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USING MACHINE LEARNING TO DEVELOP A RISK PREDICTION MODEL FOR ACUTE MOUNTAIN SICKNESS

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Abstract: Background: Acute Mountain Sickness (AMS) is a syndrome caused by individuals who are unacclimatized at high altitudes, AMS can threaten health and decrease productivity. By predicting AMS risk, workers can take measures in advance to prevent AMS. The main objective of this study was to use machine learning techniques to develop an AMS risk prediction model. Methods: A retrospective cohort study was conducted to capture AMS monitor data for State Grid workers in the Tibet-Ali project from 1 January 2019 to 31 December 2020. The data was assigned to the training and test sets in 7:3. 10-fold cross-validation was used to improve generalization abilities. Four models including Random Forest (RF) were developed and compared. Area Under the Curve (AUC) and accuracy were used to measure the performance of models. Results: The cohort consisted of 10956 workers, 10438 (95.27%) were male, and the mean age was 36.13 ± 10.49 years. The AMS incidence was 15.58% (n = 1707). The RF model was superior to others in predicting AMS risk. In the test set, the accuracy was 80.32%. After parameter optimization of all models, the RF model still outperformed others, with the best AUC and accuracy were 0.76 and 78.12% ± 7.21%, respectively. Twelve features including demographics, clinical, and altitude were included in the RF model. Conclusions: This study aimed to develop a machine learning-based model for predicting AMS risk among workers at high altitudes. The RF model was found to be the best performer among the four models, based on 12 features known before workers entered plateaus. This model can be an effective tool for estimating AMS risk and guiding decisions regarding AMS primary prevention.

Keywords: Acute Mountain Sickness, machine learning, prediction model, workers

Introduction

Acute Mountain Sickness (AMS) is a nonspecific syndrome that usually occurs in unacclimatized individuals at altitudes above 2500 m (Luks et al., 2017). Patients with AMS may experience headaches, fatigue, and other possible symptoms (Garrido et al., 2021). If the symptoms are ignored, AMS can affect the brain and lungs, causing High Altitude Cerebral Edema (HACE) or High-Altitude Pulmonary Edema (HAPE), which are life-threatening diseases (Li et al., 2018). According to statistics, more than 25% of people who arrived at altitudes above 2500 m have suffered AMS, while the AMS prevalence was higher than 50% for those who arrived at altitudes above 6000 m (Jin, 2017). As the number of people traveling or working at high altitudes increases (Luo et al., 2013), it will bring unprecedented challenges to AMS prevention. Many measures have been proven to prevent

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AMS effectively, such as high-altitude acclimatization(Imray et al., 2010), taking AMS preventive medicines(Ried et al., 1994), and avoiding drinking alcohol(Luo et al., 2013). Acclimatization is the most effective preventive measure, if individuals want to arrive at high altitudes, they should spend time acclimatizing at moderate altitudes and avoiding reaching high altitudes directly(Beidleman et al., 2009). Predicting AMS risk is also an important preventive measure to help people know their AMS risk and take appropriate preventive measures in advance(Luks et al., 2017). Some studies have developed AMS prediction and evaluation tools, such as the Lake Louise Questionnaire(Roach et al., 2018) and the Acute Mountain Sickness-Cerebral score(Meier et al., 2017). However, these tools are mostly used for research purposes rather than clinical practice(Ahluwalia and Underwood, 2022). Therefore, it is urgent to develop an AMS risk prediction tool that can be used for clinical practice.

Machine Learning (ML) techniques have shown considerable promise in developing prediction models for clinical practice(Habehh and Gohel, 2021). Compared with traditional statistical algorithms, ML algorithms can significantly improve prediction accuracy(Zhou et al., 2021). Many researchers have developed AMS risk prediction models using ML algorithms. Yang et al. developed a Support Vector Machine Recursive Feature Elimination (SVM-RFE) using 10 gene features with significant AMS predictive ability from 21 subjects to predict severe AMS. The result showed that the SVM-RFE model performed well in the validation set with the Area Under the Curve (AUC) value reaching 0.626 (Yang et al., 2023). Another study utilized physiological and environmental features from 32 participants to develop 25 ML models for AMS prediction including Weighted KNN, Bagged Trees, Cubic SVM, and Fine Tree. Their results showed that Bagged Trees had the best performance with sensitivity, specificity, accuracy, and AUC of 0.999, 0.994, 0.998, and 1, respectively(Wei et al., 2022). The successes of current studies suggested the possibility of using ML techniques to develop AMS risk prediction models. However, current studies still had some limitations. First and foremost, most of the study population was under strictly controlled experimental conditions, which did not reflect real-world situations. Other limitations included the small sample sizes, the parameters of features were hard to obtain, and researchers paid less attention to workers.

