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A study on the detection of protective helmets for the safety of construction workers

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***Abstract*— In recent years, with the rapid development of the construction industry, the number of accidents and deaths on construction sites increased, so the prevention of accidents is one of the important issues. Worker safety during construction is a major concern of the construction industry. Wearing helmets can reduce injuries among construction workers, but helmets are not always worn and used correctly for a variety of reasons. Therefore, computer vision-based automatic helmet detection systems are very important. Although many researchers have developed machine and deep learning-based motorcycle helmet detection systems, there is little research on helmet detection for construction workers. Therefore, in this research work, an automatic system for detecting the helmets of construction workers based on real-time computer vision is presented. In this study, machine learning method is used to detect helmets, and a model is trained using 1,500 images. The test results show that the average accuracy is above 95% in laboratory conditions.**

Keywords*— helmet, image processing, machine learning, artificial intelligence, technological process automation

I. INTRODUCTION

With the rapid development of the construction industry, smart buildings are increasing, and there are many studies on energy-efficient buildings, but intelligent control systems for building workers are not well developed. In this research, the protective helmet detection system, which is an important tool for ensuring the healthy and safe working conditions of construction workers, has been studied.

Construction, repair, and demolition of buildings require a lot of human labor, and during this process, engineers, construction workers, electricians, and support workers are at a high risk of being injured and killed in industrial accidents. Therefore, it is important for companies, enterprises and citizens operating in this field to always meet the occupational safety and health requirements.

According to the statistics of the International Labor Organization, accidents in the construction industry are higher than in other industries [1]. The leading causes of construction fatalities include fall, struck by an object, electrocutions, and caught-in/between – together comprising the "fatal four" – which were responsible for nearly 60% of construction worker deaths in 2017 [2]. In China, 840 workers died while working on construction projects in 2018, and 52.2% died from falls from heights [3]. However, within Mongolia in 2018, there were 8 accidents recorded at construction sites, out of which 5 resulted in fatalities.

According to the General Department of Professional Supervision, 256 cases of industrial accidents and acute poisoning were registered at the end of 2021, of which 82 (32.0%) were caused by falls, trips, or slips, 32 (12.5%) were trapped by objects, and 28 (10.9%) were struck by falling objects, 16 (6.3%) external attacks, 11 (4.3%) acid and strong motions, 10 (3.9%) steps on stationary and moving objects, 10 (3.9%) heat, burns, frostbite, electric shock 9 (3.5%) were hit, 3 (1.2%) drowned, 1 (0.4%) were exposed to toxic substances and radiation, and 54 (21.1%) others were reported [4].

Helmets absorb and dissipate the impact of a fall, reducing the risk of injury to workers who fall from a height. It is also able to reliably protect the head during mechanical operation and withstand electrical hazards. When workers wear helmets, they reduce the number of deaths from accidental falls by half and the number of deaths from slips, accidents, and being hit by falling objects [5].

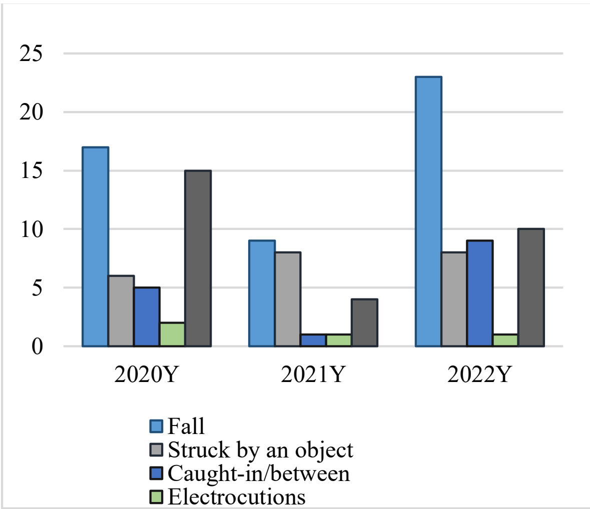

Fig. 1. Causes of construction site accidents in Mongolia

In 2016, a total of 391 people were injured in the Korean construction industry. These injuries included 161 (41.2%) head injuries, 123 (31.5%) injuries to multiple body parts, 46 (11.8%) whole body injuries, 27 (6.9%) chest and back injuries, and 34 (8.7%) other injuries[6]. Based on this information, it can be expected that there is a high possibility that the head will impact the ground first during a fall accident. Because the head is the most vulnerable body part, wearing a safety helmet to protect the head is very important. Thus, ensuring head protection is directly connected to promoting worker safety not only in falls, but also in many other types of safety accidents that occur on construction sites, such as those involving slips, being hit by objects.

