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ORIGINAL RESEARCH

Predicting Drowning Mortality Risk Using Machine Learning Models; A Retrospective Cohort Study

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Abstract: **Introduction:** Particularly in highly tourist-active coastal locations, drowning is still a serious international public health concern. This study investigates the predictive value of machine learning approaches in estimating drowning-related mortality risk. **Methods:** This retrospective cohort study analyzed drowning incident data from the Emergency Management and Medical Urgency Center of Guilan Province, covering the period from 2018 to 2023. The data were preprocessed, missing values imputed using the K-Nearest Neighbors (KNN) algorithm, and balanced using the Synthetic Minority Over-sampling Technique (SMOTE). Three models including logistic regression, decision tree, and naïve Bayes were evaluated in predicting the risk of mortality following drowning and sensitivity, specificity, and accuracy of each model was calculated and compared. **Results:** A total of 600 consecutive cases meeting the eligibility criteria were extracted for analysis, forming the final dataset. Logistic regression exhibited the highest predictive power, with an accuracy of 51.67% and an area under the curve (AUC) of 60.02%. The most influential variables in drowning-related mortality prediction were drowning location, drowning year, gender, and age. High-risk areas posed a 33-fold higher mortality risk than safe locations ($p < 0.001$). Age and gender were not statistically significant predictors of fatal drowning. **Conclusion:** Given its superior interpretability and predictive capability, logistic regression was identified as the most effective model for assessing drowning mortality risk. Preventative measures should focus on identifying high-risk areas, installing warning signs, implementing lifeguard teams, educating tourists, and enforcing strict coastal safety regulations to mitigate drowning fatalities.

Keywords: Drowning; Mortality; Machine Learning; Machine Learning Algorithms; Iran

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1. Introduction

The World Health Organization (WHO) estimates that drowning claimed 236,000 deaths in 2024 (1). With 8% of all deaths and 7% of all injury-related deaths, drowning ranked as the third most common unintentional injury cause worldwide in that same year (2).

Statistics released by Iran's Ministry of Health, reveal notable geographical variations in drowning trends all around the nation. In a coastal area of northern Iran, the mortality rate from drowning ranges from 4.1 per 100,000 population to less than 0.9 per 100,000 population, where access to the sea is absent (3).

Understanding drowning risk depends much on environmental conditions. Drowning events in areas like Gilan province are much influenced by weather-related elements including rainfall and flooding. Strong water currents and quick start of sudden flash floods can cause dangerous conditions that cause people close to rivers to miscalculate dangers (4, 5).

Open waters also pose risks, particularly in cases when people swim or fish in unguarded areas. Both structural and non-structural actions are advised to lower drowning hazards.

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Structural measures involve changing physical surroundings to improve safety, such as erecting barriers around dangerous locations. Changing community behavior and attitudes toward water safety depends critically on non-structural actions including media campaigns to raise public knowledge and education (6, 7).

The main demographic factors associated with drowning risk are age and gender, with research indicating that younger individuals and men are at a higher risk of drowning compared to other population groups (8, 9).

Furthermore, socioeconomic level could be important since different population groups have different access to swimming pools and safety instructions. Lack of water safety knowledge and incorrect risk assessment could cause people to underplay the risks involved in swimming in unsupervised areas or driving on flooded roadways. Most previous research stress the need for focused educational campaigns to raise public awareness and support better water practices by means of safer methods (10).

Due to developments in artificial intelligence (AI) and associated technologies in recent years, many different scientific disciplines, including healthcare, have seen notable changes. Predicting and offering models to evaluate the probability of an event happening is one of AI's possible strengths. AI can predict an event resulting from interactions between data and present different patterns emerging from various factors and variables by analyzing relationships between several data points in a vast database (11, 12).

Particularly in epidemiology, several branches of artificial intelligence including machine learning are increasingly applied in health sciences nowadays. Emerging as a major tool in analyzing and preventing drowning events, machine learning (ML) provides creative means for spotting and evaluating risks connected with such events. Deep learning models have been shown in several studies to be effective in identifying drowning situations and for their capacity to examine intricate trends in water safety and drowning prevention data (13).

This study investigates drowning-related mortality risk by use of machine learning approaches using recorded data from Gilan Province's pre-hospital emergency and disaster management center.