Workers are one of the main groups going to plateau areas. Although companies provided workers with AMS preventive measures such as acclimatization training and preventive medicines. Wu et al. found that the AMS incidence among 14050 railway workers working in plateau areas still reached 51%(Wu et al., 2007). Another study of 11182 plateau workers showed that the AMS incidence was 56%(Wu et al., 2012). These suggested that workers were at high risk of AMS and needed to be provided with effective AMS risk prediction. As the largest power company in China, the work areas of the State Grid cover 88% of the land area of China, and the plateau region is an important work area of the State Grid. To ensure power supply in plateau areas, the State Grid conducted the Tibet-Ali project. The project is the highest, longest, and most challenging power transmission project in the world. Workers who participated in the project needed to pass physical examinations and have high-altitude acclimatization. More than 10000 workers have participated in the project. To diagnose and treat AMS timely, the State Grid conducted unified training for medical workers and set up 20 medical stations to provide medical assistance to workers and keep physical examination, and AMS diagnosis records. These conditions enable researchers to obtain large-scale, high-quality, and real-world-based AMS monitor data for the development of AMS risk prediction models.

Based on the above reasons, we conducted a retrospective cohort study to capture the AMS monitor data for State Grid workers in the Tibet-Ali project. The primary objective of this study was to use the AMS monitor data and ML techniques to develop an AMS risk prediction models based on ML techniques. The features utilized in the model can be easily obtained before workers enter the high-altitude work environment. Since several ML models have been developed in the medical field, each model has its strengths and work nature. All of these models will perform well if chosen appropriately(Uddin et al., 2019). Therefore, we developed four ML models: Random Forest (RF), Support Vector Machine (SVM), Logistic Regression (LR), and Extreme Gradient Boosting (XGBoost), and selected the model with the highest accuracy and AUC as the AMS risk prediction model.

Materials and Methods

Study Population

A retrospective cohort study was conducted to capture AMS monitor data for State Grid workers in the Tibet-Ali project from 1 January 2019 to 31 December 2020. The project is the highest, longest, and most challenging 500 KV transmission project in the world, which represents the plateau work environment well. The inclusion criteria were (1) completed high-altitude acclimation training, (2) passed the physical examination, and (3) No key information (name, gender, ID number) missing. The exclusion criteria were (1) No record of high-altitude acclimation training, (2) Key information missing. Finally, a total of 10956 workers (1707 patients vs. 9249 healthy controls) met the inclusion criteria and participated in this study.

Dataset Description and Data Acquisition

The dataset contained demographic, altitude, and clinical information (12 features) about State Grid workers, and the AMS outcome (1 feature), which can be viewed as the dependent variable. The domicile altitude information was measured by ArcGIS software (version 10.8) and used the digital elevation model data released by the General Bathymetric Chart of the Oceans. The AMS outcome and clinical information were measured by uniformly trained medical workers. For AMS, we defined it as workers who met the AMS diagnosis in GBZ 92-2008 "Diagnostic criteria of occupational high-altitude disease"(Zhang, 2010) and confirmed by medical workers. Table 1 shows specific names, parameters, and acquisitions of features.

Table 1: Specific name, parameter, and acquisition of feature

Primary Feature	Secondary Feature	Parameter	Acquisition
Demographics	Age	year	Self-reported
	Sex	male/female	Self-reported
Altitude	Domicile altitude	meter	DEM data
	Workplace altitude	meter	From the medical station
Clinical	Heart rate	beats/min	Finger clip pulse oximeter
	BMI*	kg/m^2	Based on height and weight
	Oxygen saturation	%	Finger clip pulse oximeter
	Blood pressure	mmHg	Blood pressure monitor
	Arrhythmias	yes/no	UCG** examination
	Heart murmurs	yes/no	UCG examination
	Dry and moist rales	yes/no	Auscultation
	Nutritional status	excellent/good/average or below	Physician judgment
AMS	AMS	yes/no	Physician judgment

