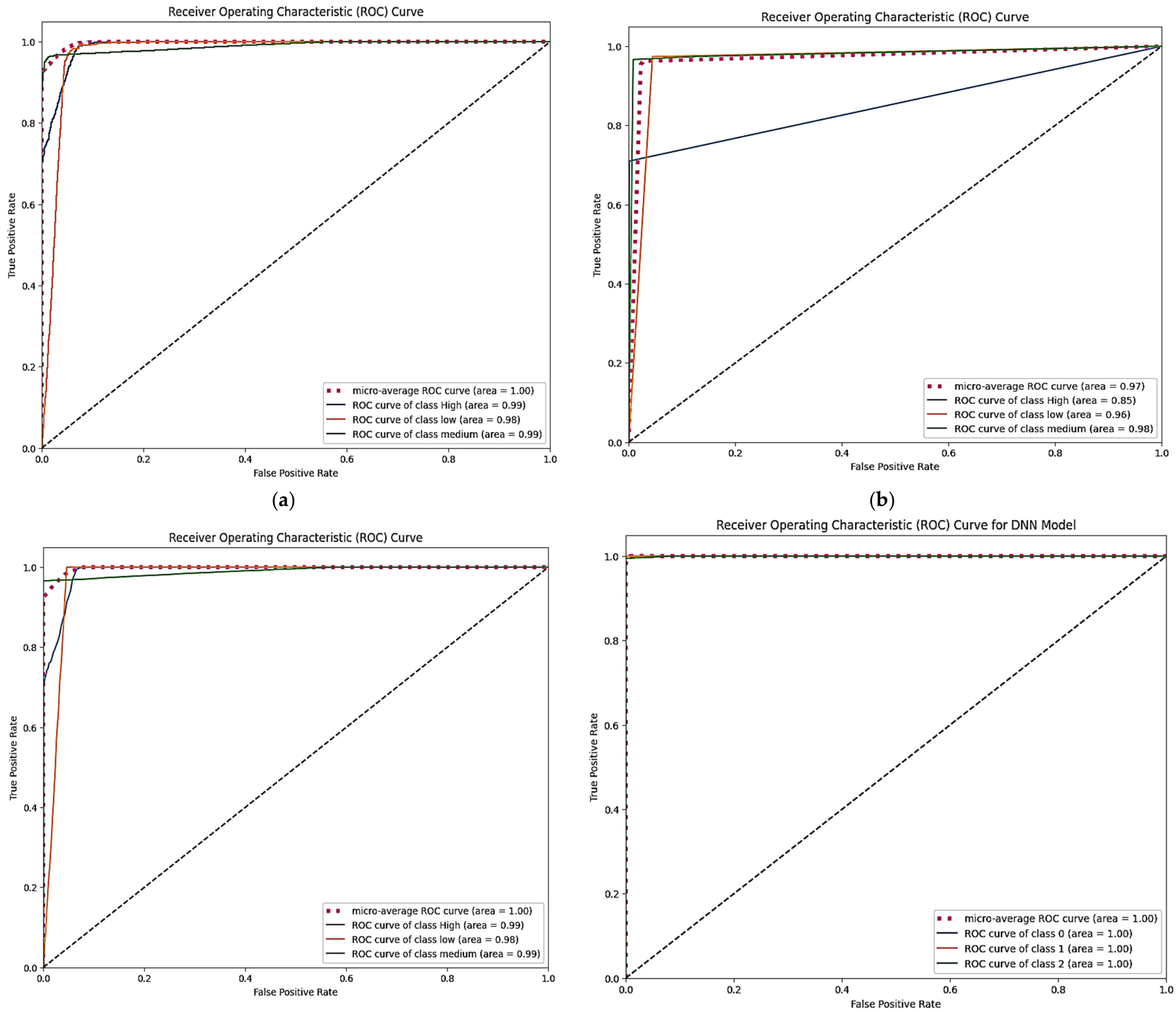
Table 2. AUROC results.

ML Models	Average AUROC (%)	AUROC for Individual Classes (%)		
		High	Medium	Low
SVM	100	99	99	98
RF	100	99	99	98
NB	97	85	98	96
DNN	100	100	100	100

All the models utilised in the experiment performed exceptionally well, with average AUROC scores exceeding 97%. Particularly noteworthy is the DNN model, which achieved the best results with an AUROC score of 100% for all the risk classes. This indicates the high predictive capability of the DNN model in accurately classifying project risk levels. The performance of the DNN model, although exceptional, is rare and may indicate overfitting [77]. Therefore, further analysis and experimentation are deemed necessary and investigations into the individual performance of each class of the target variable [76], to ascertain the model's generalisability. Such work will be undertaken as part of future research that will be applied in real time and on live highway projects.

