Mehran University Research Journal of Engineering and Technology

https://doi.org/10.22581/muet1982.2203.10

2022, 41(3) 97-105

Statistical analysis of crowd behaviour in catastrophic situation

Muhammad Ehtesham Tahir [a], Nadir Abbas [a,*], Muhammad Faisal Hayat [a], Muhammad Nasir [b]

[a] *Department of Computer Engineering, University of Engineering and Technology, Lahore Pakistan*

[b] *Department of Computer Engineering, The University of Lahore, Lahore Pakistan*

[*] Corresponding author: Nadir Abbas, Email: engrnadirabbas@gmail.com

Received: 31 May 2020, Accepted: 13 September 2021, Published: 01 July 2022

K E Y W O R D S

Crowd Behaviour Analysis

Behavioural Response

Machine Learning Algorithms

Data Mining

Earthquake Emergency

A B S T R A C T

Machine learning (ML) is one of the emerging domains in classification and prediction. It is important to understand the responses of individuals in crowd during an earthquake emergency for making appropriate earthquake emergency management plan. Our research is focused on predicting the behaviour of individuals in a crowd during Catastrophic Situation. For this purpose, intended and actual behavioural response of crowd is collected by conducting a series of surveys. The attributes that are selected for result prediction are gender, age, affiliation, health status, training level, nearby exit, earthquake intensity, earthquake location, environmental status, and individual's response. The dataset thus collected is divided into two crowds, Crowd 1 shows the intended behaviour whereas Crowd 2 shows actual. The decision tree, k-nearest neighbour, Naïve Bayes and neural network machine learning algorithms are used for predicting results. The results are analysed by using Rapid Miner as data mining tool. The dataset is split into two partitions. By applying randomization techniques like simple random sampling, shuffle random sampling, etc. we have trained and tested the machine learning algorithms. The results of this research will be a source of help in understanding critical details about crowd behaviour in earthquake emergency.

1. Introduction

Crowd is generally defined as a group of individuals gathered at any given area. Different crowds behave differently in different emergency situations [2]. They have different characteristics depending upon attributes of the individuals constituting the crowd. Crowd becomes individuals during emergency. So, analysing crowd behaviour in emergency situations leads to emergency management. Moreover, Machine learning algorithms are effective for learning some types of tasks. They are used in those domains where human might not have the understanding in knowledge engineering algorithms.

The main idea of the research work is to predict crowd behaviour in earthquake emergency. Prediction software are less accurate due to unavailability of dataset. Finding dataset using survey approach, analysing this dataset using different machine learning algorithms, and randomization techniques has been a motivation of this work. Data of individuals of crowd is used to build a model which predicts whether individual of crowd behave active or passive based on selected features/attributes.

To propose a method which performs statistical analysis of crowd behaviour in catastrophic situation using machine learning algorithms has been the goal of this research work. Researchers, so far, have focused on conducting surveys and performing some analysis to find probability distribution. But no one has trained data and predicted on the base of trained data. Analysing crowd behaviour offer emergency response management. To overcome emergency response management difficulties, this work leads to analyse crowd behaviour using machine learning and data mining techniques. The decision tree, k nearest neighbour, Naïve Bayes and neural network machine learning algorithms are used for predicting results.

This paper is organized as follows: In the next section, a literature review is done which highlights approaches of crowd behaviour analysis, emergency responses, survey research, machine learning algorithms and data mining techniques. In the following section, a Dataset collected from survey is described. A section is dedicated to approaches adopted and applied methods. There is a section for results and discussion. The last section ends on conclusions, future work and recommendations.

2. Literature Review

The initial response in emergency is a critical part in emergency management [1]. It shows direct influence after the occurrence of incident to protect lives and properties. In such situations, decision making and resource organization is a question. Many information systems have been available since decades, but they are still failing in some emergency situations. This research majorly focusses on the expansion of emergency response systems (ERSs). Mainly, this paper gives directions in understanding the various approaches and technologies for supporting emergency response, highlights major research gaps and encourages more work in this area.

Crowd behaviour is an important area of research in computer vision [2]. Crowd has several people gathered together at certain location. Crowd varies in situation to situation, as crowd in a shrine is different from crowd in a market. Analysing crowd behaviour includes number of people in crowd, their motion detection, their tracking, and their behaviour understanding. This research paper gives a review on crowd behaviour analysis from 2000 onwards. It discusses the behavioural issues of crowd, their solutions, and highlights the research gap.