Note: * Body Mass Index (BMI), ** Ultrasonic Cardiogram (UCG)

Feature selection and Data preprocessing

In most cases, multi-feature models perform better than those with fewer features. But in clinical practice, having more features is not equal to having higher performance, because irrelevant features can mislead the models(Wang *et al.*, 2021). Therefore, we adapted Variance Threshold, Chi-square, F-test, and Mutual Information to filter features. We removed features with variances of 0 and features that did not correlate with AMS outcome. Furthermore, to minimize the bias caused by variables that are measured at different scales and improve the performance of models. We used the StandardScaler function in the sklearn.preprocessing module to standardize the data and observe the performance of models before and after data standardization.

Parameter optimization

The generalization error is affected by the model structure (complexity). If the model is too complex or simple, the model will be overfitting or underfitting and result in a large generalization error(Mei and Montanari, 2022). Therefore, we optimized the key parameters to find the most suitable model structure and avoided overfitting or underfitting. We used the learning curve and the GridSearchCV function in the scikit-learn module for parameter optimization.

Training and evaluation of ML models

To develop the best AMS risk prediction model, we developed four ML models: RF, SVM, LR, and XGBoost. We split the dataset into two parts (70% training and 30% test) and used the hold-out method to evaluate the performance of models. The models were trained on the training set and tested on the test set. In addition, the 10-fold cross-validation was also applied to evaluate the performance of these models to overcome overfitting and selection bias(Cawley and Talbot, 2010). We chose accuracy and AUC as performance evaluation metrics, which are common in medical prediction studies, to compare the performance of models.

Statistical analysis

The statistical analyses were performed in Python (version 3.8) and Stata (version 17.0). All ML models were built based on the scikit-learn module (version 0.23.2) of Python. Continuous variables were presented as means ± Standard Deviation (SD), and categorical variables were presented as count (percentages). To compare the group differences, continuous variables were used on the T-test, and categorical variables were used on the Chi-square test. We considered the results to be statistically significant when the two-sided $P < 0.05$.

Ethical consideration

The trial was approved by the Institutional Review Board of Peking University (IRB00001052-21066) and adhered to the principles of the Declaration of Helsinki. To protect the privacy and confidentiality of participants, we concealed the key information of all participants in the data presentation process.

Results

Participant Characteristics

Of 10956 participants in this study, 10438 (95.27%) were male, and the mean age was 36.13 ± 10.49 years. A total of 1707 (15.58%) participants were diagnosed with AMS of which 5 progressed to HAPE. Compared with health controls, the mean domicile altitude of AMS patients (1787.94 ± 1005.86 vs. 1990.96 ± 916.18, $P < 0.001$) was lower, the mean workplace altitude of AMS patients (4654.38 ± 151.32 vs. 4510.76 ± 238.89, $P < 0.001$) was higher, and the mean oxygen saturation of

AMS patients (85.58 ± 5.02 vs. 86.85 ± 4.80, P < 0.001) was lower. Table 2 shows the characteristics of participants compared between health controls and AMS patients.

Table 2: Characteristics of participant

Characteristics	Health Controls (n=9249)	AMS Patients (n=1707)	*P* value
Gender, (%)			0.48
male	8806 (95.21)	1632 (95.61)	
female	443 (4.79)	75 (4.39)	
Age, (y)	36.06 ± 10.53	36.50 ± 10.25	0.11
Domicile altitude, (m)	1990.96 ± 916.18	1787.94 ± 1005.86	< 0.001
Workplace altitude, (m)	4510.76 ± 238.89	4654.38 ± 151.32	< 0.001
BMI, (kg/m^2)	22.89 ± 2.29	22.73 ± 2.40	0.01
Systolic blood pressure, (mmHg)	127.57 ± 11.85	129.09 ± 11.48	< 0.001
Diastolic blood pressure, (mmHg)	80.85 ± 8.78	80.94 ± 8.69	0.71
Oxygen saturation, (%)	86.85 ± 4.80	85.58 ± 5.02	< 0.001
Heart rate, (beats/min)	86.60 ± 10.29	88.44 ± 11.04	< 0.001
Dry rale			0.07
yes	208 (2.25)	51 (2.99)	
no	9041 (97.75)	1656 (97.01)	
Moist rale			0.55
yes	10 (0.11)	1 (0.06)	
no	9239 (99.89)	1706 (99.94)	
Heart murmurs			0.46
yes	6 (0.06)	2 (0.12)	
no	9243 (99.94)	1705 (99.88)	
Arrhythmias			0.46
yes	3 (0.03)	0 (0.00)	
no	9246 (99.97)	1707 (100.00)	
Nutritional status			< 0.001
excellent	1704 (18.42)	238 (13.94)	
good	6987 (75.54)	1360 (79.67)	
average or below	558 (6.03)	109 (6.39)	