3.3.2. Classification Report of Each Class

To further investigate and analyse the models' results, the classification report for each class is evaluated due to its ability to provide detailed information about the models' performance for each individual class [78]. Analysing the performance of each class reveals whether the model is performing well for all classes or if it is biassed towards certain classes. Table 3 shows the classification report of the individual classes.



(**a**) (**b**)

(**c**) (**d**)

Figure 8. AUROC for DNN and ML models. (**a**) AUROC for SVM. (**b**) AUROC for NB. (**c**) AUROC for RF. (**d**) AUROC for DNN.

Table 3. Classification report table.

Model	Precision (%)			Recall (%)			F1-Score (%)			Accuracy Score (%)
	High	Medium	Low	High	Medium	Low	High	Medium	Low	
SVM	100	97	39	71	99	35	83	98	37	96
RF	97	97	41	71	99	30	82	98	35	96
NB	96	100	40	71	97	97	82	98	57	95
DNN	100	100	96	91	100	100	95	100	98	99

The individual precision, recall and F1-score of each class shows that, although the ML models had a high accuracy score, there were biases towards the 'high' and 'medium' classes, whereas the 'low' class performed poorly as compared to the two other classes. However, it is notable that high precision, recall, and F1-score (>70) were obtained by the DNN model. The high accuracy score of the models illustrates that they are reliable and effective for prediction tasks [18]. Therefore, based on the results obtained, the DNN models are deemed the most effective algorithm.

3.3.3. Confusion Matrix

From the classification report and the AUROC results, the DNN model was the best-performing model for predicting project risk levels; therefore, a further investigation of the results obtained using the confusion matrix was conducted. The confusion matrix (refer to Figure 9) depicts the outcomes of actual classification compared to predictions, represented by a K*K matrix, where K denotes the number of individual classes the target variable has [79].

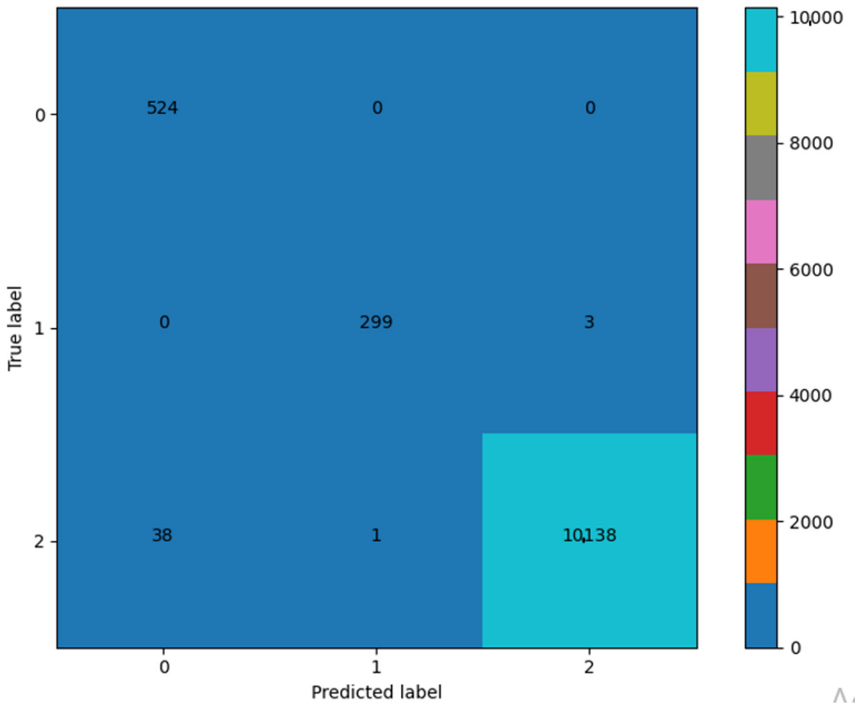


Figure 9. Confusion matrix for DNN model.