2. Methods

2.1. Study design and setting

This retrospective cohort study analyzed drowning incident data from the Emergency Management and Medical Urgency Center of Gilan Province, covering the period from 2018 to 2023. The predictive risk factors of mortality following drowning were evaluated using three statistic models including logistic regression, decision tree, and naïve Bayes, and screening performance characteristics of each model was calculated. The study was conducted in accordance with the ethical principles outlined in the Declaration of Helsinki. Additionally, the study received approval from the Ethics Committee of School of Public Health and Safety, Shahid Beheshti University of Medical Sciences, Tehran, Iran. (ethics code: IR.SBMU.PHNS.REC.1403.160).

2.2. Participants

The study population consisted of all individuals for whom a drowning incident was recorded in the center's registry during the mentioned timeframe. All recorded cases of non-fatal and fatal drowning incidents were included. The data encompassed drowning incidents occurring in all aquatic environments, including coastal waters, rivers, lakes, and private pools. Cases were excluded if the record was a duplicate entry or if the core variable of "final status" (deceased/survived) was unreportable or missing.

Participants were selected through a comprehensive review of the electronic registry. A total of 600 consecutive cases meeting the eligibility criteria were extracted for analysis, forming the final dataset. This sample size was deemed sufficient for the planned machine learning algorithms.

2.3. Data preprocessing

The initial preprocessing phase involved checking for duplicate and missing values, which revealed 61 instances of missing data. The missing values pertained to gender (12 cases), age (20 cases), and drowning location (29 cases). These were imputed using the K-Nearest Neighbors (KNN) algorithm. In this technique, missing values are estimated based on the mean or mode of the K most similar rows (neighbors) from the complete data. While this method offers high accuracy and supports nonlinear modeling, a noted limitation is the challenge of determining the optimal number of neighbors (K).

Subsequently, the dataset was split, with 70% allocated for training the models and 30% reserved for testing. To address a significant class imbalance in the response variable, where 19% of individuals died and 81% survived, the Synthetic Minority Over-sampling Technique (SMOTE) was applied to the training set. SMOTE generates synthetic samples for the minority class to improve the predictive power of the algorithms.

2.4. Study variables

The final dataset contained 600 rows (cases) and 12 columns (variables). The variables incorporated into the model were: the date of the incident (month, year, and season), gender, age, final status (deceased/survived), type of incident location (inside or outside the designated sea area), and the time of occurrence (morning, afternoon, night).

2.5. Selection of the appropriate algorithm

Three interpretable algorithms were evaluated: logistic regression, decision tree, and naïve Bayes. All models were trained using the same set of input variables. Their performance was compared based on sensitivity, specificity, accuracy, and the area under the Receiver Operating Characteristic (ROC) curve. Based on the aggregate of these criteria, logistic regression was identified as the best-performing model for this dataset.

2.6. Data analysis

Descriptive statistics, including mean, standard deviation, median, and range for continuous variables, and frequencies and percentages for categorical variables, were used to summarize the data. Descriptive and exploratory data analysis was performed using STATA 11 (StataCorp LLC, College Station, Texas, USA). All data mining and machine learning procedures, including preprocessing, algorithm training, and evaluation, were conducted using RapidMiner 9.10.
In this study RapidMiner (Altair AI Studio) software, which is a data science platform that provides a comprehensive suite of tools for data preparation, machine learning, and model validation, was used. This study employed the Windows 10 version of Altair AI Studio (Altair Inc., 2025).

3. Results

3.1. Baseline characteristics of studied patients

Table 1 compares the baseline characteristics of alive and deceased cases. The mean age was higher in deceased patients (35.7 ± 18.2 vs. 30.6 ± 16.5 years, $p = 0.004$) and a higher proportion of deaths occurred in dangerous places (21.8% vs. 3.5%, $p = 0.005$).