Comparison of Decision Tree and Random Forest

We first tested two models, Decision Tree (DT) and RF. The accuracy of the two models in the test set was 75.69% and 80.32% respectively. In 10-fold cross-validation, the accuracy of the RF model was stable between 70% to 80%, with a mean accuracy of 77.76% ± 8.34%, while the accuracy of the DT model was stable between 30% to 70%, with a mean accuracy of 62.07% ± 13.44%. The accuracy of the RF model was higher than that of the DT model in all rounds. Figure 1 shows the accuracy of two models in 10-fold cross-validation.

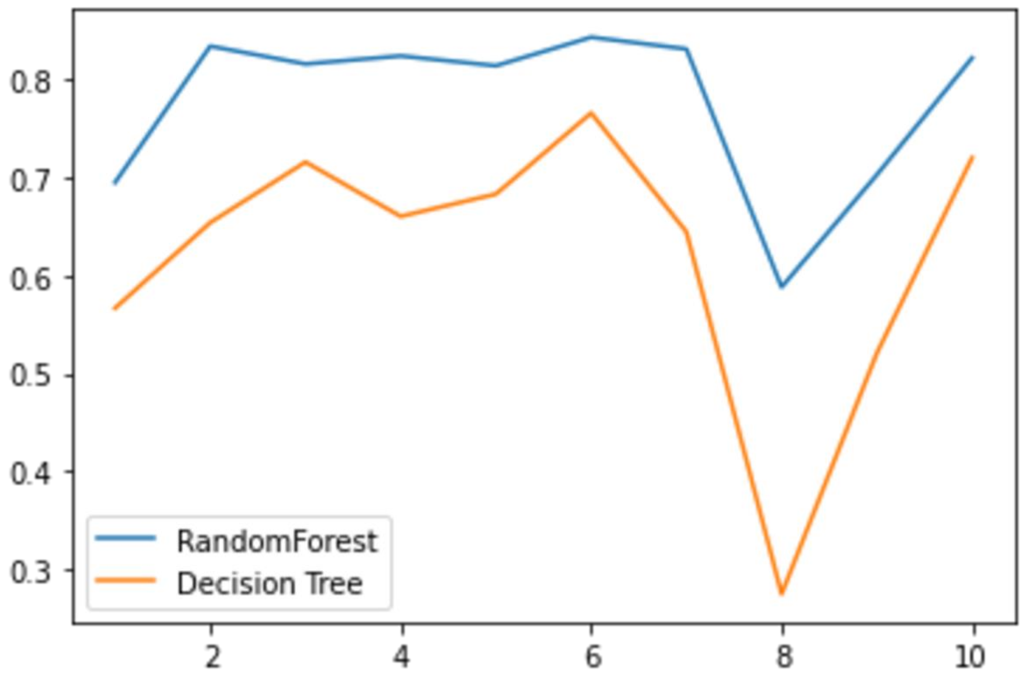


Figure 1: The accuracy of RF and DT models in 10-fold cross-validation

Effect of Feature Selection and Data Preprocessing on Model

We used the RF model to test the effects of feature selection and data preprocessing on models. After filtering by Variance Threshold and Chi-square. The results showed that there were no irrelevant features. Then we used the F-test and Mutual Information to filter the features and standardize the data. In 10-fold cross-validation, the results showed that F-test, Mutual Information, and Data Standardization did not significantly affect the accuracy of the RF model. Given the complexity of model deployment, we chose raw data for subsequent model building and optimization. Table 3 shows the effect of feature selection and data preprocessing on the accuracy of the RF model.

