IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received February 26, 2020, accepted April 2, 2020, date of publication April 6, 2020, date of current version April 22, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2986039

Relationship Between Health Status and Physical Fitness of College Students From South China: An Empirical Study by Data Mining Approach

JIAJUN WANG[1], ZIXIN XIE[2], YAN LI[3], YOUYI SONG[4], JINGWEN YAN[2,6], WEIHUA BAI[5], TENG ZHOU[2,4,6], AND JING QIN[4]

[1]Ministry of Sports, Shantou University, Shantou 515063, China
[2]College of Engineering, Shantou University, Shantou 515063, China
[3]Second Affiliate Hospital, Shantou University Medical College, Shantou 515063, China
[4]Centre for Smart Health, School of Nursing, The Hong Kong Polytechnic University, Hong Kong
[5]School of Computer Science and Software, Zhaoqing University, Zhaoqing 526061, China
[6]Key Laboratory of Intelligent Manufacturing Technology, Shantou University, Ministry of Education, Shantou 515063, China

Corresponding authors: Weihua Bai (bandwerbai@gmail.com) and Teng Zhou (zhouteng@stu.edu.cn)

This work was supported in part by NSFC under Grant 61902232, in part by the Natural Science Foundation of Guangdong Province under Grant 2018A030313291, in part by the Department of Education of Guangdong Province under Grant 2018GXJK048 and Grant 2019KTSCX199, in part by the Higher Education Reform Project of Guangdong Province under Grant 2018180247, in part by the Guangdong Special Cultivation Funds for College Students' Scientific and Technological Innovation under Grant pdjh2020b0222, in part by The Hong Kong Polytechnic University under Grant 1ZE8J, and in part by the Special Grant from the Li Ka Shing Foundation.

ABSTRACT This study aims to reveal the scientific associations between the motor competence related physical fitness and the medical health status of college students from south China. Two hundred and fourteen college students, including 112 males and 102 females, from 17 provinces were administrated with the Shantou University fitness test battery twice. All the subjects were asked for a medical examination, including a questionnaire and a physical examination. The records were assessed and concluded by three expertise medical practitioners. A machine learning model equipped with a new loss was designed to deal with the *soft* label issue. Armed with the trained model, we mine and highlight the relationship between the motor competence related physical fitness and the medical health status of the college students. The physical educators, the educational authorities, the universities, and the individuals may potentially benefit from this study.

INDEX TERMS Physical fitness, medical examination, data mining, machine learning, sport science.

I. INTRODUCTION

The medical health status (MHS) of college students attracts widespread attention from the authorities, educators, and researchers. Although the annual routine medical examination is generalized for college students in China, it is expensive yet difficult for healthcare professionals to provide an overall personal health report for every student according to the medical check-up with a large number of parameters immediately. Furthermore, the correlations among the examination results and the examination results to the physical fitness are still not fully explored. In fact, such explorations are difficult, if not impossible, since the growing number of complex examination results, the longitudinal records, and the correlations from the personal and interpersonal participants are hardly manually analyzed [1].

Motor competence related physical fitness (MCPF) is of critical importance for individual physical fitness [2], which involves a series of factors, such as cardiorespiratory fitness, musculoskeletal fitness, body mass index, and flexibility. The level of MCPF is demonstrated by the vigor for physical activities and fatigue resistance [3]. Specifically, the muscular strength and cardiorespiratory function are the leading markers for health [4], [5]. Recent studies consistently reported the development of motor competence related physical fitness is associated with the improvement of personal health status [6]–[8]. Based on this evidence, the physical fitness for college students is relevant from a public health point

The associate editor coordinating the review of this manuscript and approving it for publication was Juan A. Lara.

of view [9]. In this regard, a deep understanding of the motor attributes and the underlying causative mechanisms are required for the positive trajectories of MCPF [10].

Although the physical fitness test for the college students is administrated annually, the relationship between the MHS and the MCPF of the college students remains thoroughly unexamined [11]. Thus, the present study aims to reveal the relationship between motor competence related physical fitness to the later medical health condition using a machine learning based data mining technique. In this study, we designed a fitness test battery, and tested it on 214 college students from south China. Then, the subjects were asked to take medical examinations. The examination results were assessed by three expertise medical practitioners from the Centre for Smart Health and the Second Affiliate Hospital of Shantou University Medical College. Third, we formulate such a data mining task as a classification problem. To achieve this, we design a feature extraction scheme to extract features from the STUFIT battery. A machine learning based model is employed to learn the relationship between the MCPF and the HMS. To deal with the *soft* label issue, we integrate a new loss function in our learning based model. Armed with the learned model, we mine and highlight the correlations between the items of MCPF and the records of the medical examination.

Our belief is that the learned model can be used to support the decision of physical educators rather than to replace them. So the primary goal of this study is to draw the attention from physical educators to adjust the physical teaching program according to the individual medical health status. Moreover, the following parties can also be benefited from this study.

- The educational authorities can make or revise public health policies based on the records of the physical fitness of the college students.
- The universities can better understand the physical fitness and health status of their students.
- The individuals can be motivated to improve their health status by the suggestion to a certain physical exercise.