3.2. Mortality risk prediction modeling

Table 2 presents the screening performance of three studied models in predicting the risk of mortality following drowning. Among the three models, the Decision Tree achieved the highest accuracy [51.6% (95% confidence interval (CI): 50.0–53.4)] and the highest area under the curve (AUC) [60.0% (95% CI: 57.9–63.1)], followed by Logistic Regression [accuracy: 49.1% (95% CI: 47.3–50.9); AUC: 55.1% (95% CI: 52.8–57.4)] and Naïve Bayes [accuracy: 46.8% (95% CI: 44.9–47.7); AUC: 53.1% (95% CI: 50.9–55.3)]. In terms of sensitivity and specificity, the Decision Tree also showed the highest sensitivity [82.3% (95% CI: 81.2–83.4)] and moderate specificity [44.5% (95% CI: 42.2–46.8)], whereas Logistic Regression had lower sensitivity [71.2% (95% CI: 69.9–72.5)] and specificity [30.1% (95% CI: 27.6–32.6)] (Figure 1).
Therefore, logistic regression offers a more straightforward interpretation and understanding compared to the other models and has superior diagnostic power due to higher sensitivity and specificity. Based on the logistic regression model (Table 3), the independent predictors of mortality were dangerous place (coefficient: 3.50; 95% CI: 2.07–4.93; $p < 0.001$) and the years 2018 (coefficient: -0.94; 95% CI: -1.55 to -0.33; $p = 0.002$) and 2022 (coefficient: -0.65; 95% CI: -1.26 to -0.04; $p = 0.04$). Age, gender, and other years (2019–2021, 2023) were not significantly associated with mortality risk.
The variable weights in the logistic regression algorithm, ranking them based on their significance in predicting and identifying drowning-related mortality, are shown in figure 2. The analysis shows that drowning location is the most influential factor, followed by the year of the drowning incident, the gender of the victims, and their age.

4. Discussion

The present study demonstrated that logistic regression exhibited higher sensitivity and specificity among various machine learning models, making it the most effective method for predicting and diagnosing drowning-related mortality. A 2022 study in China that examined non-fatal drowning risk prediction found that the Stacking Ensemble Algorithm outperformed logistic regression in terms of sensitivity, accuracy, and specificity. However, a comparative analysis indicates that the findings of previous studies do not fully align with the present research. This discrepancy may be due to differences in sample size. The Chinese study analyzed 8,390 cases, while the current study included 600 cases, potentially influencing the results (14).
This study identified drowning location as the most significant predictors of fatal drowning incidents. A 2019 study in China using univariate logistic regression found that drowning location had a positive correlation with drowning events among children (14). Similarly, a 2022 study by Xie in China reported that gender was a less influential factor in non-fatal drownings (4). Additionally, a 2016 meta-analysis on on-site drowning predictions using cohort studies found no association between age and drowning frequency (15). Other studies have emphasized the importance of identifying high-risk drowning locations and prioritizing specific areas to improve drowning prevention strategies (16, 17). A comparative analysis confirms that drowning location is one of the most critical factors in predicting drowning mortality across all age and gender groups (15).
Given these findings, high-risk drowning areas must be identified, and warning signs should be installed. Additionally, restricting access to dangerous locations through strict enforcement of safety regulations is essential. Finally, deploying lifeguard teams trained in emergency response to monitor high-risk areas is strongly recommended. These teams would be able to swiftly rescue drowning individuals and transport them to medical facilities for immediate care.
The study found that drowning incidents in Gilan Province steadily increased from 2018 to 2023 despite long-established coastal regulations, identification of high-risk areas, and necessary warnings. Given that Gilan is a coastal region with high tourist activity, particularly in summer, drowning remains a significant concern.
A study conducted in Australia demonstrated that societal culture and socioeconomic factors significantly influence drowning rates. The study reported that 76% of beach visitors entered the water, while 28% were unaware of safety flags marking lifeguard-supervised areas (18). This highlights how varying levels of public awareness, risk perception, and

access to safety education—shaped by cultural norms and economic conditions—can impact drowning risk. Similarly, a 2024 intervention in New Zealand targeting young men showed that culturally tailored safety campaigns could effectively promote safer behaviors (19). These findings underscore that drowning prevention strategies cannot be universally applied; they must be adapted to local cultural attitudes, economic realities, and tourism patterns. In Gilan, where a seasonal influx of tourists may lack familiarity with local hazards, combining structural measures with targeted, culturally sensitive education is essential.

Contrary to some international studies that identify young males as a high-risk demographic, our model did not find age and gender to be statistically significant predictors of fatal drowning. This discrepancy may be attributed to the specific context of our study region, a coastal tourism destination where risk exposure is more uniformly distributed across age and gender groups due to recreational water activities. For instance, studies in China have highlighted gender and age as significant factors in child drowning (14), while a meta-analysis by Quan et al. (20) found no consistent association between age and drowning frequency in on-site predictions. This suggests that the importance of demographic variables may be context-dependent, influenced by local behavioral patterns, types of water bodies, and prevalent activities. In Gilan, where both locals and tourists of various ages and genders engage in water-related activities, the risk may be more strongly mediated by environmental and behavioral factors than by demographic ones.