Table 3: The accuracy of the RF model after feature selection and data preprocessing

Feature Selection and Data Preprocessing	Accuracy (mean ± SD, %)
Data Standardization	74.47% ± 8.46%
Mutual Information	76.27% ± 9.36%
Mutual Information and Data Standardization	76.23% ± 9.51%
F-test	77.77% ± 7.64%
F-test and Data Standardization	77.83% ± 7.21%
Raw data	77.76% ± 8.34%

Results of Parameter Optimization on Random Forest

We optimized the key parameters of the RF model. The range of n_estimators was in 1~200 (step-size 10), the range of max_depth was in 1~20 (step-size 1), the range of max_features was in 3~14 (step-size 1), and the criterion parameter was tested by Gini and entropy. We found that the RF model showed the best performance when n_estimators = 101, max_depth = 11, max_features = 5, and criterion = “Gini”. The accuracy of the RF model was improved from 74.91% ± 2.33% before optimization to 78.12% ± 7.21% after optimization. Table 4 shows the accuracy of the RF model during parameter optimization.

Table 4: The accuracy of the RF model during parameter optimization

Parameter	Accuracy (mean ± SD, %)
Default values	74.91% ± 2.33%
Default values, n_estimators =101	75.74% ± 2.71%
Default values, n_estimators =101, max_depth =11	76.19% ± 1.92%
Default values, n_estimators =101, max_depth =11, max_features = 5	77.93% ± 2.59%
n_estimators=101， max_depth=11， max_features= 5， criterion="Gini"	78.12% ± 7.21%

Comparison of Random Forests with Other Models

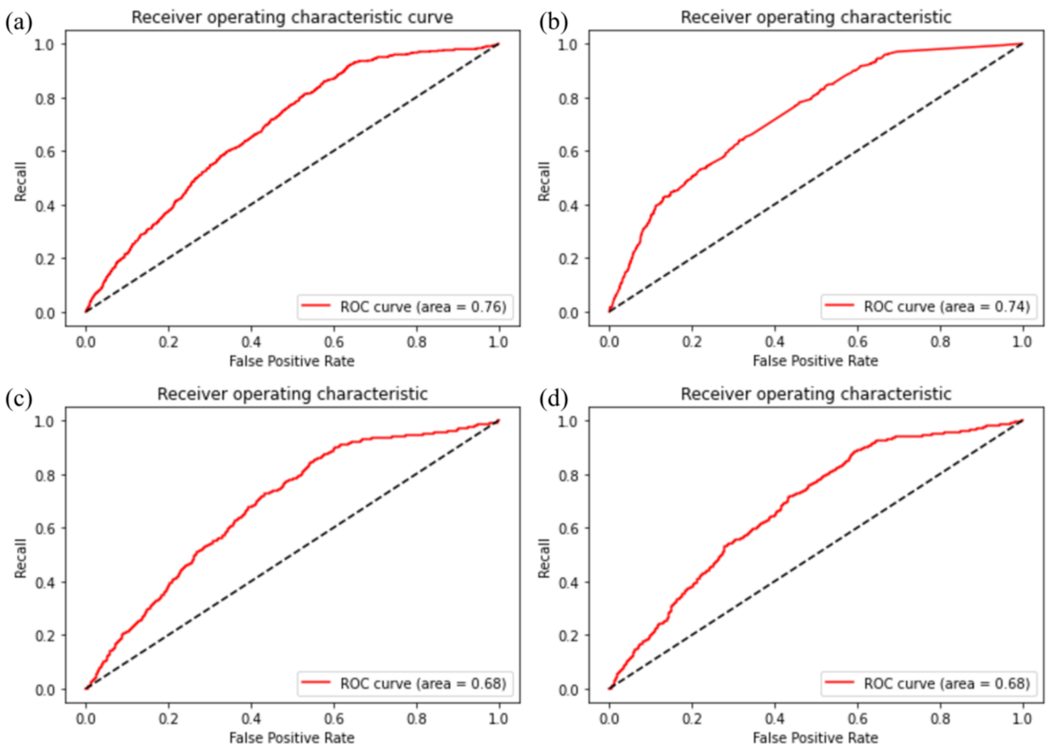
The RF model has been proven to perform well on our dataset. To develop the best AMS risk prediction model, we further tested the performance of three other models (LR, SVM, and XGBoost) on this dataset. In 10-fold cross-validation, the results showed that the RF and LR (L1 Regularization) models had the best performance, with the accuracy of 78.12% ± 7.21% and 78.01% ± 6.22% respectively, and the SVM (kernel = rbf) model had the lowest accuracy of 75.46% ± 5.99%. Table 5 shows the accuracy of four ML models.

