# DPPA: A Deep-Learning-Based Physiological and Psychological Assessment Model for Firefighter Training Injury

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***Abstract*—Firefighting is a physically demanding profession, requiring rigorous training to ensure proficiency and safety. Although it is extremely difficult to assess the physical and mental condition of firefighters in real time, with the development of the Internet of Everything and smart sensors, it is expected to be possible to access the physiological characteristics of firefighters during training. We propose a deep-learning-based physical and psychological assessment (DPPA) model that can evaluate the psychological and physical states of firefighters during training in real time. By using neural networks to predict both heart rate and mental state during training, we have developed a novel framework that enables message passing between the two models to enhance prediction accuracy. We conducted real firefighter training sessions and collected relevant data. Experimental results demonstrate that the model effectively predicts firefighters' psychological and physical states, improving prediction accuracy by 11.23% compared to baseline.**

***Index Terms*—Deep learning, fatigue assessment, firefighter training injury, Internet of Everything, psychological assessment.**

## I. Introduction

FIREFIGHTERS play a crucial role in modern society, often facing high-risk and extreme conditions in both their training and work environments. Their daily training involves hazardous tasks, such as fire response and rescue from heights, which demand not only advanced professional skills and physical fitness, but also expose them to potential injury and life-threatening situations. Research has shown that firefighters are frequently at risk of injuries and illnesses, including fractures, burns, and heat stroke, during training [1]. The intense physical exertion required in their training often leads to conditions, such as increased heart rate and heat stress, and the resulting physical fatigue can significantly impact their overall health. Moreover, mental health issues, including stress, anxiety, and tension, have become increasingly prevalent among firefighters, adding another layer of risk [2], [3].

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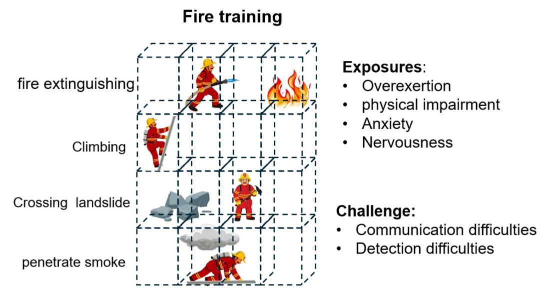



Fig. 1. Risks and challenges of firefighter training.

Given these challenges, it is essential to implement measures to assess and mitigate the risks in firefighter training, ensuring their health and safety, and enabling them to perform their rescue missions effectively. Fig. 1 illustrates the current risks and challenges facing firefighter training.

Numerous risk assessments and studies have been conducted to understand the risks faced by firefighters. Yung et al. [4] performed a literature review to examine how fatigue is conceptualized among workers in three different occupations. Yung et al. [5] developed a fatigue risk management measure and assessment tool, which evaluates fatigue across multiple dimensions, including physical and emotional fatigue. Smith et al. [6] assessed the accuracy of subjective measures of fatigue in various stressful environments, examining the impact of environmental and occupational stressors on the performance of rural firefighters through simulated fire ground deployments. With the development of artificial intelligence, deep learning methods have been applied to more accurately predict firefighter status. Bustos et al. [7] developed a physical fatigue prediction model that combines cardiorespiratory and thermoregulatory measures with machine learning algorithms. This model used 21 features extracted from physiological variables and participant characteristics to estimate the physical fatigue status of firefighters.

Despite the availability of various physical and psychological assessment methods, these tools still fail to mitigate the risks associated with firefighter training, primarily due to their inability to assess firefighters' real-time training status. Moreover, psychological tests based on test scales, while accurate, do not capture the dynamic psychological state of firefighters during training, limiting their effectiveness in understanding the full scope of stress and fatigue during active duty. With the Internet of Everything and the development of smart sensors that make it feasible to detect a firefighter's physical state in real time, this opens up the possibility of assessing a firefighter's condition in real time [8], [9].