Developing and implementing a comprehensive beach safety program, including public education, swimming skill training, and awareness of warning signs, could be highly effective in reducing drowning fatalities.

5. Limitations

This study has several limitations. First, the data were obtained from pre-hospital emergency records, which may be subject to under-reporting or misclassification of non-fatal cases. Second, the use of imputation for missing values and SMOTE for class balancing, while methodologically sound, may introduce bias or affect the generalizability of the model. Third, the model's predictive performance, while the best among the algorithms tested, was modest (accuracy 51.67%, AUC 60.02%), indicating room for improvement and the need for validation with larger, more comprehensive datasets. Fourth, the study was conducted in a single province in Iran, and the findings may not be directly applicable to other regions with different geographical, cultural, or socioeconomic characteristics. Future research should aim to incorporate more granular environmental data, real-time weather conditions, and detailed behavioral factors to enhance predictive power.

6. Conclusions

The results of this study indicate that logistic regression demonstrated relatively high sensitivity and specificity in predicting drowning-related mortality within the study context. However, the model's overall performance was moderate, and the findings should be interpreted with caution due to the limitations mentioned above. Drowning location emerged as the most critical predictive factor, underscoring the importance of identifying and managing high-risk areas. To mitigate drowning fatalities, a multifaceted approach is recommended, including the installation of warning signs, deployment of lifeguard teams in hazardous zones, targeted education for tourists and locals, and enforcement of safety regulations. Future efforts should focus on integrating more diverse data sources and advanced modeling techniques to improve risk prediction and inform proactive, context-specific prevention strategies.

7. Declarations

7.1. Acknowledgments

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7.2. Authors' contributions

The study was designed and conducted by YV, Z.Gh, and AS, also drafting of the manuscript was prepared by YV, Z.Gh, FR, AD, JM, MJ, and AS. Statistical Analysis was done by YV, and HS. In final step all coauthors have approved a final version of the manuscript.

7.3. Funding/Support

This study received no financial support.

7.4. Ethics approval and consent to participate

The study was conducted in accordance with the ethical principles outlined in the Declaration of Helsinki. Additionally, the study received approval from the Ethics Committee of School of Public Health and Safety, Shahid Beheshti University of Medical Sciences, Tehran, Iran. (ethics code: IR.SBMU.PHNS.REC.1403.160).

7.5. Consent for publication

I confirm the corresponding author has read the journal policies and submit this manuscript in accordance with those policies.

7.6. Availability of data and material

The data analyzed in the study are available from the corresponding author upon reasonable request.

7.7. Competing interests

The authors declare no competing interest.

7.8. Using artificial intelligence chatbots

No artificial intelligence chatbots were used in the data analysis, model development, or writing of this manuscript.

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Table 1: Baseline characteristics of studied patients

Variables	Alive	Dead	P value
Age (year)	30.6 (16.5)	35.7 (18.2)	0.004
Sex			
Male	363 (80.0)	91 (20.0)	0.210
Female	114 (85.1)	20 (15.5)	
Place			
Safe	82 (96.5)	3 (3.5)	0.005
Dangerous	380 (78.2)	106 (21.8)	
Year			
2016	67 (87.7)	15 (18.3)	0.295
2017	78 (86.7)	12 (13.3)	
2018	51 (73.9)	18 (26.1)	
2019	60 (75.0)	20 (21.8)	
2020	43 (78.2)	12 (21.8)	
2021	55 (84.6)	10 (15.4)	
2022	132 (83.0)	27 (17.0)	

Data are presented as mean ± standard deviation or frequency (%).

Table 2: Performance Metrics of three machine learning models in predicting the risk of mortality following drowning

Algorithm	Sensitivity	Specificity	Accuracy	AUC
Decision Tree	82.3 (81.2,83.4)	44.5 (42.2,46.8)	51.6 (50.0, 53.4)	60.0 (57.9,63.1)
Logistic Regression	71.2 (69.9,72.5)	30.1 (27.6,32.6)	49.1 (47.3, 50.9)	55.1 (52.8,57.4)
Naive Bayes	65.1 (63.7,66.5)	37.1 (34.4,39.8)	46.8 (44.9,47.7)	53.1 (50.9,55.3)

All measures are presented with 95% confidence interval. AUC: area under the curve.

