An AI-Based Action Detection UAV System to Improve Firefighter Safety

Hong Wang[1], Yuan Feng[2], Xu Huang[2], and Wenbin Guo[3](✉)

[1] School of Construction Machinery, Chang'an University, Xi'an 710064, China
hong.wang@chd.edu.cn
[2] Department of Mechanical and Aerospace, University of Missouri, Columbia, MO 65203, USA
{yfzc8,xuhuang}@mail.missouri.edu
[3] Digital Worlds Institute, University of Florida, Gainesville, FL 32611, USA
wenbin@digitalworlds.ufl.edu

Abstract. Human hazardous fires can inflict massive harm to life, property, and the environment. Close contact with fire sources threatens firefighters' lives who are critical first responders to fire suppression and rescue. Unmanned aerial vehicles (UAVs) are recently introduced to improve firefighters' performance by monitoring fire characteristics and inferring trajectory. Some UAVs studies used artificial intelligence (AI) for pattern recognition for wildfire prevention and other relevant tasks. However, how to coordinate firefighters is equally important and needs to be explored. Therefore, this research offers an analysis and comparison of AI-based computer vision methods that can annotate human movement automatically. This study proposes to use UAVs combined with AI-based human motion detection to recognize firefighters' action patterns. Based on existing human motion datasets of firefighting videos, we have successfully trained a supervised machine learning algorithm recognizing firefighters' forward movement and water splashing actions. The trained model was tested in the existing video and reached an 81.55% accuracy rate. Applying this model in the UAV system is able to improve firefighters' functioning and safeguard their lives.

Keywords: Artificial intelligence · Human motion classification · Laban movement analysis

1 Introduction

Human hazardous fires can inflict massive harm to life, property, and the environment [1]. According to National Fire Protection Association (NFPA), the United States had more than 1.35 million fires responded by local fire departments in 2021, which caused 3,800 death, 14,700 injuries and a property damage cost of $15.9 billion [2]. From 2001 to 2020, more than 68,000 wildfires were recorded and they caused average of 7 million acres burned per year. Large amounts of fine particulate matter and carbon monoxide are emitted by wildfires, resulting in air pollution and leading to many health issues [3]. Fires fighting is considered crucial preserving natural resources and ensuring personal and property safety.

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Close contact with fire sources threatens firefighters' lives who are critical first responders to fire suppression and rescue. Early fire detection and ongoing monitoring of fires can offer great help to firefighters and reduce casualties. With advancements of technologies, the detection and monitoring system now primarily rely on ground-based systems, human piloted aircrafts, and satellite-based systems [4]. Ground monitoring system is constrained by the terrain so the surveillance ranges are limited. Aircraft crews must include people with fire monitoring or detection experiences. And hazardous fire environment can be a risk for human pilots [5]. Satellites can quickly acquire images of fires in a wide area, but the image resolution and frequency of images taken are too low [6].

Unmanned aerial vehicles (UAVs) are recently introduced to improve firefighters' performance by monitoring fire characteristics and inferring trajectory [7, 8]. Compared with the three systems mentioned above, UAVs have advantages in better deployment flexibility, lower cost, long detection range, no pilot risk, live and high-resolution images.

Some UAVs studies used artificial intelligence (AI) for pattern recognition for wildfire prevention and other relevant tasks [9–11]. However, how to coordinate firefighters is equally important and needs to be explored. Communication and coordination are critical for firefighters since their work environments are dangerous and dynamic. Their skills of gathering information, optimizing coordination and sensemaking are learned mainly through their experience [12]. To increase the safety and efficiency of firefighters' work, cognitive system engineering focuses more on information flow to make efficient decisions [13].

In this study, we propose to use UAVs combined with AI-based human motion detection to recognize firefighters' action patterns. Based on existing human motion datasets of firefighting videos, we have successfully trained a supervised machine learning algorithm recognizing firefighters' forward movement and water splashing actions. The trained model was tested in the existing video and reached an 81.55% accuracy rate. Applying this model in the UAV system is able to improve firefighters' functioning and safeguard their lives.

2 Related Works

2.1 AI Applications in Firefighting

AI can learn from experience and help solve problems in various scenes, especially in pattern recognition areas. To boot, more and more researchers make AI-based methods play an important role in improving the safety and efficiency of firefighters' work and protecting their lives. DHS and NASA's Jet Propulsion Laboratory developed an AI platform, the Assistant for Understanding Data through Reasoning, Extraction, and Synthesis (AUDREY), which is a real-time system to help firefighters know more information about the environment, receive danger signals and recommendations through sensors, and also get good team communication and collaboration [14, 15]. Another study aims to predict the number of firefighters' interventions between emergency and non-emergency with machine learning methods. They applied XGBoost and LightGBM algorithms for the dataset to predict the type of deployment from 14 different categories in order to help firefighters to be well prepared and assign work efficiently [16]. In addition, the research attempted to analyze the stress of firefighters during a rescue mission and display the alerts to protect their lives. The author proposed that AI methods can study and predict stress among firefighters beforehand further [17]. Moreover, firefighters' action patterns reflect plenty of helpful information during the rescue mission. However, limited research focus on this. With the development of AI-based methods in motion detection, lots of work can be applied in recognizing firefighters' movements.

