JOURNAL OF ADVANCED MULTIDISCIPLINARY STUDIES (JAMS)
JAMS |Volume I Issue II September 2026| DOI: 10.68050/JAMS

Assessment of the Accuracy of a Newly Developed Artificial Intelligence Model for Accident Prediction in the Work Place

Nyakno Monday Udoumoh, Aondona Paul Ihom, Ndifreke Ndarake Effeng, Alexander Aniekan Offiong

Department of Mechanical and Aerospace Engineering, University of Uyo, PMB 1017 Uyo, Nigeria

Corresponding Author

DOI: https://doi.org/10.68050/JAMS.2026.378

Received: 03 Sept 2026; Accepted: 04 Sept 2026; Published: 08 September 2026

ABSTRACT

The essence of this study was to assess the accuracy of a newly developed model for occupational accidents prediction, hence ensuring workplace safety. This artificial intelligence model is to meet real-time industrial needs. To achieve this, accident history was collected from OSHEA which comprises data on worker experience, lighting condition, use of PPE, weather condition, age of machine, Economic Loss. The data obtained from OSHEA was preprocessed to ensure data uniformity and thereafter, trained with the algorithm to develop an ANN model for accident prediction. The model was trained and validated in a repetitive pattern, until the model yielded the desired output. The training process was carried out in 50 Epochs for both training and Validation. The model was thereafter tested with unseen data, which was able to give a prediction with an accuracy of 97.78%. The results obtained during training, validation and testing recorded high accuracy. The accuracy, losses, RMSE, MSE for both training and validation were established. The values of Precision, F1-score and Recall were also obtained. However, the system had a training accuracy of 100%, which shows how well the neurons were able to learn the features on the dataset, while the test accuracy of the model was 97.78%. The F1-Score, Recall and Precision values were 0.9767, 0.9545 and 1.0000 respectively. This means that the newly developed artificial intelligence model was able to correctly predict 97.78% of the accidents cases correctly, during Testing. The evaluation of the results indicates an exceptional performance, with near perfect scores across all metrics. From the evaluation of the newly developed artificial intelligence model, the model can be seen as a great addition to the body of knowledge. The ANN model developed in this study can therefore assist safety engineers, and facility managers in identifying hazards before they escalate into full accidents.

Keywords: Assessment; accuracy; Safety; Artificial Intelligence, Newly Developed Model; and Environment.