The rest of the paper is organized as follows. Section II describes the materials and methods for this study. Section III details the outcomes resulted from the machine learning based methods, and discusses correlations of the results. Section IV concludes the work and the findings in this study.

II. MATERIALS AND METHODS

A. THE STUFIT BATTERY

We designed a fitness test battery, termed the Shantou University fitness test (STUFIT) battery. A total of 214 students, including 112 boys and 102 girls aged 18 to 20, were recruited from 17 provinces of south China. Informed consents were waived, since there is no *in vivo* human experimentation. The study protocol was designed following the guidelines outlined in the Declaration of Helsinki and approved by the Ethics Committee of the Faculty of Physical Education, Shantou University. Personal identifiers of the data are kept strictly confidential. The battery was conducted from September 2016 to November 2016.

The STUFIT battery consists the following tests, e.g. the weight and height of anthropometry, lung capacity test, long-distance running for the cardiorespiratory fitness, body flexion test for the flexibility, 50-meters running for the speed-agility, standing long jump test, and pull-up (sit-up for girls) for muscular strength and endurance. Each student was assessed individually for all tests by three professional evaluators using standardized equipment. The time spent was measured in each test. The test was terminated when the subject felt uncomfortable. To assess the test-retest reliability, we administered the STUFIT battery twice under the same physical conditions by the same evaluators. The two assessments were conducted two months apart. The students were required to wear sports clothing and footwear during testing. Before the tests were applied, the students were asked for a five-minute warm-up to activate their full-bodies to achieve their best performance. The tests were divided into two groups, boys and girls, as the physical batteries are different. The boys have good muscle strength, while the girls have great body flexibility. The evaluators were continually encouraging the students to achieve their best performances. The whole test lasts one hour with each battery interval of eight minutes. Test data were strictly recorded by the evaluators.

The anthropometry includes height (cm) and weight (kg), which were measured without shoes and with light clothing. Then, the body mass index (BMI) was calculated. BMI is a commonly used index for obesity, which requires our further attention for whose BMI is higher than the standard.

The cardiopulmonary function was assessed by spirometry tests and long-distance running. The lung capacity test was measured by an electronic spirometric tester (HADTZCS-3, Hengaode Beijing Inc.). We installed a new sterilized blowing mouth on the spirometric tester for every student. The lung capacity level was measured by inhaling deeply and trying best to blow the air into the blowing mouth. The spirometric tester automatically takes the largest value of the first and second run as the final result. The results were automatically uploaded to a workstation equipped with a stock software suite. These results were recorded in milliliters (ml). The long-distance running is employed to indirectly evaluate the lung capacity, since a large amount of oxygen is needed during the running. Larger lung capacity needs a lower breathing frequency. The boys were required to participate in a 1 km run test, while the girls did 0.8 km test. The time spent for the long-distance running was recorded. Therefore, cardiorespiratory fitness could be more accurately evaluated.

The flexibility was assessed by a body flexion test. Each student sat on the mat, and kept the legs close together and the knees joint straight. A 50 cm wide, 30 cm high three-sided box framed above the legs. The hands were required to keep straight to touch the edge of the box as far as possible. The results were recorded in centimeters (cm). The purpose of this test is to measure the range of the activity that the torso, the waist, and the hip can reach, which reflects the level of development of the stretching and elasticity of the joints, ligaments and muscles in these areas, and the level of physical flexibility.

The speed-agility was measured by the duration of 50-meters running. When hearing the instructions, the students began to run as fast as possible between two parallel lines drawn on the athletics track. The time spent was be recorded by two professional evaluators. This test measures the students' speed and reaction.

The muscular strength and endurance were assessed by the standing long jump test and the pull-up (sit-up for girls). The student stood behind a line marked on the ground with the feet slightly apart. The student took off and landed using both feet, swinging the arms and bending the knees to provide forward drive. The students performed three jumps and the best one was recorded in centimeters (cm). The pull-up test refers to the hanging exercise, relying on one's self-strength to overcome his weight, which aims to test the development level of upper body muscular strength. The maximum attempts of pull-up were recorded.

The second run was the same as the previous one after two months. We averaged the measurements of these two tests as the final result. We used Person's relevance to analyze the correlation between the STUFIT battery physical tests. The level of significance is set to $P < 0.05$ for all analysis. All the statistical procedures were conducted using SPSS v.19.0.

B. MEDICAL EXAMINATION

The medical examination involves three parts, a questionnaire, a physical examination, and a result assessment by three expertise medical practitioners.

First, we design a questionnaire for the students as shown in Table 1, which helps us to learn the subjects' medical history, and to exclude who does not meet the criteria of our study.

TABLE 1. Illustration of the first section in our questionnaire.