In this letter, we propose a novel deep-learning-based psychological and physical assessment (DPPA) model designed to predict the real-time psychological and physical status of firefighters during training. We integrate deep learning algorithms into the firefighter state assessment model to predict the firefighter's physical and psychological conditions in real time. We introduce an innovative assessment framework that enhances model accuracy by combining two distinct neural networks: one for psychological evaluation and another for physical assessment. To the best of our knowledge, this is the first model capable of performing real-time psychological and physical assessments for firefighters. This innovation has the potential to significantly reduce the risk of injuries during training by providing timely insights into the firefighter's condition. We validate the model through real-world firefighter training scenarios, demonstrating its effectiveness. Experimental results demonstrate that the model converges quickly and outperforms benchmark algorithms in terms of accuracy, emphasizing its superior performance in practical applications.

## II. Physical and Psychological Assessment Models

Although firefighter fatigue can be reflected through multiple indicators, collecting real-time multidimensional metrics from firefighters during training is challenging. This is due to the complex and smoke-filled environments in which firefighters train, coupled with the interference from electromagnetic fields caused by training equipment, such as net cages. As a result, only basic metrics, such as elapsed time and heart rate, can typically be collected in real time. To overcome this limitation, we employed a deep-learning-based predictive model and enhanced its predictive capability by incorporating pretraining metrics as feature information. This model consists of two key components: 1) a physical assessment model and 2) a mental assessment model, designed to predict the physical fatigue and mental anxiety of firefighters in real time. Two neural networks are used to separately predict physical and psychological fatigue, and their integration improves the overall assessment performance.

### A. Physical Assessment Model

Since heart rate is relatively easy to detect, we use heart rate variability (HRV), derived from heart rate, as an indicator of firefighter fatigue. HRV tends to decrease as body fatigue increases because fatigue disrupts the balance of the autonomic nervous system, weakening the regularity of heart rate fluctuations and leading to lower HRV values [10], [11]. Our model focuses on predicting physical fatigue by forecasting future heart rate changes and calculating HRV values. Since firefighters are affected by smoke and heat sources when they are in the training facility, it is difficult to predict the subsequent heart rate changes by relying solely on the real-time heart rate of firefighters during training. To address this, we use the firefighters' daily training heart rate variations as input features for the neural network, including resting heart rate and the average heart rate during a 3-min jogging session on a treadmill. In addition, the neural network incorporates other features, such as the training route and duration, to better predict heart rate changes at different stages of training. This approach enables more accurate predictions of heart rate fluctuations throughout the training process.

Since emotions, such as nervousness and anxiety can also influence heart rate changes, we use the initial psychological state of firefighters as an input feature in the physical state assessment model. In the next section, we experimentally demonstrate that introducing psychological state data significantly improves the accuracy of physical state assessments. Based on the predicted heart rate, we calculate the HRV with the formula

$$\mathrm{HRV} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(RR_i - \overline{RR}\right)^2} \tag{1}$$

where $\overline{RR}$ is the average of all heartbeat intervals and $N$ is the number of heartbeat intervals.

### B. Psychological Assessment Model

The primary psychological issues faced by firefighters are stress and anxiety, which can be effectively assessed using the self-assessment scale for anxiety (SAS). SAS has become one of the most widely used psychometric tools by counselors, psychologists, and psychiatrists. The scale measures the severity of anxiety, with a maximum score of 100 points. The scores are categorized into four levels: 1) a score of 20–49 indicates a normal state; 2) 50–59 indicates mild anxiety; 3) 60–69 indicates moderate anxiety; and 4) 70–100 indicates severe anxiety. To address this, the psychological assessment model primarily utilizes neural networks to predict the SAS values of firefighters during training.

Initially, each firefighter was asked to measure their SAS score while in a resting state, establishing a baseline assessment before utilizing the psychological assessment model. During the training phase, the firefighter's SAS score was measured again after training, providing additional training data for the model. The inputs to the neural network included the resting heart rate, baseline SAS values, and real-time heart rate measurements. When the model is deployed, the psychological assessment model receives the predicted next-moment heart rate from the physical state assessment model. Based on this information, it evaluates the SAS score and issues a warning alert, classifying the firefighter's anxiety level according to the SAS scale. This approach enables real-time monitoring and assessment of both psychological and physical states, ensuring timely intervention when needed.