2.2 UAV Assistance in Firefighting

With the advantages of flexibility, stability, convenience, low cost, multiple functions and without danger to personnel safety, UAVs are competent for difficult tasks in more and more fields. For example, in [18] the author mentioned that one challenge firefighters face is accessing the upper floors of tall buildings, but UAVs can quickly and efficiently reach these areas. They developed a Firefighting UVA with a mechanism for shooting and dropping fire extinguishing balls that helps firefighters decrease the spread of fire. Applying UAVs for forest fire detection and monitoring have make a great progress recent years. One notable study generated a powerful UAV which is long-range, long-endurance, solar-powered, and with flight autonomy and pattern recognition. The real-time images and advice of fire could be provided to firefighters [19]. In order to diversify the functions of UAVs and make them more accurate, researchers try to combine them with other sciences to derive functions for more scenarios. One study applied optical remote sensing techniques and UAVs to detect the forest fire. Image processing with color and motion features from the camera on a UAV and color-based fire detection algorithm shows good performance in improving the accuracy of fire detection [11]. Along with, in [20] the author proposed an automatic forest firefighting monitoring system based on the combination of UAV and remote sensing. Their system with remote sensing algorithms and image processing techniques shows good performance on fire prediction and response. Moreover, the applications of UAVs combined with AI-based methods become more and more popular.

2.3 AI-Based UAV Applications

Combining UAVs and AI techniques together can achieve higher efficiency and safety during the difficult rescue tasks. Several research papers in last three years have compassed the topic to design and develop smart UAVs assistance for firefighters. A study developed in [21] construct a UAV with AI and image processing to monitor and estimate people stuck by fire, and support firefighters. Their study contributes to decrease loss of lives. Another study aims to detect early wildfire with deep learning-based computer vision algorithms and UAVs in order to prevent and reduce the loss of lives and resources. In their research, the author tried and compared many different computer vision algorithms and showed the great potential of the applications in firefighting combined with UAVs [22].

Hence, the contribution and novelty of this work lies in the combination of popular studies, by using AI-based motion detection algorithms and UAV to detect firefighters' different actions in order to provide useful information for firefighters to protect their safety and improve the rescue efficiency.

Several researches focus on the fire detection, environment monitor and analysis with the combination of AI and UAVs, while few of present studies focus on firefighters' motion detection, which could be meaningful during the rescue. In this research, we intend to build a UAV system, which includes software part and hardware platform, to realize real-time image collection and the identification of firefighters' action. In this paper, we mainly introduce the software part, which include the models we built with different machine learning and deep learning methods. In our further work, we will build a hardware platform, which will be built on Nvidia Jetson Nano, which is a microcomputer with powerful cores, a mini camera and STM32 Nucleo board, which is used for controlling the response of UAV. Then, we will apply the models we built in this paper on our UAV hardware platform to realize whole pipeline of real-time detection.

3 Methods

Like most AI-based methods, our approach comprised of three key stages: 1) Data preparation, 2) Training and testing, 3) Automated annotation.

In this project, we trained five traditional machine learning models and one deep neural network to receive a video sequence as input and recognize the firefighter action changes. A total of 95 videos were collected in the publicly available datasets, including two actions moving forward and water splashing. The dataset was split into a 90:10 ratio, 85 videos were used for training the model, and 10 videos were tested for models' accuracy. Table 1 shows the video distribution for train and test sets.

Table 1. Dataset

Action	Train set videos	Test set videos
Moving Forward	35	5
Water Splashing	50	5

Mediapipe is a framework to detect the human key points of skeleton joints and a total of thirty-three key points for the human skeleton [23]. The human skeleton is detected frame by frame and classified into two actions to test the model performance.

Five traditional machine learning models include Naïve Bayes, Support Vector Machines (SVM), Logistic regression, Decision tree and Random forest.

Naïve Bayes can be used for various tasks, including classification and text classification. There are different variations of the algorithm, including the Gaussian Naive Bayes, Multinomial Naive Bayes, and Bernoulli Naive Bayes.

SVM is a type of supervised learning algorithm that can be used for classification, regression, and outlier detection. The algorithm aims to find the hyperplane in a high-dimensional feature space that best separates the data into classes, or predicts the target value for regression.