Table 3: Coefficients of the logistic regression algorithm in predicting drowning mortality risk

Attribute	Coef. (CI95%)	Std. Error	z-Value	p-Value
Age	0.00 (-0.02,0.02)	0.01	0.51	0.61
Gender				
Female	0.07 (-0.34,0.48)	0.21	0.33	0.74
Place				
Dangerous	3.50 (2.07, 4.93)	0.73	4.81	0.00
Year				
2018	-0.94 (-1.55,0.33)	0.31	-3.07	0.00
2019	0.15 (-0.46,0.76)	0.31	0.47	0.64
2020	-0.24 (-0.85,0.37)	0.31	-0.77	0.44
2021	-0.03 (-0.66,0.60)	0.32	-0.08	0.93
2022	-0.65 (-1.26,0.04)	0.31	-2.07	0.04
2023	-0.44 (-0.97,0.09)	0.27	-1.66	0.10

All measures are presented with 95% confidence interval (CI). Std.: standard; Coef.: coefficient.

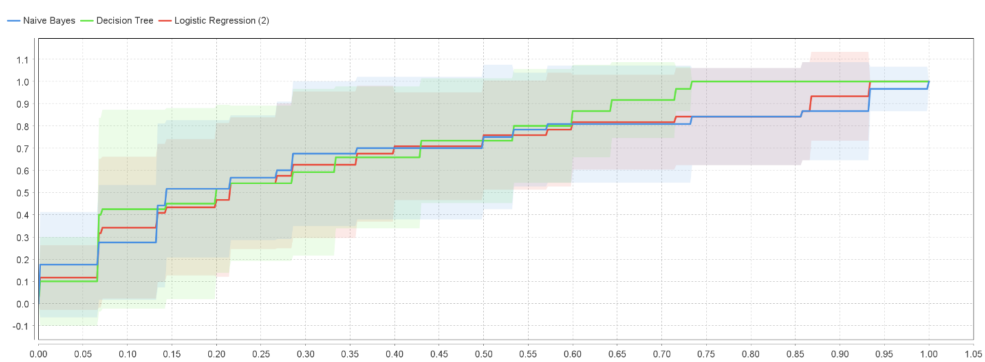

Figure 1: Receiver operating characteristic (ROC) curve of the three studied models in predicting the risk of mortality.

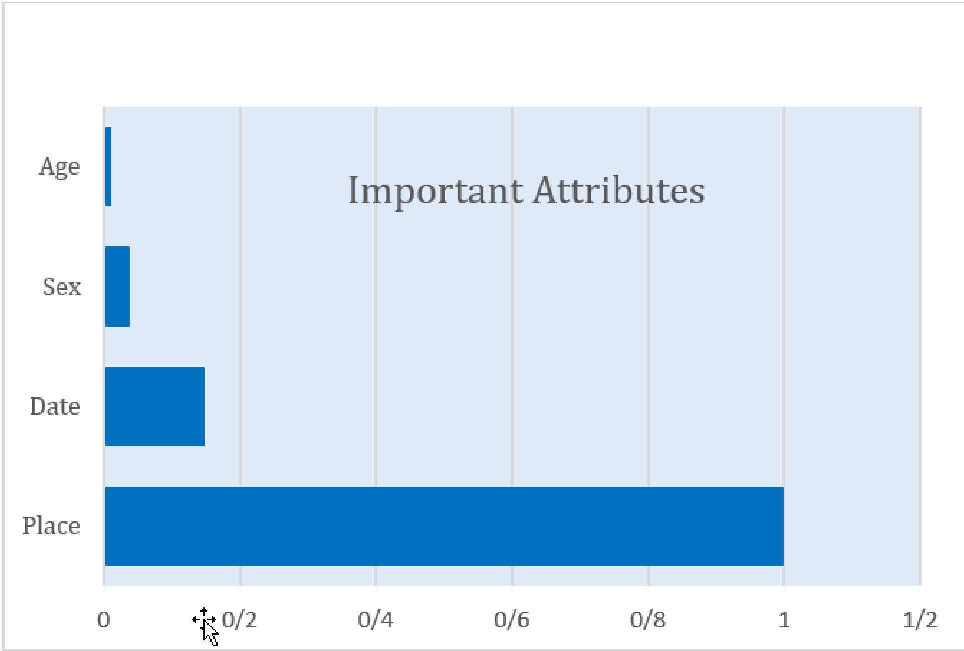

Figure 2: The weights of studied variable in predicting the risk of mortality following drowning based on the logistic regression model.