### C. Model Training and Testing

The training data for the model will be gathered from different firefighters during the training phase. Each firefighter will first undergo the SAS test and have their resting heart rate measured before engaging in the smoke and heat training. Following this, the firefighter will jog for three minutes, during which their average heart rate will be recorded to capture their exercise HRV in a noncomplex environment. After the jog, the firefighters will enter the training facility where their HRV will be recorded in real time during the training session. Once the training is complete, the SAS test will be administered again to gather data for training the psychological assessment model.

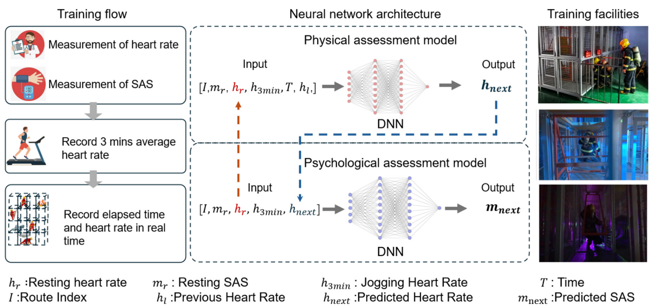



Fig. 2. Firefighter training process and modeling framework.

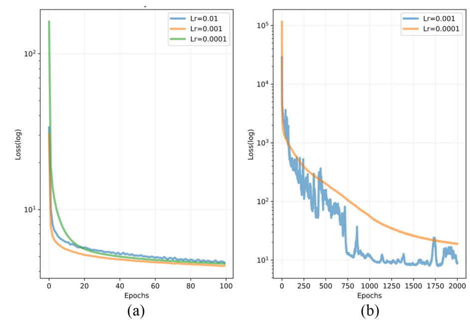



Fig. 3. Convergence performance under different learning rates. (a) Loss of body model. (b) Loss of mental model.

Fig. 2 illustrates the firefighter training process and the model framework. During the testing phase, firefighters first undergo SAS scoring and a jog before participating in smoke and heat training. Notably, each firefighter is only required to record their initial scores once for the entire training session. During the smoke and heat training, real-time heart rate data is input into the physical assessment model, which predicts future heart rate changes and calculates HRV to assess whether a fatigue warning is necessary. The predicted heart rate is then fed into the psychological assessment model to estimate the firefighter's SAS score and determine if an anxiety warning should be issued.

## III. Performance Evaluation

### A. Experimental Setup

To evaluate the effectiveness of the firefighter physical-psychological assessment model, we collected training data from firefighters performing mesh-grid-isolated smoke-heat training. Fig. 2 shows the fire training equipment used in this experiment. The training device provides a realistic and dynamic training environment for firefighters, allowing them to prepare for a wide range of emergencies.

A total of 50 firefighters participated in this study, with data collected from two different training routes. The data was denoised and cleaned before analysis. Each firefighter randomly selected a route and completed two repetitions of the exercise. In total, 962 data points were obtained for the physical assessment model, and 80 data points for the psychological assessment model. The data was randomly split, with 90% used for training and 10% reserved for testing. The model was implemented in Python, utilizing Pytorch to build the neural network, which consisted of three fully connected layers, with ReLU activation and SGD optimization.

### B. Model Convergence

To assess whether the neural network in the model can converge, we tested the change in the loss value of the neural network at different learning rates. It is important to note that, due to the normalization of the training set for the physical assessment model, the loss values for this model are lower than those for the psychological assessment model. Additionally, we used a logarithmic axis to provide clearer discrimination of the effects, which may result in the presence of negative numbers.

Fig. 3(a) demonstrates the change in loss for the physical assessment model at different learning rates. It can be observed that the loss decreases rapidly and eventually levels off with the number of training epochs, indicating that the neural network converges quickly. Among the various learning rates tested, a learning rate of 0.001 resulted in the fastest decline in loss. However, a learning rate that is too large causes fluctuations in the loss, while a rate that is too small leads to slower convergence. Therefore, a learning rate of 0.001 was chosen for the physical assessment model. Fig. 3(b) shows the change in the loss of the psychological assessment model with different learning rates. Although the learning rate of 0.001 causes a faster decrease in loss, it also leads to significant fluctuations in the network's performance. In contrast, the neural network converges more smoothly at a learning rate of 0.0001. Based on these results, we selected 0.0001 as the learning rate for the psychological assessment model.

