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Design of Personal Mobility Safety System Using AI

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***Abstract*— In this paper, we propose the implementation of a safety device that generates an alarm sound or braking operation to reduce the risk of accidents. It reduces the exposure of risks due to non-wearing by supplementing the function of the helmet for safety. For machine learning, the safety state is learned by using two types of sensing data, and when an abnormal helmet use or speed or drinking driving is detected, an alarm sound is generated and motion is broken to maintain the safe state. By measuring data using a gas sensor, alcohol is checked and this is used as abnormal data. Users form a habit of wearing safety equipment with continuous safety alarm sound and speed braking and proper driving habit by driving in a normal state without drinking alcohol. In addition, the proposed system enables real-time monitoring, thereby reducing risks by continuously maintaining safe driving and wearing protective equipment. The proposed system uses artificial intelligence to discriminate data related to helmet wearing, speed, and drinking in making an electric kickboard for safety, and triggers an alarm or operates the brake to prevent abnormal driving. If the design and function are supplemented, it will become a basic function that can be applied to various equipment of transportation.**

***Keywords*— Safety, machine learning, Sensing data, CNN image processing, AI, Personal mobility**

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I. Introduction

Electric kickboards are becoming a means of transportation in everyday life without the hassle of walking or running. Users can easily move to their desired destination and are not affected by weather or road conditions, so the number of users is increasing in recent years because of the reduction of travel time and convenience [1],[3]. Due to its small size, it is easy to store and carry, and has excellent usability as a free means of transportation, it is getting more and more popular with people. In addition, since it is operated by electric charging, there is no concern of environmentally harmful exhaust gas, and the increasing trend of users is increasing. The kickboard sharing system, which emerged as a result of the development of social systems, is expected to lead to a continued increase in users. However, unlike the rapidly developing social phenomenon, safety-related laws and regulations have not yet been established, and accidents are increasing as new safety equipment suitable for the characteristics of electric kickboards has not been properly developed [4-7]. Through this, it is possible to apply a system that can be applied to various means of transportation by reducing the incidence of accidents related to personal movement and raising the safety awareness of users [7-8].

II. Materials and Method

A. Backgrounds

Fig. 1. is data surveyed by the Korean Consumer Agency and shows the current status of electric kickboard accidents. It shows that accidents have been steadily increasing over the past four years[1-2].

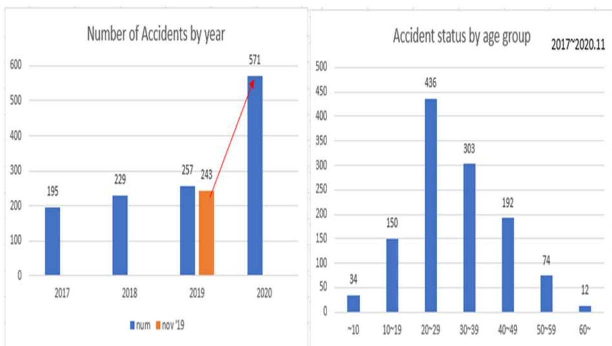

Fig. 1 Status of electric kickboard accidents number

Fig.2 shows electric kickboard accidents by cause over the past four years(2017-2020). In terms of accidents by cause, "defective accidents and breakdown accidents" were the most, followed by "driving accidents". Since "defective accidents and breakdown accidents" are accidents related to hardware defects, they were judged not to be related to the user's attention and driving were excluded from this study.

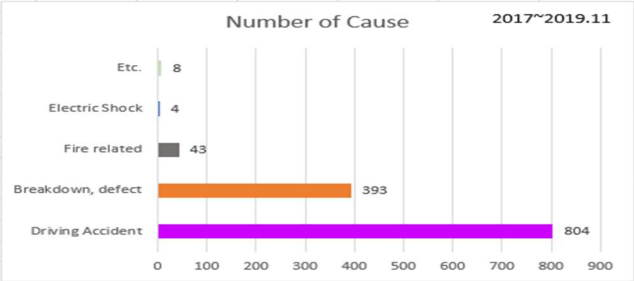

Fig. 2 Electric kickboard accident status by cause

There were 571 safety accidents, an increase of 135% (2.3 times) over the same period last year (243). 64.2% of all accidents occurred while driving due to inexperience in driving or speeding. 31.4% of accidents were caused by electric kickboard failure and product defects. Head and face were the most common injuries due to accidents at 36.3% [1]. In this study, safety and driving inexperience are included in the scope of the study to improve the problem. Due to the increase in drivers and accidents, the government has amended the law on personal mobility [1].