Logistic regression is used for binary classification problems. Logistic regression is a fast and simple algorithm to implement and can provide good results in many practical problems, especially when the relastionship between the independent variables and the target variable is approximately linear.

Decision tree is a tree-like model used for supervised learning and decision making. It is a type of algorithm that splits the data into smaller subsets based on certain conditions, with each split represented as a node in the tree. The splits are chosen based on the feature that maximizes the information gain, which measures the reduction in entropy or uncertainty of the target variable. Decision Trees can handle both categorical and numerical features, and can be used for classification and regression tasks.

Random forest is an ensemble learning method that combines multiple decision trees to make a prediction. It is a type of algorithm used for both classification and regression tasks. This combination of individual trees helps to reduce the variance and overfitting that can occur in a single decision tree, leading to improved accuracy and stability of the model.

Deep neural network is feed forward neural network that consists of an input layer, one or multiple hidden layers, and an output layer. The information flows only in one direction, from input to output, without forming a cycle. Each layer processes the input data and passes it on to the next layer, until the final output is produced. Each layer is composed of multiple neurons, and each neuron performs a simple computation on the weighted sum of its inputs and produces an output. The weights of the connections between neurons and the biases of each neuron are learned through the training process using an optimization algorithm, such as gradient descent.

For our training dataset, we sourced firefighter training and live videos from online resources for evaluation and testing purposes. 85 randomly selected videos from the collected dataset were used for supervised learning, while the remaining 10 were reserved for testing. To streamline the prototyping phase, the annotation system was coded in Python utilizing the Scikit-learn library. The system was developed and tested on a 2080 Ti GPU.

The performance was evaluated based on precision, recall, accuracy, and F1 scores. Precision reflects the classifier's ability to correctly identify negative samples, while recall represents its ability to detect positive samples, with a maximum score of 1. The F1 score, calculated as the harmonic mean of precision and recall, gives equal weight to both metrics and ranges from 0–1. The formulas are as follows:

$$\text{Precision} = \text{TP}/\left(\text{TP} + \text{FP}\right) \tag{1}$$

$$\text{Recall} = \text{TP}/\left(\text{TP} + \text{FN}\right) \tag{2}$$

$$\text{Accuracy} = \left(\text{TP} + \text{TN}\right)/\left(\text{TP} + \text{TN} + \text{FP} + \text{FN}\right) \tag{3}$$

TP = True Positive, TN = True Negative,
FP = False Positive, FN = False Negative

$$\text{F1 score} = 2 * \left(\text{precision} * \text{recall}\right)/\left(\text{precision} + \text{recall}\right) \tag{4}$$

Finally, the automated annotation was visualized using the Matplotlib library, which is a comprehensive tool for creating dynamic and interactive visualizations.

4 Results

Figure 1 compares the results of six machine learning algorithms, including Naïve Bayes, SVM, logistic regression, decision tree, random forest, and deep neural network. The results demonstrate that the deep neural network achieves the highest accuracy, 81.55%.

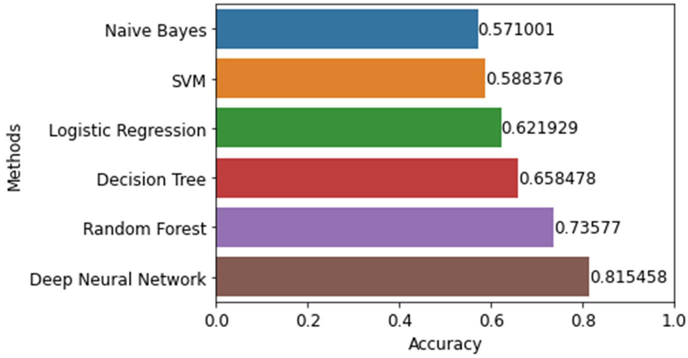

Fig. 1. Machine learning algorithms comparison

Figure 2 shows the confusion matrix for each machine learning method. The diagonal elements are correctly predicted actions. Deep neural network has the advantages in the true positive compared with other traditional machine learning models (Table 2).