Have you or your family members suffered from any of the following diseases: have suffered (✓), not have suffered (×)
☐ 1.1 Hepatitis, tuberculosis and other infectious diseases ☐ 1.2 Mental neurological diseases ☐ 1.3 Cardiovascular diseases ☐ 1.4 Digestive diseases ☐ 1.5 Nephritis and urinary system diseases ☐ 1.6 Anemia and blood system diseases ☐ 1.7 Diabetes and endocrine diseases ☐ 1.8 Malignant tumor ☐ 1.9 Other chronic diseases
Please write down the name of the disease:

Second, the students were assigned for a physical examination in the university hospital. The physical examination comprises the following check-ups including body function, internal medicine, surgery, ear, nose and throat (ENT), and blood tests, e.g. blood lipid test, blood sugar test, and kidney function test. The vital signs include blood pressure and pulse, which are measured by a blood pressure detector (KT35-ABPM50, Zhongxiyuanda Beijing Inc.). The heart examination by an electrocardiogram (EEG) recorded the rhythm, rate and electrical activity for internal medicine. Other examinations were also carried out strictly under hospital standards if further required.

Finally, these test results were sent to three expert medical practitioners from the Centre for Smart Health, the Kong Hong Polytechnic University and the Second Affiliate Hospital of Shantou University Medical College. Two medical practitioners analyzed the test results, independently. They concluded which level of medical health status a subject belongs to, e.g. good condition, fair condition, or serious condition. The levels are revised from the suggestion of the American Hospital Association [12]. The good condition means the vital signs of a subject are stable in the normal range, and the indicators are excellent. The fair condition is defined as a state with some disturbances in psychological behaviors or physical characteristics, without typical pathologic features. The serious condition is the vital signs of a subject are continually unstable in the abnormal range, and the indicators are questionable. Once the two conclusions are different, the third medical practitioners participate in the final decision. However, the health status in this study is a *soft* label, which means the label is fuzzy to a certain degree, and not exclude from each other.

C. MACHINE LEARNING BASED DATA MINING FRAMEWORK

In order to reveal the underlying correlations of the HMS and the MCPF, we employ a machine learning based data mining technique. We formulate the association of the HMS and the MCPF as a classification problem. To achieve this, we develop an enhanced learning framework based on the XGBoost algorithm. The XGBoost is an end-to-end tree boosting system, which provides a faster and more accurate way to handle classification and regression tasks. The key idea of XGBoost is to weight the predictors and keep the new decision trees away from the misclassification by the previous decision trees, which is the same with most boosting algorithms, but greatly improved by the gradient boosting machine [13].

We denote x_i as the result of the STUFIT battery for the ith student. As suggested in literature [12], the health status is classified into three *soft* levels, that is in good condition, fair condition, or serious condition. We denote $y_i \in \{1, 2, 3\}$ as the level of the health status for the ith student, where $y_i = 1$ means the health status of the ith student is in good condition, $y_i = 2$ means the health status of the ith student is in fair condition, and $y_i = 3$ means the health status of the ith student is in serious condition. Thus, the results of the STUFIT battery and the health status for the ith student is denoted as (x_i, y_i). Our task is to investigate whether can a model learn to establish the correlations between the results of the STUFIT battery and the health status for every subject student.

To achieve this, we construct a dataset as $D = \{(x_i, y_i)\}$, where $x_i \in \mathbb{R}^m$, $y_i \in \mathbb{R}$, n is the number of the students, and m is the number of items in STUFIT battery. Then, we add K functions of the results of the STUFIT battery to predict the health status.

$$\hat{y}_i = \varphi(x_i) = \sum_{k=1}^{K} f_k(x_i), \tag{1}$$

where each additive function f_k corresponds to an independent tree structure α and leaf weights ω, expressed as $f_k(x) = \omega_{\alpha(x)}, \alpha \in \mathbb{R}_T, \alpha : \mathbb{R}^d \to \{1, 2, \ldots, T\}$.

To learn the set of functions used in Eq. 1, we minimize a regularized cost function in Eq. 2.

$$L(\varphi) = \sum_i l(\hat{y}_i, y_i) + \sum_k \Phi(f_k), \tag{2}$$

where $\Phi(f) = aT + \frac{1}{2}b\|\omega\|^2$. l is a differentiable convex loss function that measure the difference between the prediction $\hat{y}_i$ and the target y_i. The $l(\hat{y}_i, y_i)$ in the first term represents how well the model fits the ith sample. The second term Φ is a regular term, which eliminates the complexity of the model to avoid over-fitting. More details about the XGBoost can be found in Chen and Guestrin [13].

In this work, the health status of a student is a soft label, which means the level of health status is fuzzy rather than mutually exclusive. The conventional loss function, e.g. *softmax*, equipped in XGBoost is not appropriate, since the exponential function leads too fast saturation. Thus, we integrate a new loss function based on *Bernoulli* distribution, which can be used for multi-label classification when the labels are not mutually exclusive. The new loss function is denoted in Eq. 3.

$$l(y_i, \hat{y}_i) = y_i \ln(1 + e^{-\hat{y}_i}) + (1 - y_i) \ln(1 + e^{\hat{y}_i}) \tag{3}$$

Then, we rewrite Eq. 2 as

$$L^{(t)} = \sum_{i=1}^{n} [y_i \ln(1 + e^{-(\hat{y}_i^{(t-1)} + f_t(x_i))}) + (1 - y_i) \ln(1 + e^{(\hat{y}_i^{(t-1)} + f_t(x_i))})] + \Phi(f_t). \tag{4}$$