INTRODUCTION

Construction industry is of great significance when it comes to securing the premises for a functional society. It contributes substantially to economic growth through building, infrastructure and industrial construction as well as real-estate development, creating many jobs along the way. However, construction industry is unfortunately also one of the most dangerous industries due to many fatal accidents at workplace caused by safety hazards on the construction site (Hämäläinen, Takala and Saarela, 2006; Mesaros, Spisakova and Mackova, 2019; Pinto, Nunes and Ribeiro, 2011). Worksite accidents and poor occupational health cause intolerable humanitarian and economic burden, massively taking a toll on sustainable economic growth and a company's reputation (International Labour Organization, 2014). The physical environment on construction sites is constantly changing due to the complexity and dynamic nature of construction projects, often creating coordination challenges, which explains the premises for frequent worksite accidents in construction. Moreover, physically demanding working conditions, often including work at great heights or working outdoors in all weather conditions, contribute to high occupational safety risks in the industry, therefore requiring more effective safety management (Rozenfeld *et al,* 2010; Törner and Pousette, 2009). According to the International Labour Organization (ILO), the construction industry has a disproportionately high rate of recorded accidents worldwide. Each year over 60 000 fatal accidents take place on construction sites around the world, and although the construction sector employs between 6% and 10% of the workforce in industrialized countries, it is responsible for between 25% and 40% of work-related deaths (International Labour Organization, 2005). In fact, construction workers are three to four times more likely than other workers to die from accidents at work according to data from several industrialized countries (International Labour Organization, 2009). In Finland, the frequency of accidents on construction sites has continuously decreased over the last few decades according to statistics (Confederation of Finnish Construction Industries, 2022; Finnish Centre for Occupational Safety, n.d.; Lantto and Räsänen, 2019). Furthermore, severe and fatal accidents on worksites in the construction industry have likewise taken a downward trend over the last few decades, although there is annually a lot of variation in the number of fatal accidents on construction sites per year (Confederation of Finnish Construction Industries, 2022; Lantto and Räsänen, 2019). While construction industry is the most dangerous compared to other industries suffering from high frequency of accidents at work, occupational safety has also progressed most significantly in the construction sector (Lantto and Räsänen, 2019). Some of the most prominent causes behind this change are a positive shift in safety culture and attitudes towards occupational safety in the construction industry, improved development and use of protective equipment and the efforts of construction companies to improve occupational safety (Lantto and Räsänen, 2019). However, there is still a lot that could be done to improve the safety and accident prevention on construction sites. Industry professionals believe that majority of the worksite accidents happening to this day, if not all, could be prevented (Immonen M, 2015) However, there is still a lot that could be done to improve the safety and accident prevention on construction sites. Industry professionals believe that majority of the worksite accidents happening to this day, if not all, could be prevented (Immonen, 2015; Leskinen, 2018; Loukkola, 2013), which has sparked initiatives for zero worksite accidents in construction sector and the ideology that all worksite accidents are unacceptable, unnecessary and preventable (Confederation of Finnish Construction Industries, 2015; Lantto and Räsänen, 2019). Moreover, according to the International Labour Organization, 'those who sustain their efforts to prevent occupational accidents and diseases will find their efforts rewarded' (ILO, 2014,). This is highlighted by the fact that poor occupational safety and health (OSH) practices and substandard safety culture cause significant economic losses for enterprises and societies, such as lost productivity and decreased work capacity, which contribute to the estimated loss of four percent of the world's gross domestic product (GDP), lost due to various direct and indirect costs like compensation, medical expenses, property damage, lost earnings and replacement training (ILO, 2014). The urgency and need for accident prevention have been widely recognized in the industry. At one of Finland's most prominent construction companies many measures have been taken and new technology has been implemented to improve work safety on construction sites. Nevertheless, there is still a lot of room for improvement especially in real-time risk-assessment and proactive risk-mitigation to ensure construction workers' safety. According to a report published by Finnish Institute of Occupational Health (TTL), the use of AI to develop diagnostic and predictive models may be the next revolutionary advancement for occupational safety in the construction industry (Lantto and Räsänen, 2019). However, the need to establish the accuracy of a newly developed AI model for accident prediction in a work place cannot be overemphasized. This will go along way in preventing accidents when deployed (Udoumoh, 2026).

Many industries rely on traditional safety measures that react to accidents rather than predict them. Current systems may fail to account for dynamic variables such as environmental changes, human behavior, and equipment malfunction, which often lead to accidents. This reactive approach creates a critical gap in workplace safety management. The study investigates how AI technologies can bridge this gap by enabling predictive and preventive safety strategies using developed models with high predictive capacities to predict accidents in the work place.

The significance of this study lies in its contribution to both theory and practice in the field of occupational health and safety through the application of Artificial Intelligence. The research provides practical insights into how AI, particularly Artificial Neural Networks, can be employed to predict workplace accidents before they occur, thereby transforming safety management from a reactive approach to a proactive and preventive system. By demonstrating the effectiveness of AI-driven accident prediction, the study offers a viable technological solution for reducing injuries, equipment damage, downtime, and associated economic losses in engineering workshops and construction environments.

From an academic perspective, this study contributes to the growing body of knowledge on the application of AI in industrial and engineering contexts. It advances scholarly discourse by integrating human, environmental, and mechanical risk factors into a single predictive framework, addressing gaps in existing literature that often examine these variables in isolation. The research also provides a validated methodological approach to data preprocessing, model development, and performance evaluation that can serve as a reference for future researchers in occupational safety, engineering management, and applied artificial intelligence with high predictive capacity (Udoumoh, 2026).

The scope of this research is centered on the application of artificial intelligence, specifically artificial neural networks, for predicting workplace accidents in high risk industries, with particular emphasis on the construction and manufacturing sectors. These industries were selected due to their complex operational environments, high exposure to mechanical hazards, and historically high rates of occupational injuries. The study focuses on identifying patterns within historical accident data by incorporating human, environmental, and equipment related variables that influence accident occurrence. The research framework is designed to demonstrate the accuracy of the newly developed AI-driven predictive model and how it can support proactive occupational health and safety management in industrial settings (Udoumoh, 2026).