Table 5: The accuracy of four ML models

Model	Accuracy (mean ± SD, %)
Random Forest	78.12% ± 7.21%
Logistic Regression (L1 Regularization)	78.01% ± 6.22%
Logistic Regression (L2 Regularization)	77.89% ± 6.03%
Support Vector Machine (kernel=linear)	76.49% ± 5.39%
Support Vector Machine (kernel=poly)	77.37% ± 6.74%
Support Vector Machine (kernel= rbf)	75.46% ± 5.99%
Support Vector Machine (kernel= sigmoid)	77.15% ± 4.82%
XGBoost	76.47% ± 4.83%

Note: All models were finished with the parameter optimizations

We plotted the Receiver Operating Characteristic (ROC) curves of the four models on the test set. The results showed that the AUC of the RF model was the largest, reaching 0.76, while the AUC of three other models was lower than that of the RF model. Figure 2 shows the AUC of four ML models.

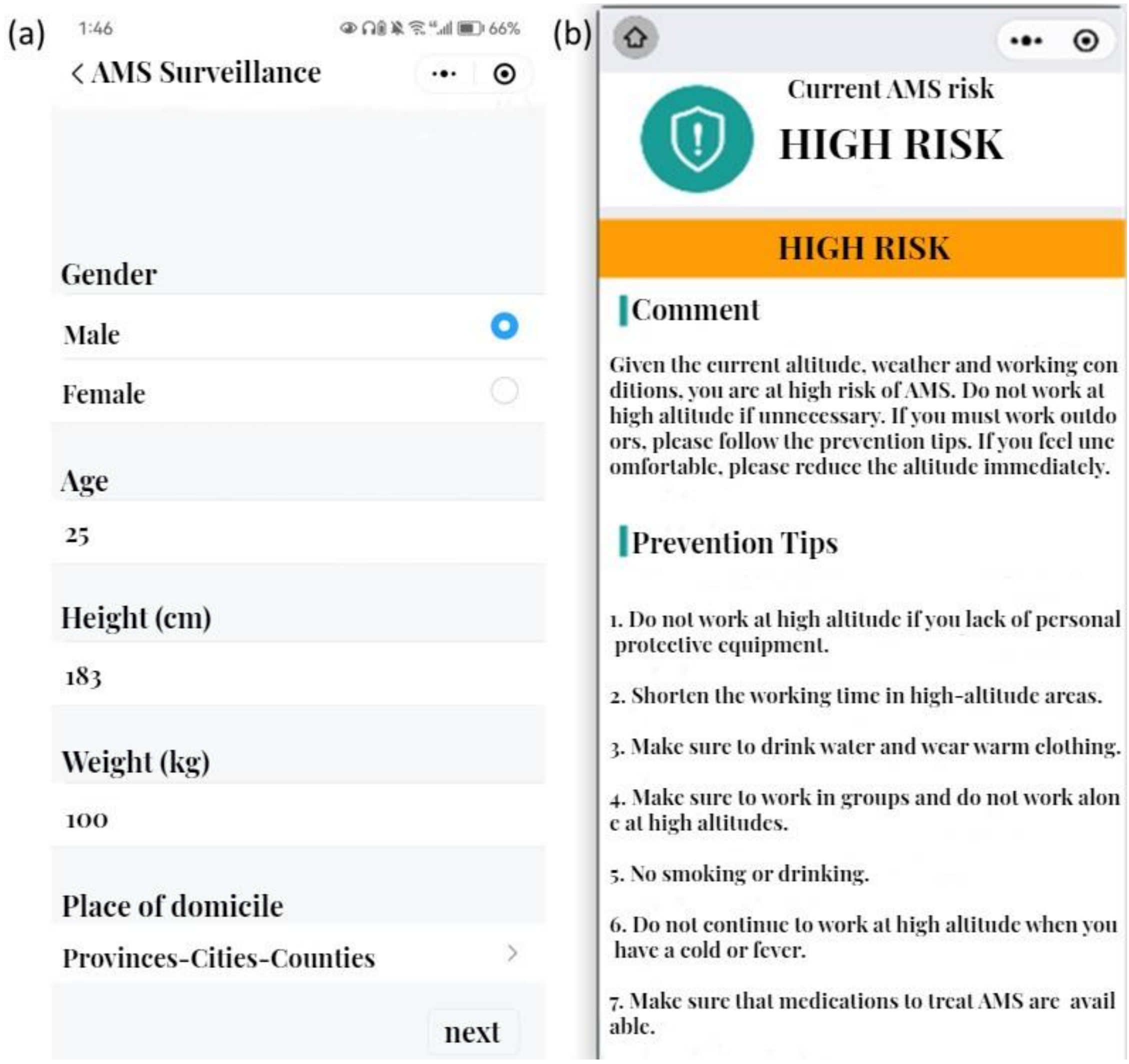


Note: (a): RF, (b): LR, (c): SVM, (d): XGBoost

Figure 2: The AUC of four ML models

Clinical Application

We chose the RF model as the AMS risk prediction model based on its best accuracy and AUC. Then we deployed the AMS risk prediction model into our AMS prediction system. The system can be easily used for clinical practice. Workers only need to input 12 variables used for prediction to derive the AMS risk. The system stratified AMS risk into low, medium, high, and extremely high, and provides workers with corresponding preventive measures. Figure 3 shows the layout and predicted result of the system.



Note: (a): layout, (b): the predicted result of high AMS risk

Figure 3: The layout and predicted result of the system.

Discussion

It is important to predict AMS risk for plateau workers. Compared with people who did not know their AMS risk, the AMS incidence in people who knew their AMS risk was relatively low(Luo *et al.*, 2013). In this study, we developed AMS risk prediction models using four ML algorithms combining twelve demographics, clinical, and altitude features. We found that the RF model had the best performance with accuracy and AUC of 78.12% ± 7.21%, and 0.76, respectively. Therefore, it is reasonable to believe that our AMS risk prediction model is robust and reliable. We further developed an AMS risk prediction system based on the AMS risk prediction model that can be used in clinical practice. The system can predict the AMS risk of plateau workers and provide them with corresponding preventive recommendations.