Human clinical trials and other biological experiments are extensively using randomization as experimental control [3]. It eliminates biasness in treatment assignments. It ensures equal chance of receiving any of the treatment. Randomization has many reasons and benefits. Different randomization methods like simple, block, stratified, and adaptive randomization has been studied with the objective to benefit researchers. The adaptive randomization method is more useful from small to moderate size clinical trials. In addition, issues relevant to randomization are also discussed here.

Behavioural data is non-normally distributed, and we cannot analyse this data by using conventional parametric statistics. Statistical problems can be solved by using resampling techniques. Non-parametric Kruskal-Wallis test and randomization tests comparison shows that randomization tests are more efficient and could indicate minor details existing in data. In addition, variance has also been calculated which shows that variance decreases as number of replications increases. It is recommended that minimum 5000 iterations are acceptable for randomization tests on behavioural data [4].

Some strategies have been discussed to handle earthquake emergencies. The importance of the paper is that these strategies were behaviour oriented. Researchers have analysed behaviour of different crowds by monitoring videos. And then proposed strategies accordingly [5].

Emergency evacuations in Japan earthquake have also discussed which revealed that behaviour was differed for survivors and non survivors [6]. The study was based on the incidents from Japan, India, Indonesia earthquakes.

Understanding crowd behaviour helps us in supporting crowd during emergency in a timely manner [7]. It can also help us in providing emergency services at public gatherings. This paper discusses psychological factors related to crowd with respect to mass-gathering settings and concludes that there is large theory-practice gap in understanding crowd behaviour psychology and behaving accordingly. The literature study has mentioned following two critical elements of crowd behaviour.

1. Crowd behaviour diverges from normal behaviour
2. People must be a part of this divergent behaviour

At end, there is need to do more research in developing crowd behaviour in public gatherings. We can change crowd behaviour outcomes by understanding these behaviours.

Emergency evacuations strategies are need of every time [8]. Human behaviour during fire emergency is analysed by several studies. However, very little work has done on how people behave according to their perceived ability in an underground station of train. This study covers survey of 1134 passengers of train. It finds that people who are interested in moving to the exit safely, waiting for guidelines from station staff, waiting at assembly areas, helping others in drastic situations, and choosing least crowded gate to get out also interested in getting out safely. Others who do nothing and push others are less safe.

Fire can be caused at any time, at any place [9]. Fire harm occupants and damage property. Due to causes related to earthquake almost 25,000 victims are occurring every year. Around 21 males and 42 females die each day on an average. Hence safety response and management is an important area of concern in India. Now it’s become day to day management concept. Many safety procedures and protection systems have been designed to ensure safety and control loss. For 100% safety, efficient safety management is the need of study. This paper presents strategies to fight with fire.

Survey research is often considered as an easy research. Conducting survey results may vary from poor quality to high quality [10]. This study provides good application in doing survey research. The basic purpose of this literature is to help researcher to conduct survey with credible results. This paper gives overview of survey research and guides the reader in data collection, its analysis, and its reporting. Finally, the parameters which should be avoided are discussed for valid and convincing results.

Data mining is basically extraction of hidden information from large databases. This field is helping companies in decision making. It uses machine learning algorithms to filter out vital information for humans [11]. Data mining tools are available in large numbers. They are helping researchers for getting viable information which is helpful in predicting future trends and behaviours. Data mining tools can easily answer those questions which were difficult in past times. This paper presents how to use data mining tools for knowledge discovery.

The paper discusses six free software tools for data mining such as R, RapidMiner, KNIME, Weka, Orange, and Scikit-learn (Jupyter Notebook) [12]. The objective is to present pros and cons for interested researchers. This also covers all the algorithms of data mining e.g., classification, clustering, regression, association rule mining, feature selection etc. The tools also support for the advanced research areas like big data, text mining etc. This research highlights the use of data mining tools as well as important advancements in these tools.