The study primarily relies on secondary data sourced from established safety agencies and institutional records. This approach was adopted due to the practical and ethical challenges associated with accessing real-time operational environments, such as live construction sites or active manufacturing workshops, where safety risks and regulatory restrictions limit direct experimentation. While the use of secondary data enables large-scale analysis and model training, it also introduces certain limitations related to data completeness, consistency, and accuracy. Some records may contain missing values, reporting bias, or inconsistencies in classification, which may influence model outcomes despite rigorous preprocessing efforts. These facts inform the need for assessment of the accuracy of the newly developed artificial intelligence model for accident prediction in the work place (Udoumoh, 2026).

Another limitation of the study relates to data quality and standardization. Historical accident datasets often vary in structure, terminology, and measurement scales, particularly when compiled over multiple years or from different sources. Although data cleaning, normalization, and augmentation techniques were employed to mitigate these issues, residual inconsistencies may still affect the predictive performance of the model. Additionally, the reliance on reported incidents means that unreported or near-miss events were not captured, potentially limiting the comprehensiveness of the analysis.

The objective of this work is to assess the accuracy of a newly developed artificial intelligence model for accident prediction in the work place. The model was developed and evaluated in an offline environment using historical data. As such, its real-world performance under dynamic operational conditions remains to be validated. Future studies incorporating real-time sensor data, on-site testing, and continuous learning mechanisms would further enhance the applicability and robustness of AI-based safety prediction systems.

METHODLOGY

Materials

This study involves prediction of occupational accidents. The study developed a model using Artificial neural network. In this current study the newly developed artificial intelligence model for accident prediction in the work place is assessed for accuracy. See Udoumoh (2026) for details of the previous work.

The following Materials were used in this research work in development of model for prediction of accidents. These were:

1. Excel spreadsheet.
2. Data of accident history.
3. Personal computer.
4. ANN Software

Experimental Process

The process involves use of Artificial Neural Network in prediction of work place accident. Artificial neural network models are good in non-linear relationship applications, hence its choice in this research work. Dataset which comprises of occupation accident history from occupational organisation was used in data training and development of model. The accident history used in this study involve data on worker experience level, age, type of accident, severity, education, use of PPE (Personal Protective Equipment). This forms a dataset which is trained with the algorithm using Artificial Neural Network. This presents complexities which can only be handled by Artificial Neural Network.

However, the performance of the model was also evaluated using tools such as Training and Validation accuracies and losses, F1-score, Recall and Precision. This gives an idea of how well the system performs during datatraining and also correlation between the seen and unseen data. This takes a step by step process which starts with formulation of dataset, pre-processing of dataset, preparation of algorithm, data training, test and evaluation of efficiency of the model.

Furthermore, the efficiency of the model lies in the ability of the model to learn the features on the dataset – the weights and biases in the input data – and how well the learnable neurons are able to learn, understand and use the knowledge gained in prediction of accidents when faced with unseen dataset. Hence, the efficiency of the model was evaluated as a probability of making accurate prediction and also thereafter represented as a percentage.

Back propagation Algorithm

The study used a back propagation during data training. Back propagation means bacerrors. This enables the network to adjust itself iteratively to close the gaps between the predicted outcome and the actual output. This was done in the following ways:

1. Ensuring that the performance of each layer is evaluated in a feed forward pass and the performance generated per neuron which helps in determination of the efficiency of the system.
2. Use of loss functions in the calculation of errors, which quantifies the errors as losses.
3. Backward propagation of the calculated errors – from the output to the input layer – which helps in computation of the gradient functions of the biases and weights, hence enabling the assessment of the contribution of each parameter to the overall system error.
4. Adjustment of the weights and biases of the model using the optimization algorithm, which ensures that the neurons get to learn the features on the dataset, hence reducing the errors.

RESULTS AND DISCUSSION

As discussed in section 2, construction accident history was obtained from Occupational Safety and Health and Environment (OSHEA) site. The data obtained was pre-processed so as to ensure uniformity of the set. The dataset was further divided into three, with the training dataset accounting for 70% of the dataset, while validation and the Test set took 15%.

However, the model was trained and validated in a repetitive pattern, until the model yields the desired output. The number of times a system was trained or validated is referred to as Epoch. The model had 50 Epoch during the training and Validation phase of the model, with a batch size of 32.

This is the newly developed model that is evaluated in this work to determine the efficiency of the system. The metric tools used in this study were, training accuracy, validation accuracy, training losses, validation losses, Test accuracy and losses, Root Mean Squared error, Mean Squared error, F1-Score, and Precision. These metrices allows the efficiency of the system to be appraised – shows how well the system performed during training, validation and Testing of the model.