However, it is questionable whether these laws will establish awareness for their own safety in users. While the means of transportation can be easily operated, it is difficult to lead to actual wearing due to the negative perception of using a helmet that is inconvenient to wear and store [5-6]. This leads to an increase in safety accidents, and it is difficult to continuously maintain proper helmet wearing due to the use of mobile phones or other interests around the vehicle while driving [7-8]. In order to solve this problem, the researchers planned to make an electric kickboard that checks in real time [9] to properly wear a helmet for safe driving, and gives a message when a drinking condition or driving other than the proper speed is detected to be alert.

B. Related Works

1) System and method that can start a motorcycle only when wearing a helmet

To ensure safety, motorcycles have implemented a system to start only when helmets are safely worn [2]. The start-up operation is determined after checking whether the helmet is worn through the pressure sensor and proximity sensor attached to the helmet.

Each step is set as follows.

- S10: Start-up preparation step
- S20: Wearing determination step
- S30: Power cut-off step
- S40: Power supply step
- S50: Starting the engine

There is a control device that applies or cuts power to the starter relay when the ignition switch operates according to the conditions set by the sensor value measured between the motorcycle's ignition switch and the starter relay. In addition, it is characterized in that it is worn on the head of an occupant riding a motorcycle to protect the head, and it is characterized in that consisting of a helmet that transmits a signal to the control device by detecting whether it is worn. In addition, solar cells were used in the helmet to generate electricity by itself.

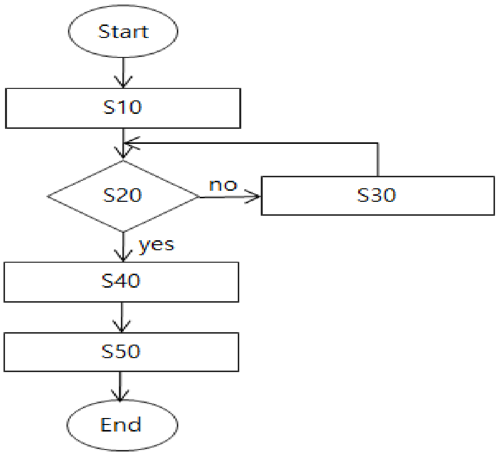

Fig. 3 System and method that can start a motorcycle only when wearing a helmet's system flow

However, it is difficult to accurately measure whether the user wears the helmet only with the sensor worn on the helmet, and it is difficult to determine during driving because it is determined whether or not the user is wearing the helmet only before starting. The trigger value of the start-up was determined whether or not the helmet was worn with only the measurement data of the sensor attached to the helmet. It can generate data values just by manipulating the sensor, and is not suitable for continuous surveillance data.

2) A vision helmet wearing monitoring system and method

Person's head image is identified through a camera attached to the hardware of the helmet, and RGB (Red, Green, and Blue) or HSV (Hue, Saturation, Value) values are applied in pixel units. However, this study cannot be applied to this paper because it is not possible to confirm whether to wear a helmet by identification of the head [20-21].

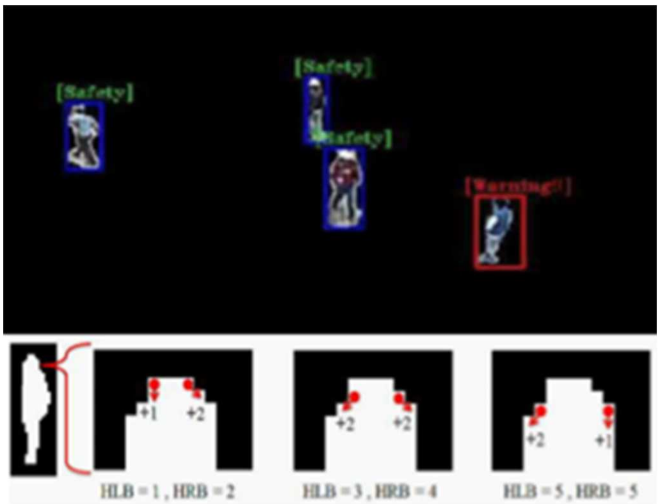

Fig. 4 A vision helmet wearing monitoring system and method's determine image signal

Based on the size and outline of the object through the image signal received from the camera, it is primarily determined whether it is a person or not. The detection of the head in an object identified as a person uses the point addition method to determine the location of each pixel with the object's outline information, and if it is determined to be the head, a point is given, and if the point exceeds the threshold, it is predicted with the head. In this example, when measuring a person with a camera with a resolution of 640*480 at a distance of 50m or more, the size is measured as 15*50 pixels, and the pixel of the head is about 8*8.