Figure 1 shows the causes of construction site accidents in Mongolia from 2020 to 2022 [7].

Wearing a helmet is an effective protective measure to reduce the risk of brain injury. Despite the important role of helmets in protecting human life, according to a study conducted by the US Bureau of Labor Statistics (BLS), 84% of workers injured in head injuries were not wearing head protection [8]. According to the US Occupational Safety and Health Administration (OSHA), failure to use or improper use of personal protective equipment is one of the most frequently violated regulations in recent years [9]. Although more than 90% of construction workers are aware of the importance of wearing helmets, survey results show that inconvenience and discomfort are the main reasons for non-compliance [10]. Currently, safety inspections related to the use of helmets depend on the supervision of labor protection officers. However, because the building area is large, it is very difficult to base it on human vision. The current monitoring of hardhat-wearing remains manual, tedious and time-consuming. Therefore, cost-effective automation of this process is necessary to create a safe environment and reduce the risk of injury and death.

A significant amount of research has been done to automatically detect the use of helmets to augment manual human inspections. Some of these studies have used sensor-based, machine learning-based, and deep learning-based methods for helmet detection.

Sensor-based techniques typically attempt to monitor helmets and workers. Some researchers have used Radio Frequency Identification (RFID) technology to detect personal protective equipment (PPE). Workers wear microcontroller-based devices to detect PPE and send information to a central unit that alerts if the worker is not wearing the PPE properly. However, RFID-based technology could not ensure that a worker was wearing a safety helmet or helmet. Moreover, sensor-based methods are expensive [11].

Helmet detection based on machine and deep learning has been much researched recently. Among them, the YOLO-based solution for helmet detection in a construction site, using a benchmark dataset containing 5000 images, achieved a real-time helmet detection test result (mAP) of 92.44% [2]. Currently the highest performing helmet detection studies have achieved a MaP of 94.47% using regression and transfer learning [12]. Automatic helmet detection is essentially an object detection problem that can be solved using deep learning and computer vision-based methods.

The article is organized as follows. Section II introduces the main theories used in this research, Section III presents the experimental methodology, and Section IV compares the experimental results. Section V contains the conclusion of the research work.

II. THEORETICAL PART

Identifying objects in an image is simple for the human brain, but not so simple for a machine. Recognizing objects in images is a computer vision task called “object detection”. Google's Teachable Machine is a web-based tool for developing machine learning models that are quick, simple, and open to anybody. This study uses the Teachable Machine as the main tool for object detection. This platform has the advantage that objects can be trained faster online without programming knowledge.

A. Machine learning

The field of artificial intelligence is vast and abstract, covering everything related to making computers think and act like humans do, and one of those fields is machine learning. While traditional programming involves writing algorithms expressed in programming languages that operate on data and give us answers, machine learning is based on computational methods and learns directly from data. Machine learning is the concept of a computer learning from its own experience [13].

Fig. 2. Machine learning process

B. Tensorflow

TensorFlow is an open source platform for creating and deploying machine learning models. It implements many common algorithms and patterns required for machine learning. The process of creating a machine learning model is called training. Here, the computer uses a set of algorithms to learn about the inputs and how they differ from each other. After training a model, the process of recognizing or classifying future inputs is called output.

C. Image processing

OpenCV library was used for this research. OpenCV (Open Source Computer Vision Library) is a library of programming functions for real-time computer vision. The library has more than 2,500 optimal algorithms, including modern computer vision and machine learning algorithms. These algorithms can detect and recognize faces, recognize objects, classify human actions in video, track camera movements, and track moving objects. OpenCV is mainly based on real-time visual applications.