The results showing Training and Validation accuracy is presented in Figure 3.1.

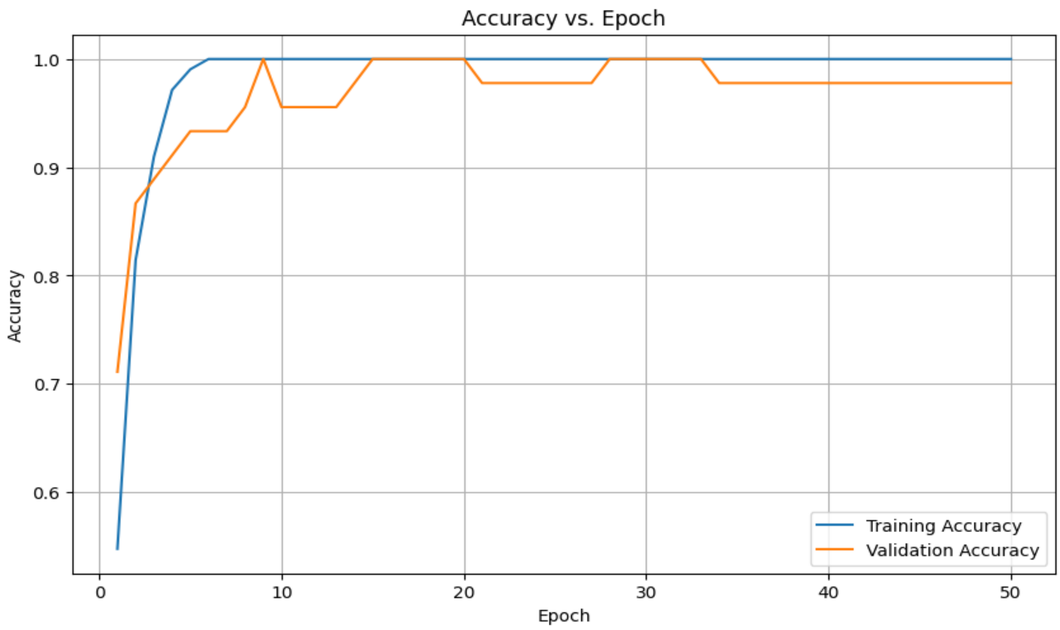

Figure 3.1: Graph of Accuracy against Epoch

Source: Compiled by the Researcher. 2026

Table 3.1: Performance of the Model during 50 Epochs

Epoch	Training Accuracy	Area Under Curve	Training Loss	Mean Squared Error	Validation Accuracy	Validation AUC	Validation Loss	Validation MSE
1	0.5487	0.6507	0.6767	0.2422	0.7111	0.9951	0.5558	0.1854
2	0.763	0.9872	0.5214	0.1707	0.8667	1	0.4196	0.1268
3	0.8929	0.9987	0.383	0.1133	0.8889	1	0.3153	0.0904
4	0.9731	1	0.2574	0.0664	0.9111	1	0.2314	0.0631
5	0.9895	1	0.1872	0.0446	0.9333	1	0.1649	0.0432
6	1	1	0.1152	0.0221	0.9333	1	0.1163	0.0302
7	1	1	0.071	0.0114	0.9333	1	0.0831	0.0218
8	1	1	0.0579	0.0083	0.9556	1	0.065	0.018
9	1	1	0.0363	0.005	1	1	0.0545	0.0159
10	1	1	0.0211	0.0021	0.9556	1	0.0503	0.0156
11	1	1	0.0131	0.00087	0.9556	1	0.0481	0.0155
12	1	1	0.0102	0.00066	0.9556	1	0.0473	0.0157
13	1	1	0.0087	0.00053	0.9556	1	0.0445	0.0147
14	1	1	0.0072	0.00037	0.9778	1	0.04	0.0128
15	1	1	0.0057	0.00041	1	1	0.0357	0.011
16	1	1	0.0052	0.00018	1	1	0.0329	0.0098
17	1	1	0.0032	0.00009	1	1	0.0309	0.009
18	1	1	0.0038	0.0002	1	1	0.0315	0.0094
19	1	1	0.004	0.00017	1	1	0.0328	0.0101
20	1	1	0.0021	4.1E-05	1	1	0.0337	0.0106
21	1	1	0.0022	0.00007	0.9778	1	0.0342	0.0109
22	1	1	0.0041	0.00039	0.9778	1	0.0349	0.0112