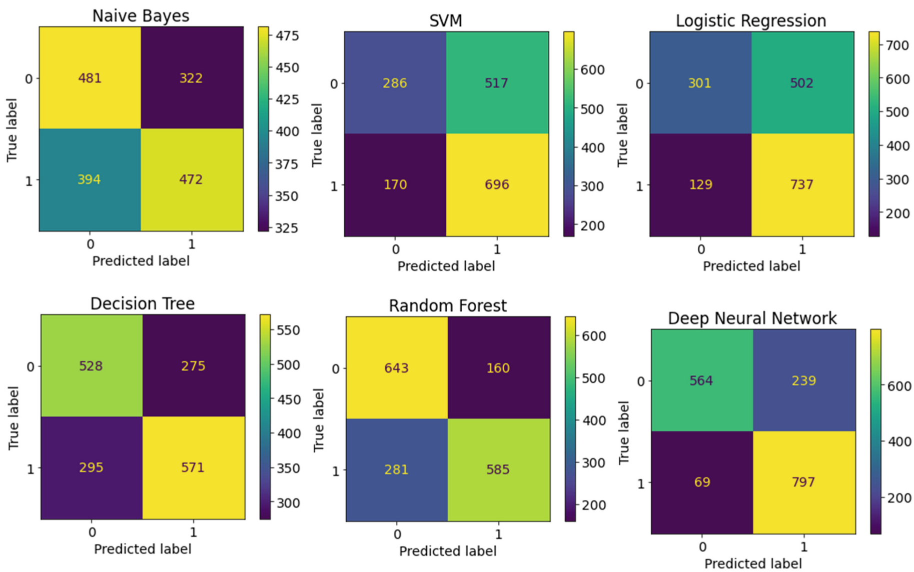

Fig. 2. Confusion matrix of each Laban movement dimension

Table 2. Firefighter action annotation using six machine learning algorithms

Algorithms	Precision	Recall	Accuracy	F1 score
Naïve Bayes	0.5945	0.5450	0.5710	0.5687
SVM	0.5738	0.8037	0.5884	0.6696
Logistic regression	0.5948	0.8510	0.6219	0.7002
Decision tree	0.6749	0.6594	0.6585	0.6671
Random forest	0.7852	0.6755	0.7358	0.7263
Deep neural network	0.7693	0.9203	0.8155	0.8381

Figure 3 shows an example of our results from a single frame of one of the input videos. The automatically detected human skeleton and the corresponding key points are superimposed on the image. For the left frame annotation is moving forward and the right frame annotation is water splashing. Our developed software was able to successfully produce firefighter action annotation for each frame of an input video. The labels reflected the firefighter action in each frame.

Fig. 3. The automated annotation on videos. Left = Moving forward, Right = Putting out fire

5 Discussion and Conclusion

In this pilot study, we developed a method for recognizing firefighter actions from input videos using machine learning algorithms. The study trained and compared six machine learning algorithms (Naïve Bayes, SVM, logistic regression, decision tree, random forest, and deep neural network) through supervised learning on existing firefighter action video datasets. By comparing six machine learning and deep learning methods, the deep neural network had the highest accuracy of 81.55% compared with Naïve Bayes at 57.10%, SVM at 58.84%, logistic regression at 62.19%, decision tree at 65.85%, and Random forest at 73.58% as shown in Table 2. Our results suggested that deep neural networks can work well on high-level, hidden, and meaningful features from firefighter action classification.

In our observation of the confusion matrix, the deep neural network only had 69 false negatives (true label 1 with predicted label 0) and 239 false positives (true label 0 with predicted label 1). Both false negative predictions were lower than those of other five machine learning methods. In addition, SVM had 170 false negatives and 517 false positives. Logistic regression had 129 false negatives and 502 false positives. Besides having the highest false rate, these two methods also had an imbalanced matrix. The other three methods (Naïve Bayes, random forest, SVM, logistic regression, and decision tree) performed relatively well on the confusion matrix of firefighter action detection. The mechanism of these models needs to be further analyzed in future works.

Moreover, we analyzed the false prediction. The phenomenon might be explained by multiple firefighters in the same frame image. What's more, some images in the frames show the firefighters' feet or arms covered by equipment, fire engines and other firefighters' body. These may lead to zero value with movement analysis. It is difficult for feature extraction if firefighters with covered persons.

However, despite these limited data, our proposed deep neural network still has relatively high accuracy for AI-based human motion detection to recognize firefighters' action patterns (forward and putting out fire movement). These results demonstrated that firefighter action analysis could be potentially automated using machine learning algorithms. These algorithms operate on raw input videos and AI-driven standardized human motion evaluation systems can be developed.

Our results indicated that such AI-driven movement classification could enable fully automated reporting in firefighter action classification.

6 Future Work

The next step includes applying the action detection model on Jetson Nano. Jetson Nano is a small, powerful computer that can be installed on a UAV and runs CNN. Online action detection with user feedback may further improve performance. Moreover, the object tracking and path planning model can be extended to the UAV as sequences of actions. Further applications like multi-task allocation and trajectory planning can be applied to a fleet of UAVs. These works are involved in complex fire rescue situations and show the full potential of saving firefighters' lives by improving putting fire efficiency.

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