The hardware used to run the experiments in this research work is a Raspberry pi 4, a low-cost, credit-card-sized microcomputer with a plug-in computer monitor that uses a standard keyboard and mouse. The Raspberry Pi has the ability to communicate with the outside world and has been used in a variety of digital manufacturing projects, including facial recognition and robot control systems.

"Raspberry pi" has been developed since 2012, and in 2019 "Raspberry Pi 4B" model was released [14]. "Raspberry pi 4 model B" can provide full use of desktop computer.

Some specifications of "Raspberry Pi 4B" and its structure:

- 1.5 GHz, 64-bit quad-core Cortex-A72 (ARM v8) processor.
- Memory: 4GB SDRAM.
- Data transmission: 2.4 GHz and 5.0 GHz IEEE 802.11ac wireless, Bluetooth 5.0, BLE Gigabit Ethernet, 2×USB 3.0 ports; 2×USB 2.0 ports.
- General purpose input and output pins (GPIO): Raspberry Pi has a standard 40 pin GPIO header.
- Video & Sound: 2×micro-HDMI ports, 2-lane "MIPI DSI" display port, "MIPI CSI" camera port, audio and composite video ports.
- SD card: Micro SD card for loading the operating system and storing data.
- Can be powered by 5V DC via USB-C connector.
- Operating temperature: 0~50 degree ambient.

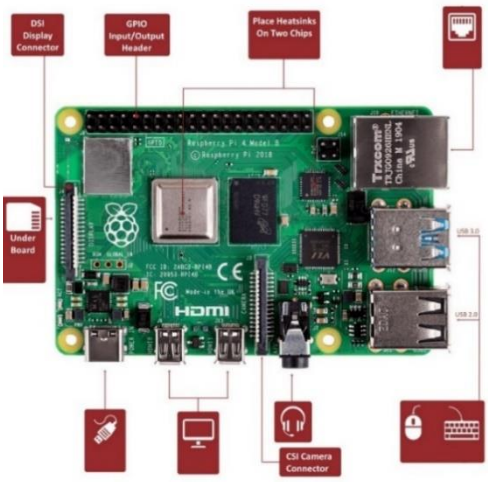

Fig. 3. Used model: The Raspberry Pi 4 model B

III. Experiments

Teachable Machine can train computers to recognize images, sounds, and shapes, and then export the models for your site, applications, and more. It is also a web-based tool that makes machine learning models fast and easy, and anyone can use it because it doesn't require coding [15].

For the overall helmet detection framework, images of helmeted and non-helmeted individuals are first collected using webcams and the internet. The collected images are pre-processed with the help of "Google Teachable Machine Learning" to create "with_helmet" and "without_helmet" categories and it works according to the structure below.

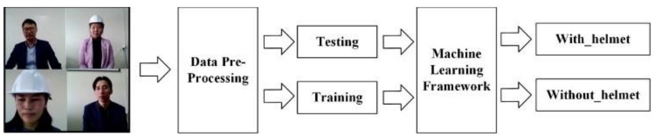

Fig. 4. A general structure for helmet detection using a Machine Learning Framework

A. Data Collection

Data is collected by 2 ways. In Test-1, 750 photos of people wearing safety helmets and 750 photos of people without helmets are downloaded from the Internet and collected. However, in test-2, a total of 1500 photos of students wearing and not wearing protective helmets is collected using a web camera. Using the "Teachable machine learning", the models were trained by creating "with_helmet" and "without_helmet" categories.

(a) (b)

Fig. 5. Examples of in Laboraty enviroment images of people (a) Wearing helmets (b) Not wearing helmets

B. Data processing

The model is trained using the "Teachable machine learning" online machine learning platform, which has created a category of with helmet (with_helmet) and without helmet (without_helmet) from the collected data.

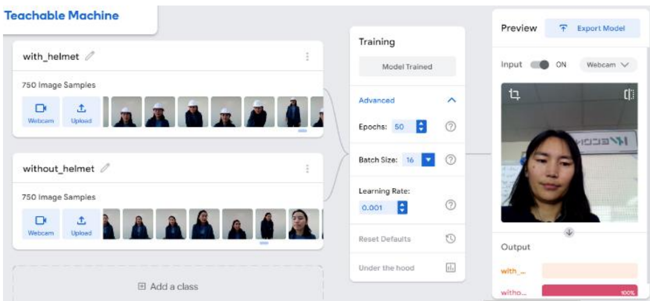

Fig. 6. The process of training data

In this case, teachable machine can export your trained model with three types: Tensorflow.js, Tensorflow, and Tensorflow Lite. Then you can download one type model that suits you best. Since we use Python to write a real-time helmet detection program, we selected Tensorflow.keras as the trained model and exported the model.