23	1	1	0.00097	7.9E-06	0.9778	1	0.0361	0.0119
24	1	1	0.0011	1.4E-05	0.9778	1	0.0358	0.0118
25	1	1	0.0011	1.4E-05	0.9778	1	0.0341	0.011
45	1	1	0.00026	4.2E-06	0.9778	1	0.0309	0.01
46	1	1	0.0006	1.1E-05	0.9778	1	0.03311	0.0101
47	1	1	0.00054	6.7E-06	0.9778	1	0.0337	0.0113
48	1	1	0.0017	6E-05	0.9778	1	0.0354	0.0122
49	1	1	0.00023	8.6E-07	0.9778	1	0.0355	0.0122
50	1	1	0.00053	1.1E-05	0.9778	1	0.0346	0.0118

Source: Compiled by the Researcher. 2026

The Test Set was evaluated and the results is as presented in Table 3.2.

Table 3.2: **Model Evaluation on Test Set**

S/N	**Metric**	**Value**
1	Accuracy	0.9778
2	Precision	1.0000
3	Recall	0.9545
4	F1-Score	0.9767
5	AUC Score	1.0000

Source: Compiled by the Researcher. 2026

DISCUSSION

The results presented in Table 3.1, and Table 3.2 shows respectively, Summary of values of key metrices in each Epoch and the Test results of the model. The full presentation of accuracy and losses during training and validation, as well as Mean Squared and Root Mean Squared Error are presented in Udoumoh (2026). The system Epoch refers to the number of iterations – number of times the training and validation of the system was done.

The accuracy of this study is 0.9778 (97.78%) while the accuracy of the Effeng *et al* (2023) was 98%. Additionally, the study of Habibzadeh *et al* (2024) on Presentation of Artificial Neural Network Models Based on Optimum Theories for Predicting Accidents Severity on Rural Roads in Iran also followed similar trend and recorded an accuracy of 91.2%.

Training and Validation Accuracy

The model had performed well during the Training and Validation in each of the iteration. This is as shown in Table 3.1.

However, from Figure 3.1, it can be seen that the graph of Accuracy against Epoch follows a progressive path and in trend.

(i) Training Accuracy

The accuracy during training depicts how well the neurons had learnt the features on the dataset. It shows how well the training process went. From Table 3.1 it can be seen that the training accuracy of the first Epoch was 0.5487, which corresponds to 54.87%. The second Epoch recorded an accuracy of 0.7630, with the accuracy increasing progressively as the number of Iterations increases.

However, the training accuracy reaches 1.0000 in Epoch 5. This corresponds to a 100% accuracy. This value is maintained to the end of the training period. This shows that the features on the dataset were well learnt by the neurons and that the training process proceeded smoothly.

Furthermore, a close look at Figure 3.1 reveals that the trend seen in Table 3.1 is well modelled in the graph, which further lays credence to the efficiency of the training process.

(ii) Validation Accuracy

The training process was also tested on how well it could perform on unseen data, hence the validation accuracy. The validation accuracy of the model is presented in Table 3.1 and also presented in graphical in Figure 3.1.

The validation accuracy of Epoch 1 was 0.7111 which corresponds to 71.11%. The validation accuracy of first four Epochs were 0.7111, 0.8667, 0.8889 and 0.9111, corresponding to an accuracy 71.11, 86.67, 88.89 and 91.11 in percentage. However, the accuracy of the model recorded a peak value of 1.000 in Epoch 9, corresponding to a 100% accuracy.

Moreso, there was a decrease in the validation accuracy in Epoch 21, recording a value of 0.9778. This value was maintained till the end of the validation period, hence, the system accuracy.

Additionally, validation accuracy was also represented as a plot, as shown in Figure 3.1. The graph shows a progressive increase in the values, but however occasioned with few spikes. These spikes occurred as a result of batch training.

However, the significance of the results of the validation accuracy is that there was no overfitting, hence the high validation accuracies.

Training and Validation Loss

The results of the training and validation losses are presented in Table 3.1.

(i) Training Loss

The values obtained in Table 3.1 shows that the model's losses were on the high in the beginning stage of the training and decreases continuously with each iteration. The model recorded 67.67%, 52.14%, 38.30%, 25.74% and 18.72% in the first five Epoch, hence a steady decrease in the value. The values recorded in the last five Epochs were; 0.00059931, 0.00054241, 0.0017, 0.00022972 and 0.00053192. It can be seen that the values of the last five Epochs gradually approaches 0. This shows how efficient the training process went. It means that there were no untrained neurons during the training period, hence the low values of losses.