3. Dataset

The intended and actual behavioural dataset is collected from a Faculty of Earth Sciences, University of Engineering and Technology (UET), Lahore building, which includes three departments named as mining engineering, geological engineering, and petroleum and gas engineering. The collected dataset is divided into two groups, where Group 1 (Intended Behaviour) shows their intended behaviour that how they would react in some sort of catastrophic situation while Group 2 (Actual Behaviour) depicts their actual behaviour when the emergency happened. This data was characterised as intended behaviour and actual behaviour of individuals in a crowd. The dataset of intended behaviour is categorically obtained from a sample of students using survey questionnaires and also by monitoring videos. This dataset consists of 200 occupants which are randomly selected students, staff, and faculty members. The attributes are chosen which are best fit for the selected sample. It has 10 attributes with multiple values. Ten attributes are gender, affiliation, age, health status, training levels (10-none, 20-First-Aid, 30-Combat Earthquake, 40-Rescue, 50-Health and Safety), closest and alternative emergency exits, earthquake location, earthquake intensity, environment status is basically building status (Strong, Moderate, and Weak) and behavioural response which is labelled as class attribute. These attributes are outlined in Table 1, whereas the attributes of actual crowd behaviour are collectively outlined in Table 2.

The intended behaviour is selected as one crowd and the dataset of actual behaviour comprised of 4 different crowds of earthquake emergency. The dataset is collected from students of UET Taxila who experienced different earthquake emergencies during their stay at hostels (Quaid-e-Azam Hall, UET Taxila). These two datasets are separately analysed. Table 3 showing their comparison.

Table 1

Attributes of intended crowd behaviour

Attribute	Type	Values	Statistics
Gender	Polynomial	708-Male 92-Femail	Min: F Max: M
Affiliation	Polynomial	672-Students 92-Staff 36-Faculty	Min: Faculty and Staff Min: Student
Age	Integer	Less than 20 to more than 50	Min: 0 Max: 6
Health Status	Polynomial	388-Good 352-Excellent 56-Fair 4-Poor	Min: Poor and Fair Max: Good and Excellent
Training Level	Integer	10-50	Min: 10 Max: 50
Exit	Integer	0-2	Min: 0 Max: 2
Environ-mental Status	Polynomial	200-Strong 300-Moderate 300-Weak	Min: Weak and Medium Max: Strong
Earthquake Location	Polynomial	600-Indoor 200-Outdoor	Min: Indoor Max: Outdoor
Earthquake Intensity	Polynomial	400 High (H-4+) 200 Medium (M-2-4) 200 Low (L -<4)	Min: M and L Max: High
Behaviour/ Response	Polynomial	564-Active 236-Passive	Min: Passive Max: Active

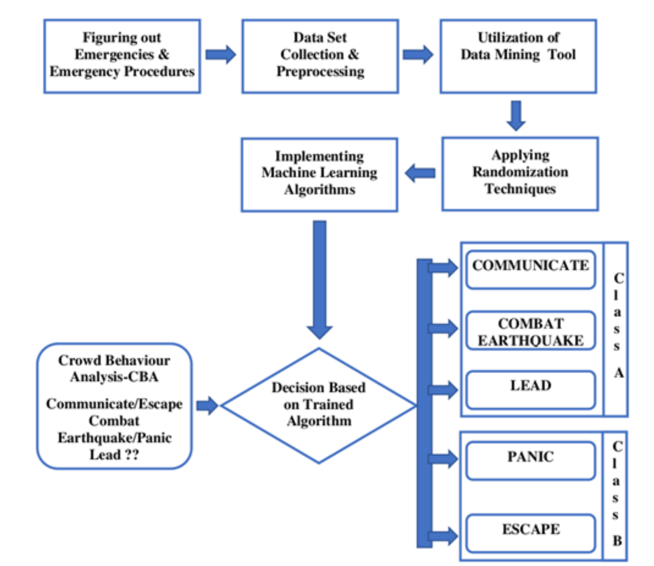

Fig. 1. Proposed crowd behaviour analysis technique

4. Material and Methods

The methodology adopted has practical approach having steps like figuring out emergencies and emergency procedures, dataset collection and its pre-processing, utilization of a data mining tool, applying randomization techniques, implementation of machine learning algorithms. After covering these steps decision is based on trained algorithm. Decision includes communicate, combat earthquake, lead, panic, and escape. The practical approach can be examined by the Fig. 1. After through writing audit, various crises have been experienced yet just tremor crisis is chosen for this examination.