C. Visibility of the helmet detection system

Our helmet detection system consists of "Raspberry Pi 4B", camera and 4.3 inch display, and a suitable case is made for it.

IV. Test Result

Using the 'Teachable machine learning' online platform, the collected data is classified into helmet wearers and non-wearers, and then the model is trained. While doing that total of 1,500 images are checked with 85% or 1,275 for training and 15% or 225 for testing. Accuracy is a very important concept when computing a machine learning model. Accuracy is the ratio of the true results to the total results and represents the results of our correct predictions.

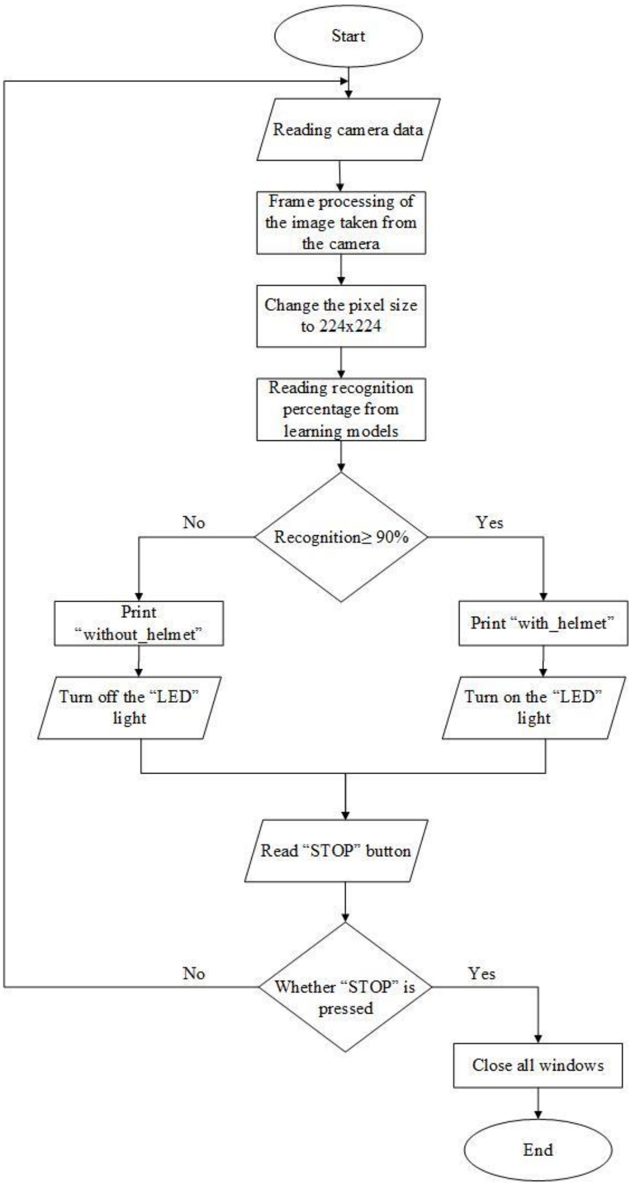

Fig. 7. Main algorithm of operation

Fig. 8. Case of the control system

A. Test-1.

We calculate the accuracy results and show them in table 1. The Fig. 9 shows how precision and loss depend on epoch, and the loss is higher due to the diversity of the training data. When calculating the accuracy from the confusion matrix, it recognizes a person wearing a helmet with 95% and a person without a helmet with 97%.

B. Test-2.

We also collected 750 helmeted and 750 non-helmeted images of more than 30 people using only webcams to improve the results, and trained result is shown in Fig. 11. The loss has decreased and its accuracy has increased compared to the previous training model.