### C. Model Effectiveness

To evaluate the effectiveness of the proposed model, we selected several benchmark algorithms, including both deep learning and traditional fitting algorithms, as follows: Logarithmic fitting algorithm (LLS), Physical assessment model without psychological data (DPPA_WM) and Physical assessment model without resting heart rate (DPPA_WR). Additionally, we incorporated the linear mixed effects (LME)-based body prediction algorithm [6], which uses training route, number of heart rate acquisitions, and current heart rate as inputs. Given the absence of algorithms capable of detecting firefighters' mental states in real time, we adopted the HRV-based machine learning algorithm (HRVA) [11] and used the same network architecture as in DPPA. Moreover, we compared the firefighter's pretraining psychological state as a baseline to assess the validity of the psychological assessment models.

Fig. 4 shows the test set loss variation of the physical assessment model against other methods. The figure demonstrates that the physical assessment model exhibits the fastest decrease in loss and achieves the lowest loss value upon convergence, indicating that it is the most effective model. In contrast, models without mental and resting heart rate features had higher loss values, highlighting the importance of these two features for accurately predicting the physical condition of firefighters during training. This experiment confirms that the

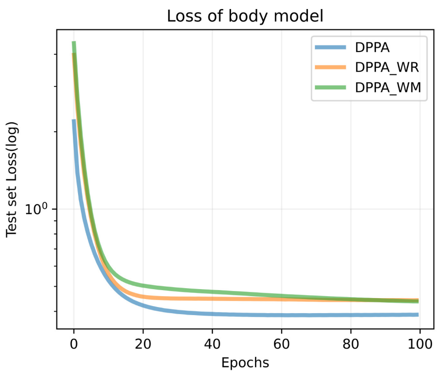
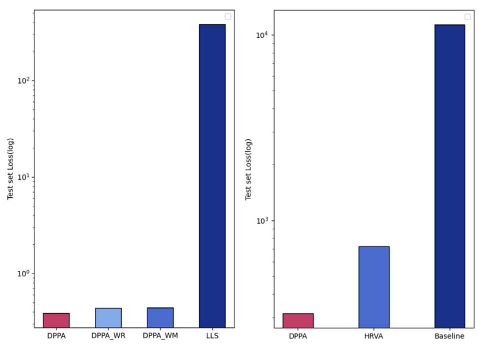



Fig. 4. Comparison of different methods on the test set.




(a) (b)

Fig. 5. Performance comparison of different methods. (a) Body model. (b) Mental model.

physical assessment model can effectively assess the physical conditions of firefighters and that the features it utilizes play a crucial role in improving its performance.

Fig. 5(a) illustrates the performance of the physical assessment model in predicting firefighter conditions, compared to other methods after training. The vertical axis represents the sum of the loss values on the test set. It can be seen that the logarithmic fitting function performs the worst, indicating its inability to accurately predict the physical condition of firefighters during training. In contrast, deep-learning-based algorithms effectively predict firefighters' physical conditions, with the proposed model outperforming the others by at least 11.23%. This highlights the effectiveness of the features utilized in the current model, contributing to improved prediction accuracy. Fig. 5(b) presents the prediction performance of the psychological assessment model, compared to the baseline. The experimental results demonstrate that the psychological assessment model significantly outperforms the benchmark, reflecting the dynamic changes in firefighters' psychological states during training. This validates that the model effectively captures and mirrors these changes.

We use two criteria to assess accuracy. The average heart rate error (AHRE) is defined as the average absolute difference between the heart rate predicted by the model in the test set and the actual future heart rate. The average psychological assessment error is the average absolute difference between the psychological scores predicted by the model in the test set and the actual post-training psychological scores.