Get points method

1) From the detected object, grab the top 2 points with the largest Y value, and if 2 points are greater than the threshold, it is not a head.

2) Otherwise, the nearest point to the left and right is selected from each point, and +1 is given if the direction is downward, and +2 is given if it is diagonal.

3) The method of 2) is continued by predicting the size of the head in proportion to the size of the detected object.

4) If the sum of the left and right points exceeds the threshold, it is judged by the head.

The point addition method seems to be used in this study because it enables relatively accurate prediction even in low-resolution images and does not require many calculations, so it is possible for real-time processing.

Fig. 5 MBR (Minimum Bounding Rectangle)

For objects judged to be human, whether or not to wear a helmet was determined based on the color (H) value of the human head RGB (Red, Green, Blue) value or HSV (Hue, Saturation, Value). To determine whether to wear a hard hat, extract the RGB (Red, Green, Blue) value or HSV (Hue, Saturation, Value) color (H) value according to the color of the hard hat, and the RGB (Red, Green, Blue) value or HSV (Hue, Saturation) The color (H) value of, Value) is compared with the preset standard RGB (Red, Green, Blue) value or the color (H) value of HSV (Hue, Saturation, Value).

As shown in Fig. 4, it was set to MBR (Minimum Bounding Rectangle). However, threshold for determining whether to wear a hard hat must be manually assigned through prediction.

C. Proposed System

1) Personal Mobility System Overview

In the proposed system, the photographic data obtained through the camera attached to the front of the kickboard is used as a measurement value and combined with the helmet sensor value to determine whether a helmet is worn. In addition, we propose a method to implement a kickboard that learns the sensor value measured from the helmet and the image captured by the camera through artificial intelligence technique, analyzes the exact state of wearing the helmet of the user, and determines whether the user wears it in real time while driving. The following figure shows the overall system configuration and data flow.