(ii) Validation Loss

The losses recorded during validation of the model takes similar path as that of the training losses, thus giving similar trend. The validation loss of Epoch1 was 0.5558. The values of the succeeding losses were 0.4196, 0.3153, 0.2314 and 0.1649 in Epochs 2,3,4 and 5, which shows a decreasing trend. This trend (decrease) continues until a value of 0.0346 is recorded in Epoch 50, which corresponds to 3.46%.

Furthermore, the low score recorded in validation accuracy shows that the model was able to learn, understand and apply the knowledge learnt in an unseen data. Also, the training and validation losses remains very close to each other which means that there was minimal overfitting (Udoumoh, 2026).

3.2.3 Implication of the Results

The performance of the study was evaluated on various indices. The summary of the newly developed artificial intellegence model performance is as follows:

1. Accuracy: the model recorded an accuracy of 0.9778 (97.78%), indicating that 97.78% of all predictions were correct.

2. Precision: the model recorded 1.0000 precision score. This means that the model an accident (class 1) correctly, without any false positive.

3. Recall: the model had a recall value of 0.9545. This means that the model was able to correctly identify 95.45% of all actual accident cases. This indicates a very low rate of false negatives.

4. F1-Score: the model had an F1-Score of 0.9767. This value is a harmonic mean between the Precision score and the Recall score. This shows a high balance between the two metric values.

5. AUC Score: the model recorded an AUC score of 1.0000. This means that the model is capable of distinguishing between positive and negative classes. It also means that the model rank accident cases higher than non-accident cases.

6. Confusion Matrix: confusion matrix represents the prediction outcomes. However, during prediction, the model correctly predicted 21 accident cases, while the system correctly identified 23 non-accident cases. The model did not falsely predict any non-accident cases as accident (Actual 1, Predicted 0). In False negative, the model incorrectly predicted 1 actual accident case as accident (Actual 1, Predicted 0).

The evaluation of the results indicates an exceptional performance, with near perfect scores across all metrics, including the AUC and the Precision. The single false negative being the only error. The high performance can be attributed to careful data preparation, features (Economic Loss and Root cause score in synthetic non-accident data) and the balanced nature of the dataset.

From the evaluation of the newly developed artificial intelligence model, the model is robust, which is a big addition to the body of knowledge, hence, could be deployed in an industrial level in predicting accidents based on the provided features.

Validation of the Results

The efficiency of the study was established which gives an insight to the effectiveness of the newly developed artificial intelligence model. The model was also validated comparatively using previous studies on Accidents and Artificial Neural Network. The study was compared to previous studies on Predicting types of Occupational Accidents at Construction Sites in Korea using Random Forest Model by Ryu and Kang (2019), Presentation of Artificial Neural Network Models Based on Optimum Theories for Predicting Accident Severity on Rural Road in Iran by Habibzadeh *et al* (2024) and Application of Stochastic Gradient Boosting Approach to Early Prediction of Safety Accidents at Construction Site by Shin (2019). The summary of the accuracy of these models is presented in Table 4.4.

Table 3.3: Comparison of the Study with Previous Work

References	Approach	Feature	Accuracy
Shin (2019)	Stochastic	Pixel Based	76.7%
Kang (2019)	Random Forest	Pixel Based	71.3%
Habibzadeh *et al* (2024)	ANN	Pixel Based	91.25%
Proposed Model	ANN	Pixel Based	97.78%

Source: Compiled by the Researcher. 2026

From Table 3.3, it can be seen that ANN models recorded high accuracies which underscores the effectiveness of the ANN tools, as a potent tool in problems involving non-linear relationship.

However, these are related works on Accident prediction modelling. The work of Habibzadeh *et al* (2024) was on Road Accident prediction, using the ANN model which is closer to the study, with the difference being that the model developed in this study was to address workshop based model. Habibzadeh *et al* (2024) had an accuracy of 91.25%. Other studies were Shin (2019) with an accuracy of 76.7%, which was a stochastic model , Ryu and Kang (2019) with an accuracy of 71.3% using a Random Forest Method.

Furthermore, the result obtained in this study was similar to that of previous studies, but with a better accuracy. Also, the narrow gap between training accuracy and validation accuracy gives further prove that there was no overfitting in the system, hence making it a robust model (Willquist, and Törner, 2003).