Table 2

Attributes of actual crowd behaviour

Attribute	Type	Values	Statistics
Gender	Polynomial	97-Male 0-Femail	Min: F Max: M
Affiliation	Polynomial	47-Employee 31-Visitor 15-Other 4-Owner	Min: Owner Min: Employee
Age	Integer	Less than 20 to more than 50	Min:0 Max: 6
Health Status	Polynomial	51-Good 36-Excellent 10-Fair 0-Poor	Min: Poor and Fair Max: Good and Excellent
Training Level	Integer	10-50	Min: 10 Max: 50
Exit	Integer	0-2	Min: 0 Max: 2
Environ-mental Status	Polynomial	32-Strong 38-Moderate 27-Weak	Min: Weak and Moderate Max: Strong
Earthquake Location	Polynomial	79-Indoor 18-Outdoor	Min: Indoor Max: Outdoor
Earthquake Intensity	Polynomial	18 High (H-4+) 57 Medium (M-2-4) 22 Low (L -<4)	Min: M and L Max: High
Behaviour/ Response	Polynomial	67-Active 29-Passive	Min: Passive Max: Active

The data is provided by percentage split Test Method for training and testing the machine learning algorithms and a suitable portion of the dataset is selected.

Table 3

Comparison of Intended and Actual Behaviour

Dataset	Number of crowds	Total entries in each crowd
Intended behaviour	1	Crowd 1: 200
Actual behaviour	4	Crowd 1: 18
		Crowd 2: 15
		Crowd 3: 21
		Crowd 4: 43

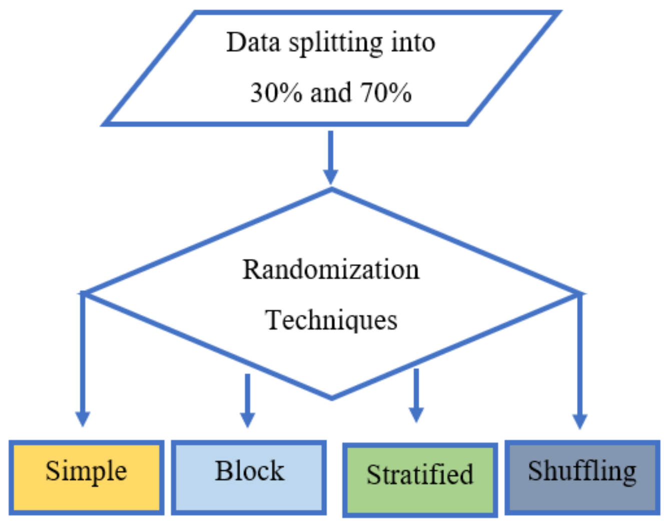

Fig. 2. Randomization techniques on training and testing data

Commonly, 70% data with randomization techniques is used for the training of the algorithm and 30% dataset with randomization techniques is used for testing. In this section four machine learning algorithms are applied on the data.

Their results and performance is empirically discussed here in detail.

4.1 Decision Tree

Decision Tree (DT) is supervised learning scheme in which classification rules are made from the given dataset. It is tree like graph in which outcome of decision is elaborated. Classification is performed by tree and results generate leave nodes. We have applied DT on intended and actual crowd behaviour. Parameters considered are gain ratio, maximal depth of the tree, confidence, and pruning techniques. Pruning techniques include minimal gain, minimal leaf size, minimal size of split, and number of pruning alternates.

Decision tree has shown accuracy of 68.97% (simple random sampling), 86.21% (shuffle random sampling), 79.31% (stratified random sampling) for actual crowd behaviour and 68.33% (simple random sampling), 63.75% (shuffle random sampling), 69.58% (stratified random sampling) for intended crowd behaviour.

4.2 KNN

K-Nearest Neighbour (KNN) is supervised learning system used for classifying dataset. K means to selecting points from dataset. The algorithm selects data using *K* value and then point is added to the given sample. We have applied KNN on both behaviours keeping *K* value = 3 as default. KNN Shows best accuracy of 73.11% (simple random sampling), 87.63% (shuffled random sampling), 87.59% (stratified random sampling) for actual crowd behaviour with respect to intended crowd behaviour.