Table I presents the accuracy assessment of the different models. It is evident that DPPA outperforms the other models

TABLE I
ACCURACY ASSESSMENT OF DIFFERENT MODELS

| Phys. Model | **DPPA** | DPPA_WR | DPPA_WM | LME | LLS |
|---|---|---|---|---|---|
| AHRE | **97.01%** | 96.94% | 96.9% | 96.18% | 92.69% |
| Psy. Model | **DPPA** | HRVA | Baseline | NA | NA |
| APAE | **91.27%** | 90.05% | 89.19% | NA | NA |

in terms of accuracy. For the physical assessment model, DPPA significantly surpasses LMZ and LLS, achieving an AHRE value of 97.01%, which corresponds to a prediction error of just 4 beats when estimating the firefighter's future heart rate. For the psychological assessment model, DPPA also demonstrates superior accuracy compared to the baselines and the HRVA model, with an APAE value of 91.27%. This represents a very high level of accuracy for a psychological assessment model, especially on a percentage scale.

## IV. CONCLUSION

We propose a deep-learning-based physical-psychological assessment model for firefighters. This model can predict firefighters' physical and psychological state in real time and provide early warning during firefighter training. We experimentally verified that the model converges quickly and outperforms other benchmark algorithms in terms of assessment accuracy. In future work, we will explore the impact of additional features on the psychological state of firefighters and continue refining the model to improve its accuracy.

## REFERENCES

[1] S. Rodrigues, D. Dias, J. S. Paiva, and J. P. Cunha, "Psychophysiological stress assessment among on-duty firefighters," in *Proc. 40th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, 2018, pp. 4335–4338.
[2] N. Crombez-Bequet, F. Schiffler, and F. Legrand, "Assessment of the condition of psychic health of French firefighters: Burnout," *Encephale*, vol. 50, no. 3, pp. 284–288, 2024.
[3] A. A. Vujanovic and J. K. Tran, "Providing psychological services to firefighters," *J. Health Service Psychol.*, vol. 47, no. 3, pp. 137–148, 2021.
[4] M. Yung, B. Du, J. Gruber, and A. Yazdani, "Developing a Canadian fatigue risk management standard for first responders: Defining the scope," *Saf. Sci.*, vol. 134, Feb. 2021, Art. no. 105044.
[5] M. Yung, B. Du, J. Gruber, A. Hackney, and A. Yazdani, "Fatigue measures and risk assessment tools for first responder fatigue risk management: A scoping review with considerations of the multidimensionality of fatigue," *Saf. Sci.*, vol. 154, Oct. 2022, Art. no. 105839.
[6] B. P. Smith, M. Browne, T. A. Armstrong, and S. A. Ferguson, "The accuracy of subjective measures for assessing fatigue related decrements in multi-stressor environments," *Saf. Sci.*, vol. 86, pp. 238–244, Jul. 2016.
[7] D. Bustos et al., "Machine learning approach to model physical fatigue during incremental exercise among firefighters," *Sensors*, vol. 23, no. 1, p. 194, 2022.
[8] M. Urbina, T. Acosta, J. Lázaro, A. Astarloa, and U. Bidarte, "Smart sensor: SoC architecture for the industrial Internet of Things," *IEEE Internet Things J.*, vol. 6, no. 4, pp. 6567–6577, Aug. 2019.
[9] R. H. Eltom, E. A. Hamood, A. A. Mohammed, and A. A. Osman, "Early warning firefighting system using Internet of Things," in *Proc. Int. Conf. Comput., Control, Elect., Electron. Eng. (ICCCEEE)*, 2018, pp. 1–7.
[10] A. T. Jeklin, A. S. Perrotta, H. W. Davies, S. S. D. Bredin, D. A. Paul, and D. E. R. Warburton, "The association between heart rate variability, reaction time, and indicators of workplace fatigue in wildland firefighters," *Int. Arch. Occup. Environ. Health*, vol. 94, pp. 823–831, Jan. 2021.
[11] U. Pluntke, S. Gerke, A. Sridhar, J. Weiss, and B. Michel, "Evaluation and classification of physical and psychological stress in firefighters using heart rate variability," in *Proc. 41st Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, 2019, pp. 2207–2212.