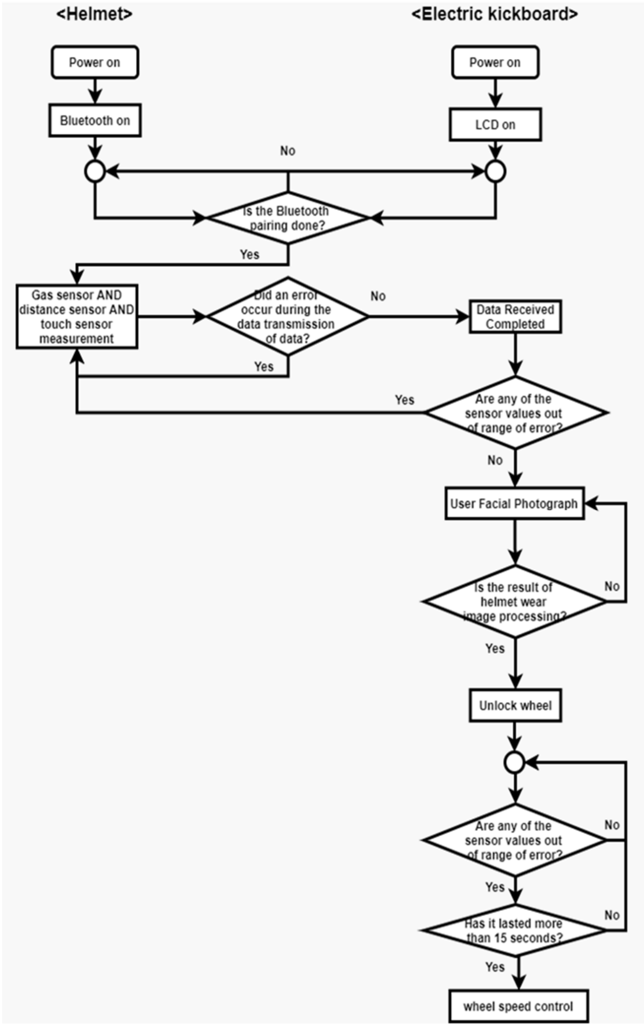

Fig. 6 System Flow

2) How Personal Mobility System Works

When the power is turned on, the Bluetooth of the helmet and the LCD of the electric kickboard are turned on. When the Bluetooth of each helmet and the electric kickboard are paired, the user wears the helmet and receives the data value calculated by measuring the sensor module in the helmet through the Bluetooth of the electric kickboard. If an error occurs in the data transmission process of the electric kickboard, the process of re-measurement and re-reception takes place. When the reception is complete, the data value transmitted from the electric kickboard is compared with the set error range. If it is within the error range, the image processing process is executed. If the result value calculated by taking a picture of the user wearing a helmet and testing the picture on the TensorFlow CNN module is 'Yes', the wheel is unlocked, and if the result is 'No', the process is taken by taking a picture again [22-26]. During driving, periodic measurements are made with the sensor module in the helmet and the infrared camera, and the speed of the wheel is controlled if it is out of the error range for more than 15 seconds [27-29].

D. Connection of parts and artificial intelligence processing

1) Arduino sensor module measurement data and Bluetooth transmission connected flow

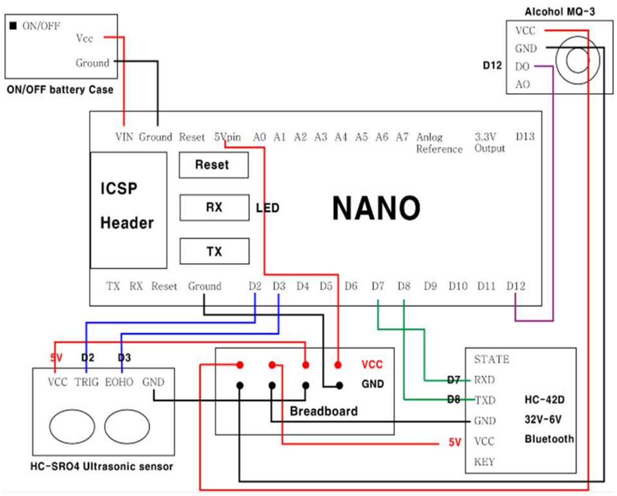

Fig. 7 Arduino Sensor module

Connect the Bluetooth RXD-D7 / TXD-D8, ultrasonic sensor Trig-D2 / Echo-D3, alcohol gas sensor DO-D12, and external power to the corresponding pins. The ultrasonic sensor and the touch sensor are modules that check whether the user is wearing a helmet properly, and continuously try to measure alcohol consumption by using an alcohol gas sensor to prevent the user from drunk driving. The Bluetooth module transmits the measured sensor value of the helmet to the Raspberry Pi using short-range wireless communication. Also, use an external power source to apply a suitable power to the helmet.

2) TensorFlow CNN image processing deep learning

The second core technology among helmet wearing detection technologies is the TensorFlow CNN image processing deep learning technique using the Raspberry Pi's infrared camera module [16-19]. This technique complements the problems of the first core technology while helping to implement functions more precisely and carefully. The use of this technique is this.

E. Operation and performance of each module

1) Arduino Bluetooth module

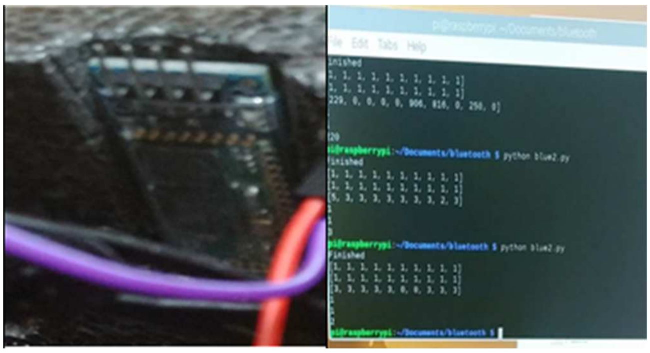

Fig. 8 Bluetooth module's data receiving

When receiving data from the Raspberry Pi to the Arduino Bluetooth module, it takes less time to receive the data value, and errors that occur during the data reception process were not identified.