CONCLUSION

The study ''Assessment of the Accuracy of a Newly Developed Artificial Intelligence Model for Accident Prediction in the Work Place'' has been carried out and the findings of this study conclusively demonstrate that the newly developed Artificial intelligence Model is highly effective in predicting workplace accidents within engineering environments. Other conclusions drawn from the study are:

i. The model achieved a high prediction accuracy of 97.78%, alongside perfect precision and an AUC value of 1.000.
ii. The low values of loss, mean squared error, and root mean squared error further confirmed the robustness and stability of the model, indicating that it effectively captured the complex non-linear relationships inherent in construction safety data.
iii. The results clearly showed an excellent performance across all evaluation criteria. The close alignment between training, validation, and testing results demonstrated that the model did not suffer from overfitting and was capable of making reliable predictions on unseen data.
iv. The reliability of the model has provided insight into the relative importance of each contributing factor, thereby enhancing transparency and practical usability.
v. By accurately distinguishing between potential accident and non-accident scenarios, the system enables early identification of hazards and timely intervention before incidents occur. This represents a significant shift from traditional reactive safety practices to a proactive, data-driven safety management approach.

ACKNOWLEDGEMENT

The authors would like to express their gratitude to the International Labour Organization (2005). Facts on Safety at Work. Online. Available at: https://www.ilo.org/global/resources/WCMS_067574/lang--en/index.htm [Accessed 27.1.2022] and Construction industry from Occupational Safety Health and Agency for kindly providing the necessary data for our research

REFERENCE

1. Confederation of Finnish Construction Industries (2015). Rakennusteollisuuden kannanotto: Tavoitteena nolla tapaturmaa rakennusteollisuudessa 2020. Online. Available at: https://www.rakennusteollisuus.fi/globalassets/tyoturvallisuus/2015/turvallisuuskann aotto_syksy_2015.pdf [Accessed 28.1.2022]
2. Confederation of Finnish Construction Industries (2022). Tapaturmatilanne marraskuu 2021.Online. Available at: https://www.rakennusteollisuus.fi/globalassets/tyoturvallisuus/tapaturmatilanneseurannat/marraskuu-2021-kuukausittain seuranta.pdf [Accessed 27.1.2022]
3. Effeng, N. I., Akpan W. A., Orazulume, C. M., Awaka-Ama, E. J.(2023): Artificial Intelligence Based Quality Assurance of Surface Finish of Parta in Assermbly Line. Everant Journals. DOI: 10.47191/etj/v8i9.02,I.F.-7.136.
4. Finnish Centre for Occupational Safety (n.d.). Työtapaturmat rakennusalalla. Available at:
5. Fradkov, A., 2020. Early History of Machine Learning. IFAC-PapersOnLine, 53(2), pp.1385-1390. doi: 10.1016/j.ifacol.2020.12.1888