On the confusion matrix above, the labels 0, 1 and 2 correspond to the target classes high, low and medium, respectively, as assigned by the label encoding algorithm. From the visualisation, all the 'high' labels were predicted accurately, 299 out of 302 'low' labels were predicted accurately and 10,138 'medium' labels were predicted accurately out of the total 10,177 'medium' labels. This result indicates a superior performance of the DNN model.

4. Discussion

Stipulating the model's architecture is an important step which not only helps in conceptualising the functionalities of the system but also provides a structured guide to the design, development, and maintenance of the system [59]. The innate design of layered architecture makes it the preferred choice in this study because it organises the entire system into distinct layers to separate their responsibilities and challenges [71]. Hence, an independent development and modification of each layer of the HSAM system can be easily implemented, with the integration of new technologies without significant disruptions [70]. The layered architecture presented, therefore, delineates the functional and non-functional components of the system, providing a common understanding of its design to all stakeholders including developers and managers. Ajayi et al. [41] provide an example of how the layered architecture can be adopted in predicting health and safety risks which is broadly in congruence with the present study. The architecture of the HSAM is evaluated (tested and validated) by EDA and predictive modelling.

Emergent results indicate that the distribution of undesired circumstances/near misses occurs most among the incidents recorded (f = 48,671 or 74.55%). A near-miss is described by National Highways as an occurrence that, while not actively causing harm, has the potential to hurt by inflicting injury or resulting in poor health of an individual(s) [80]. Additionally, they describe undesirable circumstances as a collection of conditions or circumstances that have the potential to cause harm or ill health (*ibid*.). Although voluminous in the dataset, it is suspected that some near misses go unreported for various reasons. For example, fear of disciplinary actions for the near-miss or getting a co-worker reprimanded; excessive documentation needed in reporting; fear of tarnishing a clean event record and potential rewards for maintaining it; the incident seems amusing and not serious; or a bad experience in the past when disclosing an incident [81]. Even though it might seem clear, failing to notify a near-miss can result in more serious or dangerous occurrences later. This may be the result of employees not knowing how to report a near-miss or not understanding the protocol [82]. Workers must therefore be incentivised and encouraged to report near misses and undesirable circumstances to allow more proactive measures to be put in place to effectively curb future harm.

Furthermore, studies have shown that the level of risk or risk severity associated with an incident is often linked to various factors, such as time of incident, location, and site/project [35,40,41]. Therefore, analysing how severe a risk could be will aid in exploring the relationship between the risk levels and the associated variables [35]. Findings also indicate a greater likelihood of a medium risk being in present in any given highway operation. Understanding how risk variables contribute to increased project risk levels allows for deeper exploration of injury patterns and the implementation of safety improvement initiatives based on evidence [72].

The EDA provides a more thorough knowledge of the elements determining accident risk severity by including more variables related to the severity of possible and actual outcomes (project risk levels), incident features, injury occurrences, and incident locations. These results align with the practicality of current theoretical frameworks [18,35], which emphasise how crucial it is for accident severity prediction models to take a wider range of factors into account. Including new features such as '*vehicle involvement*', '*site/project*' and '*event type*' emphasises the necessity of an all-encompassing method for evaluating the severity of accidents. Features that consider not only the accident's specific characteristics but also its possible aftereffects and contributory causes [38].

The prediction accuracy of the three ML models was comparatively lower than that of the DNN model. The ML approaches achieved a prediction accuracy between 95% and 96%, whereas the DNN outperformed the other predictors with an accuracy score of 99%. Thus, the system selected the DNN model for severity prediction while noting its performance in terms of accuracy (99%), precision (98%), recall (98%), F1 score accuracy (97%), and AUROC (100%). The performance of the predictive model indicates its generalisability and reliability when implemented and introduced to new data. Based on the findings, highway safety management 'safe systems of working' (SSoW) can be developed and implemented. SSoW can be used in highway project sites and locations to identify workers/factors that are mostly prone to high-risk levels which could eventually lead to fatalities and consequently, implement practical control measures to mitigate them. The analysis results can also be applied to effectively characterising root causes of fatal accidents and proactively tackling them before they result in unplanned incidents. This is a diametrically opposed contrast to reactive control measures that implement change after an event—by which time the control has failed to prevent injury or save a life.