2) Arduino ultrasonic distance sensor module

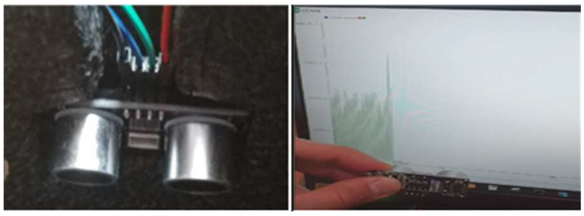

Fig. 9 Ultrasonic distance module

In the picture on the right of Fig.9, the result value was properly measured from the minimum distance of 2cm or more, and when measuring a distance closer than the minimum distance, the measured value was extremely high and an unstable value was measured.

3) Arduino MQ-3 alcohol gas sensor module

Fig. 10 Alcohol gas sensor module

In the photo on the right side of Fig.10, it was confirmed that the temperature of the module increased during the heating time of the internal heater and the measured value increased temporarily. When the temperature reached a certain temperature, the measured value decreased and stabilized. When alcohol gas was added in the middle, it could be confirmed that the measured value was extremely increased.

4) Arduino touch sensor module

Fig. 11 Touch Sensor

As a result of the Arduino touch sensor module measurement experiment, when the body part touches the metal plate, the green LED turns on and the measured value is measured as 1, and if not, the LED turns off and the measured value is measured as 0. In addition to the body parts, measurements were made with various objects, and as a result, it was confirmed that the measurements were made only on objects that carry current.

5)Raspberry Pi Touch Screen

Fig.12 Touch Screen

When I checked the operation after connecting the Raspberry Pi touch screen and performing additional installation, the touch operation was performed, but there were many cases where the use of a touch pen was necessary due to lack of delicate touch recognition.

6) Raspberry Pi infrared camera module

Fig. 13 Camera Module

Looking at the photo on the right of Fig.13., when compared with the basic camera module, it was confirmed that the picture came out in purple, and when the light was turned off, it was confirmed that it was easier to identify people than the basic camera module.

7) System operation

When external power is applied to the helmet, the data value of each sensor is measured, combined into a single string, and transmitted to the Raspberry Pi through Bluetooth communication. The data value of the sensor is transmitted to the Raspberry Pi in real time while the user is driving.

We also implemented a helmet wearing detection technology using artificial intelligence using TensorFlow CNN image processing deep learning technology using Raspberry Pi's infrared camera module. Fig. 14. CNN image processing shows a flow chart of a system implemented to make accurate judgments by training a helmet wearing picture using deep learning. First, each 400 photos with helmets and no helmets are taken, and a folder is created for photos with helmets'Yes' and photos without helmets'No'. The pictures were saved in the appropriate folder and the CNN training code and CNN test code were written.

As shown in Fig. 14, the CNN test code operation process is the process of transferring a picture taken with the Raspberry Pi's infrared camera module as a picture to be identified, converting it to a 3D binary data array through preprocessing, and loading the previously generated model. The file model predicts the training set containing the data values and outputs the final result values for'which training set is included and how accurate'.

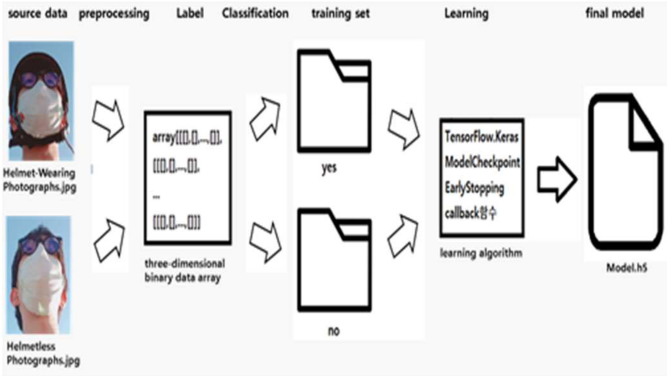

Fig. 14 TensorFlow CNN image processing deep learning training algorithm

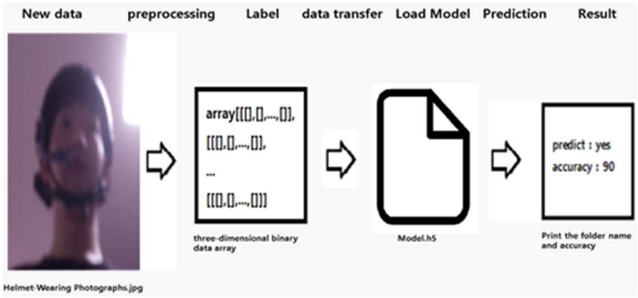

Fig. 15 TensorFlow CNN image processing deep learning test algorithm

First, each 400 photos with helmets and no helmets are taken, and a folder 'yes' for photos with helmets and 'no' for photos without helmets are created. Photos were saved in the folder and CNN training code and CNN test code were written.