6. Habibzadeh, M., Mirabimoghaddam, M. H., Haghighi, S. M. S., Ameri, M. (2024): Presentation of Artificial Neural Network Models Based on Optimum Theories for Predicting Accident Severity on Rural Roads in Iran. DOI: https://doi.org/10.1016/j.trip.2024.101090.
7. Hämäläinen, P., Takala, J. and Saarela, K., (2006). Global estimates of occupational accidents. Safety Science, 44(2), pp.137-156. doi: 10.1016/j.ssci.2005.08.017
8. Immonen, M., 2015. Työturvallisuudella säästötalkoisiin. [Blog] Rakennuslehti. Online. Available at: https://www.rakennuslehti.fi/blogit/tyoturvallisuudella-saastotalkoisiin/ [Accessed 28.1.2022]
9. International Labour Office, 2003. ILO standards-related activities in the area of occupational safety and health: An in-depth study for discussion with a view to the elaboration of a plan of action for such activities. International Labour Conference. [online] Geneva: International Labour Organization. Available at:
https://www.ilo.org/wcmsp5/groups/public/---ed_protect/---protrav/--
safework/documents/publication/wcms_177455.pdf [Accessed 3.2.2022].
10. International Labour Organization (2005). Facts on Safety at Work. Online. Available at:
https://www.ilo.org/global/resources/WCMS_067574/lang--en/index.htm [Accessed 27.1.2022]
11. International Labour Organization (2009). Facts on Safety and Health at Work. Online. Available at: https://www.ilo.org/global/topics/safety-and-health-at-work/resources
library/publications/WCMS_105146/lang--en/index.htm [Accessed 27.1.2022]
12. International Labour Organization (2014). Safety and Health at Work: A Vision for Sustainable Prevention. Online. Available at:
https://www.ilo.org/global/topics/safety-and-health-at-work/resources-library/publications/WCMS_
301214/lang- en/index.htm [Accessed 27.1.2022] References 52
13. International Labour Organization (2021). Impact of COVID-19 on the construction sector. ILO Sectoral Brief. Available
https://www.ilo.org/sector/Resources/publications/WCMS_767303/lang-en/index.htm [Accessed 9.6.2022]
14. International Labour Organization. Safety and Health in Shipbuilding and Ship Repair. Available online: https://www.ilo.org/resource/other/safety-and-health-shipbuilding-and-ship-repair-revised-edition
(accessed on 15 January 2025).
15. International Labour Organization. Safety and Health in the Non-Ferrous Metals Industries. Available online: https://www.ilo. org/resource/other/safety-and-health-non-ferrous-metals-industries (accessed on 18 January 2025).
16. International Organization for Standardization. Occupational Health and Safety Management Systems: Requirements with Guidance for Use; ISO: Geneva, Switzerland, 2018. Processes 2025, 13, 1312 45 of 57
17. Kang, K. and Ryu, H., 2019. Predicting types of occupational accidents at construction sites in Korea using random forest model. Safety Science, 120, pp.226-236. doi: 10.1016/j.ssci.2019.06.034
18. Lantto, E. and Räsänen, T., 2019. Rakennusalan työturvallisuuden kehitys. NOLLA TAPATURMAA RAKENNUSTEOLLISUUDESSA 2020 -HANKE. Finnish Institute of Occupational
https://www.rakennusteollisuus.fi/ Health (TTL). Online. Available at:
globalassets/tyoturvallisuus/2020_sekalainen/raportti_final.pdf?utm_source=eJokka+
2/2020+%7c+Aiheina+mm.+nolla+tapaturmaa,+turvallisuusviikko,+koronaohjeita,+
hiljainen+hetki&utm_medium=email&utm_campaign=eJokka [Accessed 27.1.2022]
19. Leskinen, M., 2018. Kajaanin sairaalatyömaalla on sattunut vain lieviä työtapaturmia – Kainuussa vakavat työtapaturmat ovat pysyneet kurissa. Yle Uutiset. Online. Available at: https://yle.fi/uutiset/3-10307390 [Accessed 28.1.2022]
20. Loukkola, P., 2013. Turvapuistossa opitaan turvalliset työtavat. Yle Uutiset. Online. Available at: https://yle.fi/uutiset/3-6908161 [Accessed 28.1.2022]
21. Mesaros, P., Spisakova, M. and Mackova, D., (2019). Analysis of Safety Risks on the Construction Site. IOP Conference Series: Earth and Environmental Science, 222, p.012012. doi: 10.1088/1755-1315/222/1/012012
22. Pinto, A., Nunes, I. and Ribeiro, R., (2011). Occupational risk assessment in construction industry – Overview and reflection. Safety Science, 49(5), pp.616-624. doi: 10.1016/j.ssci.2011.01.003
23. Rozenfeld, O., Sacks, R., Rosenfeld, Y. and Baum, H., (2010). Construction Job Safety Analysis. Safety Science, 48(4), pp.491-498.

24. Shin, Y., 2019. Application of Stochastic Gradient Boosting Approach to Early Prediction of Safety Accidents at Construction Site. Advances in Civil Engineering, 2019, pp.1 9. doi: 10.1155/2019/1574297
25. Törner, M. and Pousette, A., 2009. Safety in construction – a comprehensive description of the characteristics of high safety standards in construction work, from the combined perspective of supervisors and experienced workers. Journal of Safety Research, 40(6), pp.399-409. doi: 10.1061/(asce)0742-597x(1996)12:4(33)
26. Udoumoh, N.M. (2026) Development of Artificial Intelligence Model for Accident Prediction in the
27. Workplace, M.Eng Degree Dissertation in the Department of Mechanical and Aerospace Engineering, University of Uyo-Uyo-Nigeria.
28. Willquist, P. and Törner, M. Identifying and analysing hazards in manufacturing industry—A review of selected methods and development of a framework for method applicability. Int. J. Ind. Ergon. 2003, 32, 165–180. [CrossRef]