To optimize the model equipped with the new loss, we deduce the first-order partial derivative and the second-order partial derivative for the gradient descent algorithm. The first-order partial derivative for the new loss can be deduced as

$$\frac{\partial l(y_i, \hat{y}_i^{(t-1)})}{\partial \hat{y}_i^{(t-1)}} = -y_i(1 - \frac{1}{1 + e^{-\hat{y}_i^{(t-1)}}}) + (1 - y_i)\frac{1}{1 + e^{-\hat{y}_i^{(t-1)}}} = \frac{1}{1 + e^{-\hat{y}_i^{(t-1)}}} - y_i. \tag{5}$$

The second-order partial derivative for the new loss can be deduced as

$$\frac{\partial^2 l(y_i, \hat{y}_i^{(t-1)})}{(\partial \hat{y}_i^{(t-1)})^2} = \frac{e^{-\hat{y}_i^{(t-1)}}}{(1 + e^{-\hat{y}_i^{(t-1)}})^2} \tag{6}$$

In this way, we can easily obtain an optimal tree structure to achieve high accuracy and speed up the training process.

III. RESULTS & DISCUSSION

The medical examination results are reviewed by two expertise medical practitioners, independently. The review is double-blind. The third medical practitioner intervenes in the review, once the health status is contradictorily concluded by the first two practitioners. The students' health status assessed by the medical practitioners is shown in Table 2. Ninety-three male college students and eighty female college students were in good health condition. Nineteen male college students and twenty-two female college students were in fair health conditions. No male or female students were in serious health conditions.

TABLE 2. The level of health status for the college students from South China.

	Male	Female
Good condition	93	80
Fair condition	19	22
Serious condition	0	0
Total	112	102

A. DESIGN DECISION

We aim to mine the correlations between the test results of the STUFIT battery and the health status of the college students from south China. We process the physical fitness tests separately for boys and girls. We normalize the physical fitness test results, and transform the normalized results into a vector of features. The data is divided into two parts, e.g. 70% for training, and the rest for evaluation.

We use two commonly-used criteria to quantitatively evaluate how well the proposed framework learns the correlations between the test results of the STUFIT battery and the medical health status of the college students. The first one is the accuracy criteria.

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

where TP, TN, FP and FN are true positives, true negatives, false positives, and false negatives, respectively. Since the accuracy is a description of systematic errors, we employ the second criteria call F_α-score to obtain a more balanced evaluation by considering the recall and the precision.

$$F_\alpha = \frac{(1 + \alpha^2)TP}{(1 + \alpha^2)TP + \alpha^2 FN + FP}, \tag{8}$$

where α balances the importance between the recall and the precision. We consider the recall and the precision are equally important, so we let $\alpha = 1$ in this study. Note that the best F_α-score is 1, while the worst is 0.

B. MODEL TRAINING

We compare the proposed framework with other frequently-used classifiers, e.g. naive Bayes (NB), artificial neural

TABLE 3. The accuracy and $F_1 - score$ of our framework comparing with other classifiers.

	Boys		Girls	
	Accuracy(%)	$F_1 - score$	Accuracy(%)	$F_1 - score$
DT	85.29%	0.915	83.97%	0.906
KNN	91.18%	0.951	74.19%	0.840
SVM	88.24%	0.938	87.10%	0.931
NB	85.20%	0.921	93.55%	0.962
ANN	83.78%	0.906	80.00%	0.885
XGBoost	94.12%	0.968	90.32%	0.943
Ours	97.06%	0.984	96.77%	0.963

network (ANN), support vector machine (SVM), k-nearest neighbors (KNN), decision tree (DT), and XGBoost. The evaluation criteria of accuracy and F_α-score of the proposed framework and the control methods are listed in Table 3. The naive Bayes classifiers are a family of simple probabilistic based on applying Bayes theorem with naive independence assumptions between the features, which is often used as a baseline for the data mining tasks. The artificial neural network is a kind of mathematical model for information processing or intelligent operation using the structure of synaptic connections similar to the brain, which stimulates the activity of neurons with a mathematical model. The support vector machines avoid the complexity of high-dimensional space and are not vulnerable to be affected. Compared with the KNN and DT models, the SVM achieves relatively higher accuracy. The decision tree needs a large dataset to make reliable estimations for classification, and it is difficult to process multi-category classification with limited samples, so it yields the lowest accuracy of 85.29% for boys and 83.97% for girls. In addition, the redundances between features also degrade the performance of KNN. For both boys and girls, the results of the accuracy obtained by ANN, XGBoost, and the proposed framework range from 80% to 97%, whereas our enhanced learning framework achieves the highest accuracy, respectively. It is because the Bernoulli loss function equipped in our framework can accurately and effectively maximize the differences of the predictions and the groundtruth. We notice that the F_1-score has the same trend as the accuracy. Obviously, our method achieves the best accuracy and the highest F_1-score, because our framework captures the distinguished features and effectively eliminates the influence of skewed data.

C. RESULTS & DISCUSSIONS

Armed with the well-trained machine learning framework, we establish the relationship between the medical examination results and the physical fitness of the college students. The test results of the STUFIT battery are described in Table 4. The correlation coefficient of the STUFIT battery for boys is listed in Table 5, and the correlation coefficient of the STUFIT battery for girls is listed in Table 6. From Table 4, Table 5 and Table 6, we can see that the STUFIT battery is feasible, without any major problem when it was administrated.