4.3 Naïve Bayes

Naive Bayes mostly based on base theorem in which probability theory is predicted. It makes use of probability theory for the classifying data. It requires class type feature also called as label of dataset. It implements conditional probabilities e.g., if coin is tossed than who is first one to toss the coin (team A or a team B). Bayes conditional probabilities have been applied to intended and actual crowd behaviour dataset.

Naïve Bayes shows more accuracy for actual crowd behaviour as comparison with intended crowd behaviour.

4.4 Neural Network

Neural network is learning algorithm having different layers for learning of data. They allocate weights to different neurons separately when data is processed.

Actual crowd behaviour dataset has more accuracy for simple, shuffled, and stratified random sampling as compared to intended crowd behaviour.

Randomization techniques with training models name Decision Tree, Naïve Bayesian, K Nearest Neighbour, and Neural Network are used for this analysis.

The derived accuracies, class recall, and class precision for the two datasets are mentioned in Tables 4 and 5.

5. Results and Discussion

Performance summary and results can be seen in comparison tables for intended and actual crowd behaviour. Dataset is analysed using four algorithms as Decision Tree, Naïve Bayesian, and K-Nearest Neighbour (KNN), and Neural Network with randomization techniques such as Simple randomization, Shuffle randomization, and Stratified randomization.

Table 4

Accuracy, class recall and class precision for intended crowd behaviour

Randomization Technique	Training Model	Accuracy (%)	Class Recall		Class Precision	
Simple Randomization	Decision Tree	68.33	True No	True Yes	Pred. No	68.33%
			100.00%	0.00%	Pred. Yes	0.00%
Shuffled Randomization		63.75	True No	True Yes	Pred. No	73.75%
			100.00%	0.00%	Pred. Yes	0.00%
Stratified Randomization		69.58	True No	True Yes	Pred. No	70.17%
			92.82%	0.00%	Pred. Yes	0.00%
Simple Randomization	Naïve Bayes	62.50	True No	True Yes	Pred. No	70.33%
			78.05%	28.95%	Pred. Yes	37.93%
Shuffled Randomization		65.83	True No	True Yes	Pred. No	74.87%
			80.79%	23.81%	Pred. Yes	30.61%
Stratified Randomization		68.75%	True No	True Yes	Pred. No	73.50%
			86.98%	25.35%	Pred. Yes	45.00%
Simple Randomization	KNN	65.83	True No	True Yes	Pred. No	72.28%
			81.10%	32.89%	Pred. Yes	44.64%
Shuffled Randomization		60.42	True No	True Yes	Pred. No	74.40%
			70.62%	31.75%	Pred. Yes	27.78%
Stratified Randomization		63.33	True No	True Yes	Pred. No	70.15%
			83.43%	15.49%	Pred. Yes	28.21%
Simple Randomization	Neural Network	68.33	True No	True Yes	Pred. No	70.37%
			92.68%	15.79%	Pred. Yes	50.00%
Shuffled Randomization		69.58	True No	True Yes	Pred. No	77.66%
			82.49%	33.33%	Pred. Yes	40.38%
Stratified Randomization		70.42	True No	True Yes	Pred. No	72.27%
			94.08%	14.08%	Pred. Yes	50.00%

Table 5

Accuracy, class recall and class precision for actual crowd behaviour

Randomization Technique	Training Model	Accuracy (%)	Class Recall		Class Precision	
Simple Randomization	Decision Tree	68.97	True No	True Yes	Pred. No	47.06%
			57.17%	100.00%	Pred. Yes	100.00%
Shuffled Randomization		86.21	True No	True Yes	Pred. No	62.50%
			86.96%	83.33%	Pred. Yes	95.24%
Stratified Randomization		79.31	True No	True Yes	Pred. No	75.00%
			92.24%	37.50%	Pred. Yes	80.00%
Simple Randomization	Naïve Bayes	68.97	True No	True Yes	Pred. No	47.06%
			57.14%	100.00%	Pred. Yes	100.00%
Shuffled Randomization		75.86	True No	True Yes	Pred. No	35.29%
			52.17%	100.00%	Pred. Yes	100.00%
Stratified Randomization		68.75	True No	True Yes	Pred. No	53.33%
			66.67%	100.00%	Pred. Yes	100.00%
Simple Randomization	KNN	73.11	True No	True Yes	Pred. No	50.00%
			88.73%	30.77%	Pred. Yes	77.78%
Shuffled Randomization		87.63	True No	True Yes	Pred. No	73.33%
			88.73%	84.62%	Pred. Yes	94.03%
Stratified Randomization		87.59	True No	True Yes	Pred. No	73.33%
			88.73%	84.62%	Pred. Yes	94.03%
Simple Randomization	Neural Network	72.41	True No	True Yes	Pred. No	50.00%
			90.48%	25.00%	Pred. Yes	76.00%
Shuffled Randomization		75.86	True No	True Yes	Pred. No	45.45%
			73.91%	83.33%	Pred. Yes	94.44%
Stratified Randomization		86.21	True No	True Yes	Pred. No	66.67%
			80.95%	100.00%	Pred. Yes	100.00%