A limitation of this research is that the entirety of all significant input variables that could have enhanced the model's prediction were not utilised due to their unavailability. It is recommended that future work explores other significant input variables to assess the impact of these variables on the outcome of the predictions; these include the following: (i) road budgets; (ii) vehicle fleet quality, and composition and autonomous vehicles; (iii) road infrastructure characteristics; and (iv) real-time traffic congestion. Other variables bordering on driver behaviour, such as speeding, can be explored to ascertain how driver behaviour influences the safety risks faced by HTOs.

The specificity of the dataset to the UK also presents a limitation on generalising the findings made to other regions or countries. This is because safety risk factors or variables may vary across different countries and highway organisations. Therefore, to improve the generalisability and applicability of the model to different countries, future research could involve collecting similar incident data from various highway agencies in different countries to test the model's applicability in diverse contexts. Furthermore, future work could explore the impact of mental health and well-being severity challenges that can be incorporated into the model. Lastly, this study is not an exception to the 'black box' nature of the ML model which makes it difficult for humans to comprehend the inter-relationship between variables. It is therefore recommended that further steps such as obtaining expert feedback should be undertaken to validate the model.

Practical Implications and Proposed GUI

Based upon the findings presented, this study proposes the development of a web-based software which brings practical application of the model (HSAM) for real-world applications. Figure 10 illustrates the intended GUI for the proposed software. The GUI allows end users to enter input variables associated with the project operation—similar to the variables used in training the ML model. When the project risk level button on the dashboard is clicked, an instruction is sent to the ML model to predict risk severity outcomes based on the trends and patterns it finds in the data. The output results will then be displayed on the dashboard. The dashboard also presents a visualisation of results obtained from the EDA process in a descriptive analysis section.