We find that excess weight has become a health problem in college students from south China. The medical examination reports reveal a positive correlation between the excess

TABLE 4. The test results of the STUFIT battery. The first run is denoted as Test #1, and the second run is denoted as Test #2.

	Boys		Girls	
	Test #1	Test #2	Test #1	Test #2
Weight (kg)	60.62±8.48	61.64±10.02	50.95±6.96	50.73±6.77
Height (cm)	173.89±5.52	172.72±5.94	160.19±5.48	160.69±5.32
Body mass index (kg/m^2)	20.04±2.53	20.63±2.96	19.84±2.40	19.63±2.27
Lung capacity (cc)	3731.88±752.56	3769.17±780.84	2471.83±512.69	2493.58±528.25
Body flexion test (cm)	8.90±7.26	8.44±7.74	11.90±6.59	13.75±7.03
Standing long jump (m)	2.23±0.20	2.23±0.23	1.60±0.16	1.63±0.18
50-meters running (s)	7.65±0.46	7.73±0.74	9.82±0.88	9.73±1.05
1 km running (s)	269.382±36.93	268.03±37.43	254.22±34.46	256.84±30.89
Pull-up (times)	3.21±3.34	3.77±3.63	–	–
Sit-up (times)	–	–	32.26±7.39	33.41±8.70

TABLE 5. The correlation coefficient (*P*) of the STUFIT battery for boys.

	Height	Weight	Lung capacity	Body flexion	50-meters running	Standing long jump	Pull-up	1 km running
Height	–	0.409**	0.337**	0.331**	0.011	0.190*	0.285**	0.029
Weight	0.409**	–	0.407**	0.043	0.297**	0.160	0.469**	0.185
Lung capacity	0.337**	0.407**	–	0.044	0.061	0.133	0.179	0.072
Body flexion	0.331**	0.043	0.044	–	0.140	0.105	0.259**	0.226**
50-meters running	0.011	0.297**	0.061	0.140	–	0.503**	0.356**	0.304**
Standing long jump	0.190*	0.160	0.133	0.105	0.503**	–	0.274**	0.270**
Pull-up	0.285**	0.469**	0.179**	0.259**	0.356**	0.274**	–	0.246**
1 km running	0.029	0.185	0.072	0.226**	0.304**	0.270**	0.246**	–

*Significant correlation $p < 0.01$ (two sides).
**Significant correlation $p < 0.05$ (one side).

TABLE 6. The correlation coefficient (*P*) of the STUFIT battery for girls.

	Height	Weight	Lung capacity	Body flexion	50-meters running	Standing long jump	Sit-up	0.8 km running
Height	–	0.438**	0.365**	0.127	0.065	0.006	0.186	0.175
Weight	0.438**	–	0.476**	0.142	0.069	0.049	0.053	0.134
Lung capacity	0.365**	0.476**	–	0.115	0.043	0.099	0.027	0.104
Body flexion	0.127	0.142	0.115	–	0.028	0.286**	0.042	0.170
50-meters running	0.065	0.069	0.043	0.028	–	0.462**	0.401**	0.359**
Standing long jump	0.006	0.049	0.099	0.286**	0.462**	–	0.211**	0.466**
Sit-up	0.186**	0.053**	0.027**	0.042**	0.401**	0.211**	–	0.224**
0.8 km running	0.175	0.134	0.104	0.170	0.359**	0.466**	0.224**	–

*Significant correlation $p < 0.01$ (two sides).
**Significant correlation $p < 0.05$ (one side).

weight to the incidence of cardiovascular diseases, which is consistent with previous studies [14]–[16]. An inverse correlation was detected among the weight and the speed-related motor. This can be explained by the increased fat mass that may slow the acceleration of entire body mass [17]. In this regard, the BMI is a critical important index, which should be paid more attention to college students.

The lung capacity is a functional index in the standard medical examination. As shown in Table 5 and Table 6, the weight and height have a close relationship to the lung capacity. A student with heavier weight and taller height often has a larger lung capacity, since more oxygen is needed. However, the students with larger lung capacity did not always perform well in long-distance running tests.

From Table 4, the students do not perform very well for standing long jump and pull-up of the STUFIT battery. For the boys, the pull-up shows a positive relationship with the weight, whereas the weight of the girls does not demonstrate a positive relationship with the sit-up. Another positive association between cardiorespiratory function in medical examination and the times of pull-up or sit-up. A few studies have also investigated the relationship between the cardiorespiratory fitness and muscle strength and endurance by walk/run test, and confirm the positive relationships [18]–[22].

D. LIMITATIONS

We did not reveal the relationship between every kind of medical examination results and the physical fitness test battery. This study does not analyze the association of the physical fitness, such as cardiorespiratory fitness, motor agility, or muscular fitness on cognitive performance, since a lot of works [23]–[26] have done. We do not explore the association between physical fitness and academic achievements among college students, which would be interesting. Our model is general, and can be extended other applications, such as traffic flow modeling [27]–[35], biomedical computing [36]–[38], intelligent computing [39]–[41] and algebraic immunity [42]–[45].