Table 6

Comparison of the machine learning algorithms applied for intended crowd behaviour

S. No.	Algorithm	Total Entries	Training Entries (70%)	Testing Entries (30%)	Simple Randomization (%)	Shuffled Randomization (%)	Stratified Randomization (%)
1	Decision Tree	800	564	236	68.33	63.75	69.58
2	KNN	800	564	236	65.83	60.42	63.33
3	Naïve Bayes	800	564	236	62.50	65.86	68.75
4	Neural Network	800	564	236	68.33	69.58	70.42

Table 7

Comparison of the machine learning algorithms applied for actual crowd behaviour

S. No.	Algorithm	Total Entries	Training Entries (70%)	Testing Entries (30%)	Simple Randomization (%)	Shuffled Randomization (%)	Stratified Randomization (%)
1	Decision Tree	200	140	60	68.97	86.21	79.31
2	KNN	200	140	60	73.11	87.63	87.59
3	Naïve Bayes	200	140	60	68.97	62.07	75.86
4	Neural Network	200	140	60	72.41	75.86	86.21

Tables 6 and 7 are showing overall accuracy of the applied algorithm with comparison of simple, shuffled, and stratified randomization. All the results show that, actual behaviour prediction is more accurate as compared to intended behaviour. Hence it is more effective for analyst for examining critical details about crowd behaviour. The legends in the below figures having name series 1, series 2 and series3 representing accuracies of simple randomization, shuffled randomization, and stratified randomization, respectively.