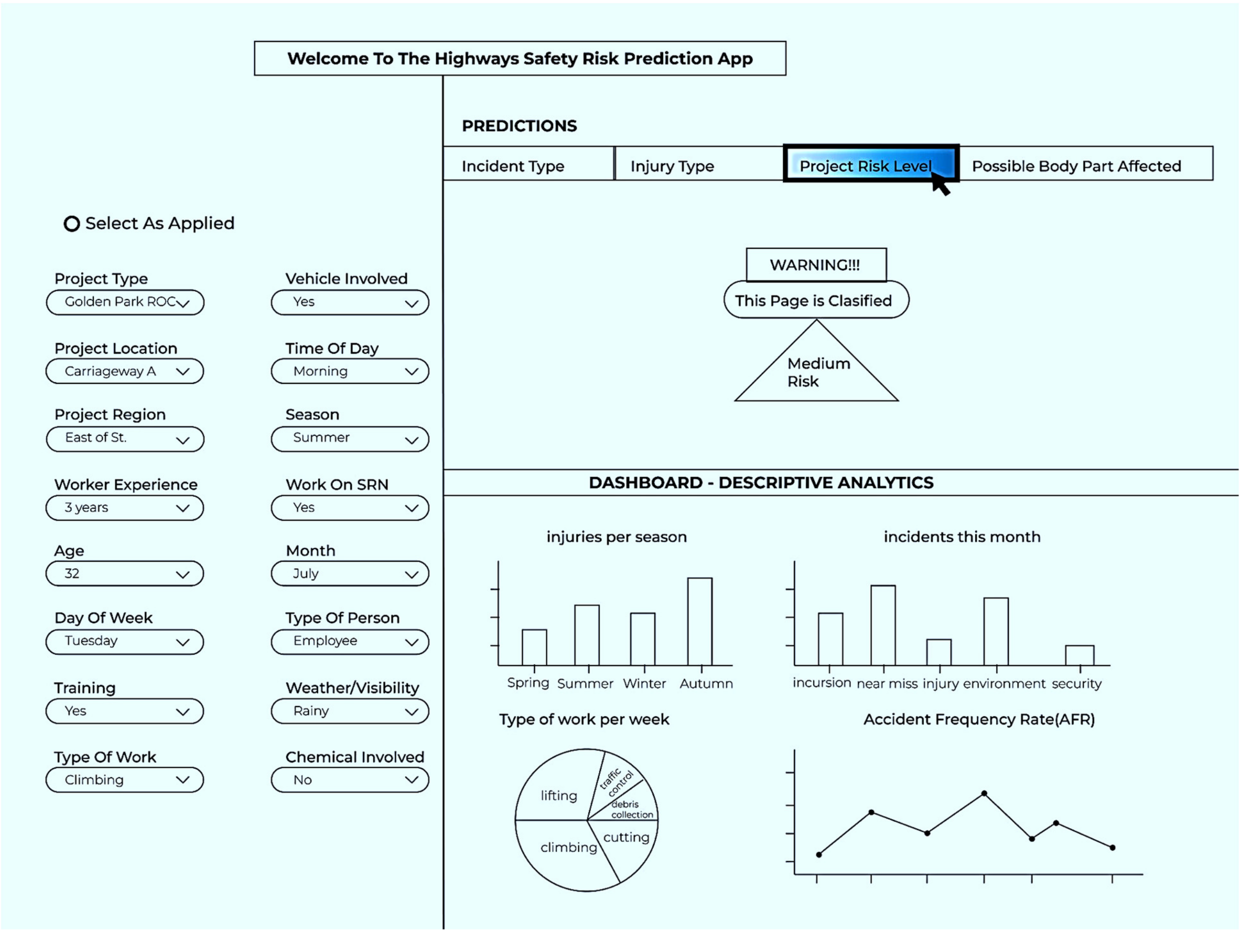


Figure 10. Proposed GUI.

The development of a GUI and dashboard for the ML has the potential to significantly improve the safety and well-being of HTOs in many ways. First, the ability of ML models to provide a more objective assessment of existing risks allows for a proactive and evidence-based approach to decision making [40]. For example, if a 'high risk' outcome is predicted due to variables such as rainy weather, no training or no experience, then a proactive decision of postponing operations or providing tailored training for staff could be implemented to prevent the impending risk from materialising. Also, the presence of variables such as age, experience, weather, etc., allows for personalised predictions to be made for individual HTOs. This is because HTOs could be exposed to varying levels of risks based on environmental conditions or their demographic characteristics. It is therefore pertinent that the model could provide a basis for tailoring safety protocols or policies to suit the individual needs of each HTO—thereby improving the overall safety of the team. Resources can also be effectively allocated and prioritised based on the objective outputs of the model. The availability of a GUI will enable stakeholders and end users with different levels of expertise to access the model and make practical use of it. Lastly, a major implication of this model is the resilience it offers to safety management systems [6]. Some features of resilience as described by other studies [9,83] include awareness, anticipation, flexibility, learning and management commitment. Predicting risk levels equips safety teams with the listed resilient features and allows them to take proactive actions that will either minimise or prevent impending risks. Entering these variables in the system to assess risks helps to encourage anonymous incident reporting since there are no personal identifiers that could expose the identity of a worker. This will help prevent some of the unreported near misses found in the EDA and promote the establishment of a good reporting culture in the organisation.

5. Conclusions

The ever-evolving work operations of HTOs present various safety risks and challenges which must be proactively tackled [3]. However, current practices in the highway sector point to reactive approaches taken to mitigate risks after their occurrence [13]. It is in this light, that this study employs DNN and ML models in risk level prediction to ascertain the severity of impending risks on highway operations for HTOs. The architecture of the model developed was defined as a layered structure with four levels, namely the data storage layer; the data access layer; the FAL; and the application layer. The architecture was then tested and validated using EDA and predictive modelling. Findings made from the EDA indicated that undesired circumstances and near misses were the most prevalent incidents reported. Also, most operations had a medium risk level attached to them and operations carried out at night posed the highest risks. The carriageway operation locations were discovered to also pose the most risk as most event occurrences reported were from there. The predictive modelling stage also showed the DNN model putting up a comparatively better performance than the three other ML models (SVM, RF, and NB) it was benchmarked with. Based on the findings, a novel software with a GUI was proposed to provide a real-world application of the model.

Proactively investing in the development of an ML model to assess and predict risk levels of highway operations for HTOs will significantly improve safety decisions taken by safety managers and encourage efficient allocation and prioritisation of resources [42]. To achieve such efficiency, the ML model will be integrated into the existing safety management framework to ensure that predictions are actionable and aligned with the operational needs of safety officers. Adequate training will also be provided to end users of the software, such as safety officers, so they can effectively interpret results and apply them in safety decisions. Insights gained from EDA can help project managers and safety managers better understand the underlying factors contributing to risk and inform long-term strategies to reduce incidents [41]. For example, if the data show that accidents are more likely during certain weather conditions, additional training or preventive measures can be implemented for those scenarios. It is recommended that expert feedback is obtained in future works to expand the scope of significant input variables which could further improve the model's performance and better capture the nuances of highway operations.

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