IV. CONCLUSION

In this study, we explore the relationship between physical fitness and the reports of the medical examination of college students from south China. To achieve this, we first design a physical fitness test battery, termed STUFIT battery. The STUFIT battery was administrated on 214 students from 17 provinces of south China double times. Then, all subjects were required to have a medical examination. The examination results were evaluated by three expertise medical practitioners. We established a machine learning model for data mining, and we also evaluated our framework with common state-of-the-art models. The empirical study demonstrate that our model can learn to identify the health status from the test results of the STUFIT battery. Armed with the learned model, pairs of positive correlations between the test results of the STUFIT battery and the health status are finally revealed.

DECLARATION OF COMPETING INTEREST

The authors declare there are no conflicts of interest regrading the publication of this paper.

REFERENCES

[1] L. Chen, X. Li, Y. Yang, H. Kurniawati, Q. Z. Sheng, H.-Y. Hu, and N. Huang, "Personal health indexing based on medical examinations: A data mining approach," *Decis. Support Syst.*, vol. 81, pp. 54–65, Jan. 2016.

[2] M. Brandes *et al.*, "Physical fitness," in *Instruments for Health Surveys in Children and Adolescents*. Cham, Switzerland: Springer, 2019, pp. 277–289.

[3] M. T. Cattuzzo, R. dos Santos Henrique, A. H. N. Ré, I. S. de Oliveira, B. M. Melo, M. de Sousa Moura, R. C. de Araújo, and D. Stodden, "Motor competence and health related physical fitness in youth: A systematic review," *J. Sci. Med. Sport*, vol. 19, no. 2, pp. 123–129, Feb. 2016.

[4] F. B. Ortega, J. R. Ruiz, M. J. Castillo, and M. Sjöström, "Physical fitness in childhood and adolescence: A powerful marker of health," *Int. J. Obesity*, vol. 32, no. 1, pp. 1–11, Jan. 2008.

[5] J. R. Ruiz, J. Castro-Piñero, E. G. Artero, F. B. Ortega, M. Sjostrom, J. Suni, and M. J. Castillo, "Predictive validity of health-related fitness in youth: A systematic review," *Brit. J. Sports Med.*, vol. 43, no. 12, pp. 909–923, Nov. 2009.

[6] E. G. Artero, J. R. Ruiz, F. B. Ortega, V. España-Romero, G. Vicente-Rodríguez, D. Molnar, F. Gottrand, M. González-Gross, C. Breidenassel, L. A. Moreno, and A. Gutiérrez, "Muscular and cardiorespiratory fitness are independently associated with metabolic risk in adolescents: The HELENA study," *Pediatric Diabetes*, vol. 12, no. 8, pp. 704–712, Dec. 2011.

[7] F. B. Ortega, K. Silventoinen, P. Tynelius, and F. Rasmussen, "Muscular strength in male adolescents and premature death: Cohort study of one million participants," *BMJ*, vol. 345, no. 3, p. e7279, Nov. 2012.

[8] J. J. Smith, N. Eather, P. J. Morgan, R. C. Plotnikoff, A. D. Faigenbaum, and D. R. Lubans, "The health benefits of muscular fitness for children and adolescents: A systematic review and meta-analysis," *Sports Med.*, vol. 44, no. 9, pp. 1209–1223, Sep. 2014.

[9] C. Cadenas-Sanchez, B. Martinez-Tellez, G. Sanchez-Delgado, J. Mora-Gonzalez, J. Castro-Piñero, M. Löf, J. R. Ruiz, and F. B. Ortega, "Assessing physical fitness in preschool children: Feasibility, reliability and practical recommendations for the PREFIT battery," *J. Sci. Med. Sport*, vol. 19, no. 11, pp. 910–915, Nov. 2016.

[10] H. W. Kohl and K. E. Hobbs, "Development of physical activity behaviors among children and adolescents," *Pediatrics*, vol. 101, no. 2, pp. 549–554, 1998.

[11] O. Yarmak, Y. Galan, A. Hakman, L. D. B. Oleksandra, and T. Yurii, "The use of modern means of health improving fitness during the process of physical education of student youth," *J. Phys. Educ. Sport*, vol. 17, no. 3, pp. 1935–1940, 2017.

[12] *AHA: Advisory: HIPAA Updated Guidelines for Releasing Information on the Condition of Patients*, Amer. Hospital Assoc., Chicago, IL, USA, 2008, pp. 1–28.

[13] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining (KDD)*, 2016, pp. 785–794.

[14] R. Bass and I. Eneli, "Severe childhood obesity: An under-recognised and growing health problem," *Postgraduate Med. J.*, vol. 91, no. 1081, pp. 639–645, Nov. 2015.

[15] E. J. Gallagher and D. LeRoith, "Obesity and diabetes: The increased risk of cancer and cancer-related mortality," *Physiol. Rev.*, vol. 95, no. 3, pp. 727–748, Jul. 2015.

[16] G. O. Collaborators, "Health effects of overweight and obesity in 195 countries over 25 years," *New England J. Med.*, vol. 377, no. 1, pp. 13–27, 2017.