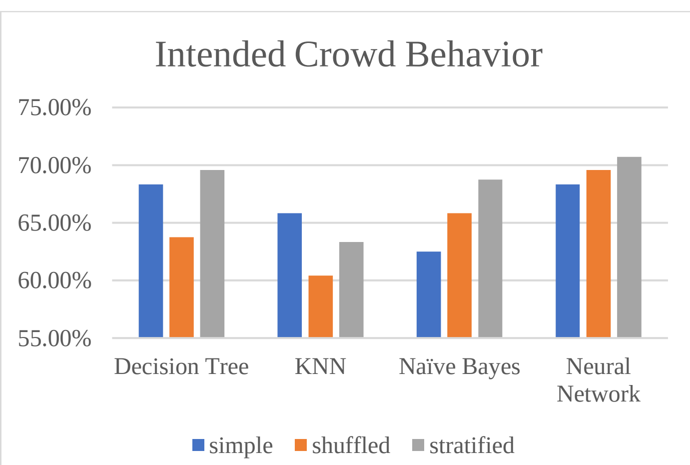

Fig. 3. Overall accuracy for intended crowd behaviour

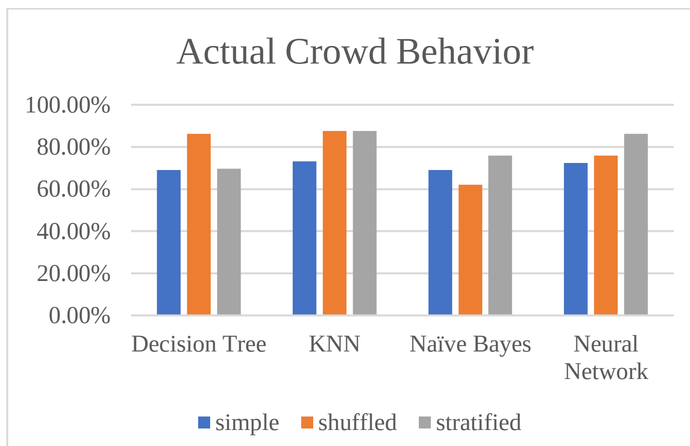

Fig. 4. Overall accuracy for actual crowd behaviour

6. Conclusions

Predicting crowd behaviour using machine learning algorithms depends on the use of good data and machine learning algorithms. Most of the research done on crowd behaviour analysis is based on computer vision techniques. The machine learning algorithms are utilized having goal for properly classifying crowd behaviour from survey data with the training parameters like sample size, earthquake intensity and earthquake location in the emergency scenarios as the key parameters is the novel feature of this work. The results show that the accuracy of intended crowd behaviour is above 60% and the accuracy of actual crowd behaviour is above 70% for simple, shuffled, and stratified randomization respectively while using any of the four machine learning algorithms selected for this analysis.

Our limitation is that we took only a small dataset. We predicted intended behaviour of crowd of particular department only. This research can be extended to predict intended behaviour of crowd from entire university. The attributes/features can be enhanced for deep crowd behaviour analysis. The accuracy of prediction can be improved by combining two or more ML algorithms. Furthermore, Implementation of a standalone Behaviour Prediction Software (BPS) is recommended for future work

7. References

[1] A. Y. Shahrah and M. A. Al-Mashari, "Emergency response systems: research directions and current challenges", Proceedings of the Second International Conference on Internet of things and Cloud Computing, ACM, p. 161, 2017.

[2] S. H. Y, G. Shivakumar, and H. S. Mohana, "Crowd Behavior Analysis: A Survey", International Conference on Recent Advances in Electronics and Communication Technology, pp. 169-178, 2017.

[3] S. K. P, "An overview of randomization techniques: An unbiased assessment of outcome in clinical research", Journal of Human Reproductive Sciences, vol. 4, no. 1, pp. 8-11, 2011.

[3] S. K. P, "An overview of randomization techniques: An unbiased assessment of outcome in clinical research", Journal of Human Reproductive Sciences, vol. 4, no. 1, pp. 8-11, 2011.

[4] A. R. Craig and W. W. Fisher, "Randomization tests as alternative analysis methods for behavior-analytic data", Journal of the Experimental Analysis of Behavior, vol. 111, no. 2, pp. 309-328, 2019.

[5] R. Gabriele Bernardini, "Proposing behavior-oriented strategies for earthquake emergency evacuation: a behavioral data analysis from New Zealand, Italy and Japan", Safety Science, vol. 116, pp. 295-305, 2019.

[6] C. Y. Lam, and T. Shimizu, "A network analytical framework to analyze infrastructure damage based on earthquake cascades: A study of earthquake cases in Japan", International Journal of Disaster Risk Reduction, vol. 54, p. 102025, 2021.

[7] D. H. Khazaie, and S. Khan, "Shared social identification in mass gatherings lowers health risk perceptions via lowered disgust", British Journal of Social Psychology, vol. 59, no. 4, pp. 839-856, 2020.

[8] N. Shiwakoti, R. Tay, P. Stasinopoulos, and P. J. C. Woolley, "Passengers’ perceived ability to get out safely from an underground train station in an emergency situation", Cognition, Technology and Work, vol. 20, no. 3 pp. 1-9, 2018.

[9] A. Vidyadharan, J. John, C. Thomas, and B. P. Yadav, "Earthquake Safety Management in India: A Review", Advances in Earthquake and Process Safety, Springer Singapore, pp. 171-181, 2018.

[10] J. O . Ledyard, "2. Public Goods: A Survey of Experimental Research", in The Handbook of Experimental Economics edited by John H. Kagel and Alvin E. Roth, Princeton University Press, pp. 111-194, 2020.

[11] Y. Paul, and N. Kumar, "A Comparative Study of Famous Classification Techniques and Data Mining Tools", Proceedings of International Conference on Recent Innovations in Computing, Springer, pp. 627-644, 2020.

[12] D. Buenaño-Fernandez, W. Villegas-CH, and S. Luján-Mora, "The use of tools of data mining to decision making in engineering education—A systematic mapping study", Computer Applications in Engineering Education, vol. 27, no. 3, pp. 744-758, 2019.

[13] K. Nakayachi, et al., "Residents’ reactions to earthquake early warnings in Japan", Risk Analysis, vol. 39, no. 8, pp. 1723-1740, 2019.