The CNN training code operation process loads JPG files of the “yes” category and the “no” category as shown in Fig.8, converts them into a 3D binary data array through preprocessing, and stores the data in the training set. After all the data is stored in the training set, the model checkpoint of TensorFlow. Keras and the EarlyStopping callback function are called, and the model with high accuracy is selected and saved from the models created in the learning algorithm process, and the learning algorithm process is terminated. After that, the final model, h5 format file, is created.

The CNN test code operation process is as shown in Fig.15., by transferring the picture taken by the Raspberry Pi's infrared camera module as a picture to be identified, converting it into a 3D binary data array through preprocessing, and loading the previously generated model file The model predicts which training set contains the data value, and outputs the values for'which training set is included' and'how accurate is it.

III. Results and Discussion

The values of the Arduino gas sensor, distance sensor, and touch sensor mounted on the helmet are combined in a string format, and then passed to the Raspberry Pi through Bluetooth communication at predetermined times. The data values passed to the Raspberry Pi and the data values were compared with Arduino's serial monitor, and they matched.

In the Raspberry Pi, the strings of the sensor values received were divided and arranged, and the average of each sensor value was measured and converted into a number in a percentage format. Using the Raspberry Pi's infrared camera module, 200 bright photos and 200 dark photos with helmets were taken and saved. For photos without a helmet, 100 photos with the chin strap off and only the helmet worn, 100 photos with the helmet upside down, 100 photos with the helmet in front of the face, and 100 photos without the helmet. They were saved in 'Yes' and 'No' files, respectively, and the corresponding photos were preprocessed as TensorFlow CNN training data [16]. After training, using the generated model file, taking a new picture of wearing a helmet on the Raspberry Pi and testing it, it was confirmed that the text “Yes” was output.

Fig. 16 Wearing Helmet Image processing

The Raspberry Pi's CNN data result was quantified in a percentage format and combined with the sensor values to determine whether a helmet was worn.

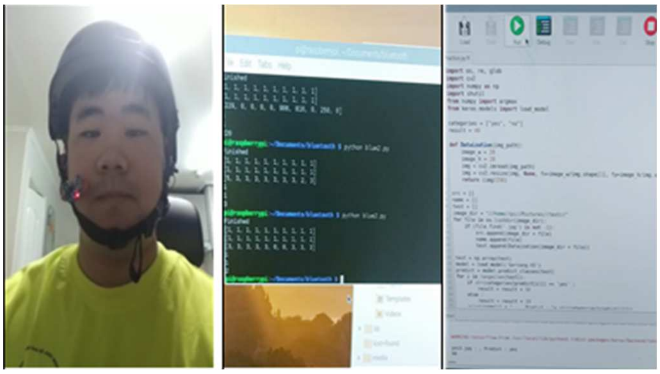

Fig. 8 Image Processing Deep learning tech.

For the helmet wearing detection function, an image processing deep learning technique [13-15] using an infrared camera module and a method using data values measured by the Arduino sensor module can be used to determine in depth whether a user is wearing a helmet. As a result of the experiment, the accuracy of the results obtained by using the artificial intelligence analysis technique was more than 80%. Using this data, it is possible to help safer driving by accurately judging the wearing of the helmet.

IV. Conclusion

Various errors may occur when determining whether to wear a helmet using only the sensor value of the helmet or when determining whether to wear a helmet using only the camera module. Through the experiment, it was confirmed that the two methods can be properly mixed for more accurate judgment. Applying and using TensorFlow CNN technology requires a lot of training photo data. The CNN example already has a large amount of data set, but in this study, we need to collect a lot of data as we will create and use a new data set, and I think that if you want to use it yourself, further study on the implementation of the interface is required.

Acknowledgment

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