[17] E. D'Hondt, B. Deforche, I. De Bourdeaudhuij, and M. Lenoir, "Relationship between motor skill and body mass index in 5-to 10-year-old children," *Adapted Phys. Activity Quart.*, vol. 26, no. 1, pp. 21–37, Jan. 2009.

[18] M. Haga, "The relationship between physical fitness and motor competence in children," *Child, Care, Health Develop.*, vol. 34, no. 3, pp. 329–334, May 2008.

[19] M. Haga, "Physical fitness in children with high motor competence is different from that in children with low motor competence," *Phys. Therapy*, vol. 89, no. 10, pp. 1089–1097, Oct. 2009.

[20] S. A. Pereira, A. T. Seabra, R. G. Silva, W. Zhu, G. P. Beunen, and J. A. Maia, "Correlates of health-related physical fitness levels of portuguese children," *Int. J. Pediatric Obesity*, vol. 6, no. 1, pp. 53–59, Feb. 2011.

[21] V. P. Lopes, J. A. R. Maia, L. P. Rodrigues, and R. Malina, "Motor coordination, physical activity and fitness as predictors of longitudinal change in adiposity during childhood," *Eur. J. Sport Sci.*, vol. 12, no. 4, pp. 384–391, Jul. 2012.

[22] V. Vedul-Kjelsås, H. Sigmundsson, A.-K. Stensdotter, and M. Haga, "The relationship between motor competence, physical fitness and self-perception in children," *Child, Care, Health Develop.*, vol. 38, no. 3, pp. 394–402, May 2012.

[23] I. Esteban-Cornejo, C. Cadenas-Sanchez, O. Contreras-Rodriguez, J. Verdejo-Roman, J. Mora-Gonzalez, J. H. Migueles, P. Henriksson, C. L. Davis, A. Verdejo-Garcia, A. Catena, and F. B. Ortega, "A whole brain volumetric approach in overweight/obese children: Examining the association with different physical fitness components and academic performance. The ActiveBrains project," *NeuroImage*, vol. 159, pp. 346–354, Oct. 2017.

[24] S.-C. Kao, D. R. Westfall, A. C. Parks, M. B. Pontifex, and C. H. Hillman, "Muscular and aerobic fitness, working memory, and academic achievement in children," *Med. Sci. Sports Exerc.*, vol. 49, no. 3, pp. 500–508, Mar. 2017.

[25] S. Esmaeilzadeh, E. Hartman, R. Farzizadeh, L. Azevedo, H. A. Kalantari, I. Dziembowska, A. Kostencka, M. Narimani, and A. Abravesh, "Association between physical and motor fitness with cognitive performance in youths," in *Biology of Sport*. Termedia Publishing, Jul. 2018.

[26] A. Moradi, E. S. Damirchi, M. Narimani, S. Esmaeilzadeh, I. Dziembowska, L. B. Azevedo, and W. L. do Prado, "Association between physical and motor fitness with cognition in children," *Medicina*, vol. 55, no. 1, p. 7, 2019.

[27] T. Zhou, G. Han, X. Xu, Z. Lin, C. Han, Y. Huang, and J. Qin, "δ-agree AdaBoost stacked autoencoder for short-term traffic flow forecasting," *Neurocomputing*, vol. 247, no. 4, pp. 31–38, 2017.

[28] T. Zhou, G. Han, X. Xu, C. Han, Y. Huang, and J. Qin, "A learning-based multimodel integrated framework for dynamic traffic flow forecasting," *Neural Process. Lett.*, vol. 49, no. 1, pp. 407–430, Feb. 2019.

[29] T. Zhou, D. Jiang, Z. Lin, G. Han, X. Xu, and J. Qin, "Hybrid dual Kalman filtering model for short-term traffic flow forecasting," *IET Intell. Transp. Syst.*, vol. 13, no. 6, pp. 1023–1032, 2019.

[30] L. Cai, Q. Chen, W. Cai, X. Xu, T. Zhou, and J. Qin, "SVRGSA: A hybrid learning based model for short-term traffic flow forecasting," *IET Intell. Transp. Syst.*, vol. 13, no. 9, pp. 1348–1355, Sep. 2019.

[31] L. Cai, Z. Zhang, J. Yang, Y. Yu, T. Zhou, and J. Qin, "A noise-immune Kalman filter for short-term traffic flow forecasting," *Phys. A, Stat. Mech. Appl.*, vol. 536, Dec. 2019, Art. no. 122601. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0378437119314876

[32] S. Zhang, Y. Song, D. Jiang, T. Zhou, and J. Qin, "Noise-identified Kalman filter for short-term traffic flow forecasting," in *Proc. 15th Int. Conf. Mobile Ad-Hoc Sensor Netw.*, 2019, pp. 1–5.

[33] W. Cai, J. Yang, Y. Yu, Y. Song, T. Zhou, and J. Qin, "PSO-ELM: A hybrid learning model for short-term traffic flow forecasting," *IEEE Access*, vol. 8, pp. 6505–6514, 2020.

[34] L. Cai, Y. Yu, S. Zhang, Y. Song, Z. Xiong, and T. Zhou, "A sample-rebalanced outlier-rejected k -Nearest neighbor regression model for short-term traffic flow forecasting," *IEEE Access*, vol. 8, pp. 22686–22696, 2020.