Although traditional parameter regression models perform well when variables have a linear relationship with the outcome. The relationships between variables and outcomes are not just linear. Compared with traditional parametric regression models, ML models perform better when variables and outcomes are non-linear, and can predict more accurately(Afrash *et al.*, 2023; Delen *et al.*, 2005). Other advantages of ML models include avoiding overfitting and selection bias(Cawley and Talbot, 2010). Several studies have been conducted to develop AMS risk prediction models using machine learning algorithms(Wei *et al.*, 2022; Yang *et al.*, 2023). However, the study population of previous studies was mostly under strict experimental simulation conditions, which could not reflect the real-world situation. And limited to the experimental conditions and costs, the sample sizes were small. The main distinguish of our study was that the dataset we used for model development was derived from the real world, which can well reflect the plateau work environment and had a sufficient sample size.

The main advantage of our study is the use of large-scale data from the Tibet-Ali project for modeling. Other advantages include the standardized diagnosis of AMS by uniformly trained medical workers, and the features used for the AMS risk prediction model are obtained easily. There are some limitations to this study. First, due to the self-limiting of AMS(Clarke, 2006), there may be missed cases, which may mislead the model. Second, due to the limitation of the dataset, the model did not include smoking(Vinnikov *et al.*, 2015), anxiety(Boos *et al.*, 2018), and other possible influencing factors. Third, we cannot perform external validation of the model due to the lack of high-quality datasets.

For future studies, large-scale surveys should be organized to obtain more real-world-based AMS monitor data to improve the AMS risk prediction model, and a variety of external validations of the model should be conducted to verify its performance and stability. The AMS risk prediction system should be deployed in occupational hazard prevention applications and its effectiveness in clinical practice will be further tested.

Conclusion

In conclusion, this study utilized 12 accessible features to develop four ML models for predicting AMS risk. The RF model had the highest accuracy and AUC, performing better than others. This model provided a reference for the construction of the AMS risk prediction system and helping medical workers guide decisions regarding AMS primary prevention.

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Declaration of Interest Statement

The authors declare that they have no conflict of interest.

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