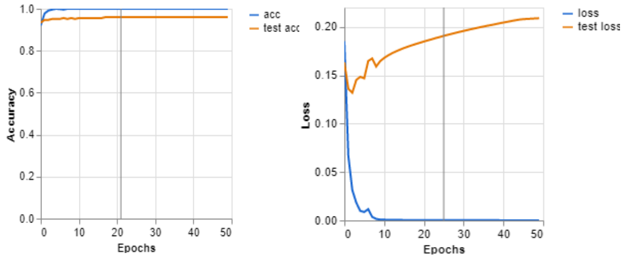

Fig. 9. Accuracy and loss for epoch in Test-1

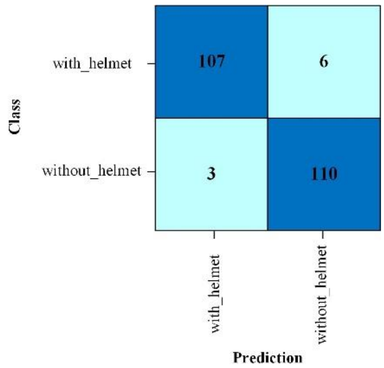

Fig. 10. Confusion matrix for safety helmet detection in Test-1

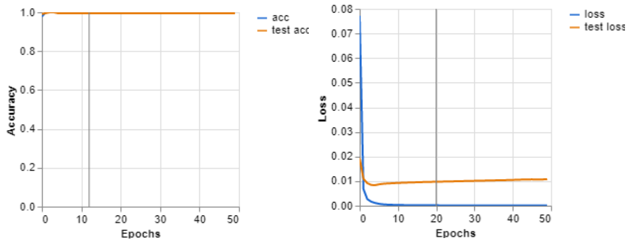

Fig. 11. Accuracy and loss for epoch in Test-2

The results of Test-1 and 2 show that the number of training methods and models is the same, but how the training data of the training models produces results. For Test-1, the accuracy is 95-97% with or without a helmet. On the other hand, judging from the fact that the accuracy has increased in test-2, it is 99-100%, and depending on where and what to use the model used in training, training the model correctly improves the results.

C. Test-3.

In order to compare the results of training the newly trained model with many images and few images, training is carried out with a total of 400 images of 30 people.

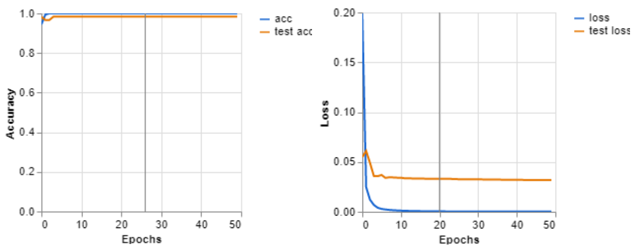

Fig. 12. Accuracy and loss for epoch in Test-3

For Test-3, the accuracy is 97% and the loss is 3%. It can be concluded that the trained data model is the same, but the results are different depending on the number of training sessions. This suggests that training with multiple images is less error-prone.

TABLE I. TEST RESULTS OF ACCURACY

Class	Accuracy		
	Test-1	***Test-2***	***Test-3***
with_helmet	0.95	0.99	0.97
without_helmet	0.97	1.0	1.0

According to the results of the above training model, firstly, depending on where and what it will be used for, it is possible to train the model correctly, and secondly, training with many models can have low errors and high accuracy.

The recognition is also high when we check the trained data with real-time performance indicators using raspberry pi 4B.

Fig. 13. Running the trained model on Raspberry pi 4B

V. CONCLUSIONS

In this research, a real-time safety helmet detection system using machine learning is considered to detect whether workers are wearing safety helmets, which is one of the occupational safety and health violations in construction sites.

The training results show that the model is correct and training with multiple models has lower error and higher accuracy depending on the application conditions. In laboratory conditions, it is more than 95% familiar, which shows that this system can be further improved and used in a real environment. In this way, there is full potential to quickly detect labor protection and safety violations and to become more reliable by relying not only on human vision but also on computer vision.

Based on the safety helmet detection system, it is possible to install and use the safety helmet detection system in all high-risk places such as buildings, industrial sites, power plants, and locations where safety may be violated, and to further improve it, it can be tested in the outdoor environment.

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