[35] L. Cai, M. Lei, S. Zhang, Y. Yu, T. Zhou, and J. Qin, "A noise-immune LSTM network for short-term traffic flow forecasting," *Chaos, Interdiscipl. J. Nonlinear Sci.*, vol. 30, no. 2, Feb. 2020, Art. no. 023135.

[36] T. Zhou, G. Han, B. N. Li, Z. Lin, E. J. Ciaccio, P. H. Green, and J. Qin, "Quantitative analysis of patients with celiac disease by video capsule endoscopy: A deep learning method," *Comput. Biol. Med.*, vol. 85, pp. 1–6, Jun. 2017.

[37] B. N. N. Li, X. Wang, R. Wang, T. Zhou, R. Gao, E. J. Ciaccio, and P. H. Green, "Celiac disease detection from videocapsule endoscopy images using strip principal component analysis," *IEEE/ACM Trans. Comput. Biol. Bioinf.*, early access, Nov. 15, 2019, doi: 10.1109/TCBB.2019.2953701.

[38] Y. Song *et al.*, "CNN in CT image segmentation: Beyond loss function for exploiting ground truth images," in *Proc. IEEE Int. Symp. Biomed. Imag. (ISBI)*, Apr. 2020.

[39] W. Cai, D. Yu, Z. Wu, X. Du, and T. Zhou, "A hybrid ensemble learning framework for basketball outcomes prediction," *Phys. A, Stat. Mech. Appl.*, vol. 528, Aug. 2019, Art. no. 121461.

[40] D. Jiang, K. Wu, D. Chen, G. Tu, T. Zhou, A. Garg, and L. Gao, "A probability and integrated learning based classification algorithm for high-level human emotion recognition problems," *Measurement*, vol. 150, Jan. 2020, Art. no. 107049.

[41] D. Jiang, Z. Liu, L. Zheng, and J. Chen, "Factorization meets neural networks: A scalable and efficient recommender for solving the new user problem," *IEEE Access*, vol. 8, pp. 18350–18361, 2020.

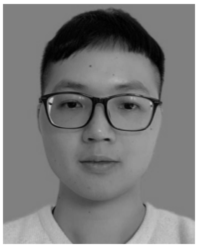
[42] Y. Chen, F. Guo, Z. Gong, and W. Cai, "One note about the Tu-Deng conjecture in case $w(t) = 5$," *IEEE Access*, vol. 7, pp. 13799–13802, 2019.

[43] Y. Chen, L. Zhang, D. Tang, and W. Cai, "Translation equivalence of Boolean functions expressed by primitive element," *IEICE Trans. Fundam. Electron., Commun. Comput. Sci.*, vol. E102.A, no. 4, pp. 672–675, Apr. 2019.

[44] Y. Chen, F. Guo, and J. Ruan, "Constructing odd-variable RSBFs with optimal algebraic immunity, good nonlinearity and good behavior against fast algebraic attacks," *Discrete Appl. Math.*, vol. 262, pp. 1–12, Jun. 2019.

[45] Y. Chen, F. Guo, H. Xiang, W. Cai, and X. He, "Balanced odd-variable RSBFs with optimum AI, high nonlinearity and good behavior against FAAs," *IEICE Trans. Fundam. Electron., Commun. Comput. Sci.*, vol. E102.A, no. 6, pp. 818–824, Jun. 2019.

JIAJUN WANG is currently an Assistant Professor with the Ministry of Sports, Shantou University, China. His research interests include kinematic analysis and education.



ZIXIN XIE is currently pursuing the master's degree with the Department of Engineering, College of Engineering, Shantou University, China. His research interests include machine learning, image process, and data analysis.

YAN LI is currently pursuing the master's degree with the Department of Medical Imaging, College of Medical, Shantou University, China. Her research interests include magnetic resonance imaging, magnetic resonance spectrum, and deep learning.

YOUYI SONG is currently pursuing the Ph.D. degree with the Centre of Smart Health, The Hong Kong Polytechnic University. His research interests include intelligent traffic systems, medical image segmentation, machine learning, and shape analysis.

JINGWEN YAN is currently a Full Professor with the College of Engineering, Shantou University, China. His research interests include machine learning, computer vision, and remote sensing.

WEIHUA BAI received the M.Sc. degree from the School of Computer Science, South China Normal University, in 2006, and the Ph.D. degree from the School of Computer Science and Engineering, South China University of Technology, China, in 2017. He is currently an Associate Professor with Zhaoqing University. His research interests include cloud computing, parallel scheduling, and software architectures. He is a member of the China Computer Federation.

TENG ZHOU is currently an Assistant Professor with the Department of Computer Science, Shantou University. He is also a Research Associate with the Center of Smart Health, The Hong Kong Polytechnic University. His research interests include intelligent transportation systems and machine learning.

JING QIN received the Ph.D. degree from the Department of Computer Science and Engineering, The Chinese University of Hong Kong. He is currently an Assistant Professor with the Centre for Smart Health, School of Nursing, The Hong Kong Polytechnic University. His research interests are in intelligent traffic systems, VR-based surgical simulation, multisensory human–computer interaction, and biomechanical modeling.