International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Image Processing Based Alarm System for Rod Cutters to Prevent Finger Cutting using CNN

Kachireddy Siva Jyothi[1], Boyapalli Gayatri[2], Cheva Navyasri[3], Billapati Sowmya[4], N. Sreenivasa Rao[5]

[1, 2, 3, 4] Department of Electronics and Communication, Santhiram Engineering College, India,

[5]Asst. Prof. Department of Electronics and Communication, Santhiram Engineering College, India

ABSTRACT

In a lot of metal fabrication units, the cutting of metal rods happens by manually operated electric cutter. A lot of finger cutting accident occurs in such units. In this project, a camera module integrated with an embedded system that can actuate an alarm when the camera detects a person's finger placed in the path of the blade is implemented. The automaton of the above system is a CNN image processing model trained by images of hands placed in the cutting unit. Once the finger in the path of the cutting is identified by the camera module, the alarm is raised by a sound buzzer triggered by the embedded module.

Keywords: Image processing, CNN, Embedded module

1. INTRODUCTION

Metal fabrication sector is the foundation of all infrastructures globally. The civil structures of concrete entirely rely upon metal structures for strength and form. Safety in metal fabrication has always been an issue of concern. The Industrial Safety Market was valued at USD 3.12 Billion in 2018 and is projected to reach USD 5.8 Billion by 2026, growing at a CAGR of 8.03% from 2019 to 2026 [Credits: www.verifiedmarketresearch.com]. One of the incidents where workers can lose their fingers is cutting metal rods with motorized rotary blades. Here a simple solution is presented for preventing finger cutting accidents employing image processing. A camera is placed in the right position where the vertical cutting profile of the blade is visible. The finger if placed in front of the blade, a high pitched alarm is triggered. The above module is implemented by CNN image processing algorithm. A dataset consisting of images of blades without fingers in front of them and blades with fingers in front of them are used to train a CNN module to classify a captured real time image as unsafe or safe. Once the CNN trained automaton is obtained, it is loaded into an embedded control unit and connected with a camera placed with the same field of view as the training dataset.

2. PROPOSED SYSTEM

The proposed system consists of a Raspberry pi 4, a Pi camera and a buzzer. The process goes as follows. The Pi camera acquires the image data and it is then sent to the Raspberry pi. The Raspberry pi processes the image and feeds it into the model and activates the buzzer if the human fingers are detected in the image that is captured. The system is trained to identify the human fingers. The model is trained with 150 images of human fingers using the YoloV3 algorithm. The trained weights and configuration files are then deployed in the raspberry pi. During deployment, the data is acquired from pi camera and it is processed in the Raspberry pi and if it detects a human hand or a finger in the image, an alarm is raised as an alert using the piezoelectric buzzer.

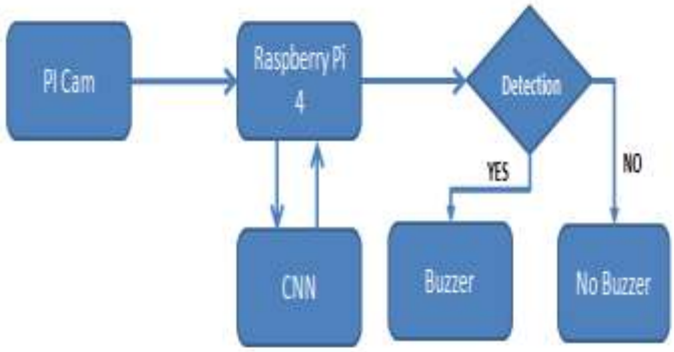

Figure 1. Block Diagram

3. RASPBERRY PI MICROCONTROLLER

The trained CNN model is uploaded in Raspberry Pi Board for this image processing requirement.

3.1 Introduction

Raspberry Pi 4 Model B is the latest product in the popular Raspberry Pi range of computers. It offers ground-breaking increases in processor speed, multimedia performance, memory, and connectivity compared to the prior-generation Raspberry Pi 3 Model B+, while retaining backwards compatibility and similar power consumption. For the end user, Raspberry Pi 4 Model B provides desktop performance comparable to entry-level x86 PC systems. This product's key features include a high-performance 64-bit quad-core processor, dual-display support at resolutions up to 4K via a pair of micro-HDMI ports, hardware video decode at up to 4Kp60, up to 4GB of RAM, dual-band 2.4/5.0 GHz wireless LAN, Bluetooth 5.0, Gigabit Ethernet, USB 3.0, and PoE capability (via a separate PoE HAT add-on). The dual-band wireless LAN and Bluetooth have modular compliance certification, allowing the board to be designed into end products with significantly reduced compliance testing, improving both cost and time to market. [2]

Figure 2. Raspberry Pi 4 Model B

3.2 Hardware

The Raspberry Pi hardware has evolved through several versions that feature variations in the type of the central processing unit, amount of memory capacity, networking support, and peripheral-device support. [3]

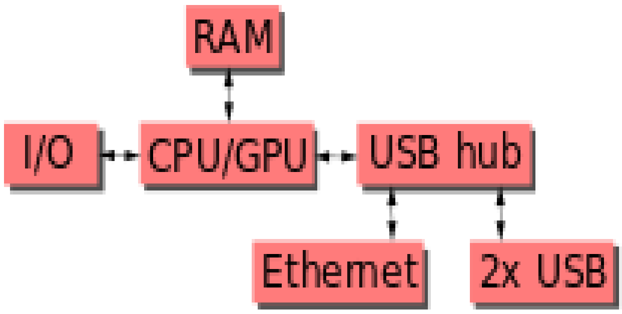

Figure 3. Raspberry Pi Block Diagram

The above block diagram describes models B, B+, A and A+. The Pi Zero models are similar, but lack the Ethernet and USB hub components. The Ethernet adapter is internally connected to an additional USB port. In Model A, A+, and the Pi Zero, the USB port is connected directly to the system on a chip (SoC). On the Pi 1 Model B+ and later models the USB/Ethernet chip contains a five-port USB hub, of which four ports are available, while the Pi 1 Model B only provides two. On the Pi Zero, the USB port is also connected directly to the SoC, but it uses a micro USB (OTG) port. Unlike all other Pi models, the 40 pin GPIO connector is omitted on the Pi Zero, with solderable through-holes only in the pin locations. The Pi Zero WH remedies this. [3]

Processor:

Processor speed ranges from 700 MHz to 1.4 GHz for the Pi 3 Model B+ or 1.5 GHz for the Pi 4; on-board memory ranges from 256 MB to 1 GB random-access memory (RAM), with up to 8 GB available on the Pi 4. Secure Digital (SD) cards in MicroSDHC form factor (SDHC on early models) are used to store the operating system and program memory. The boards have one to five USB ports. For video output, HDMI and composite video are supported, with a standard 3.5 mm tip-ring-sleeve jack for audio output. Lower-level output is provided by a number of GPIO pins, which support common protocols like I²C. The B-models have an 8P8C Ethernet port and the Pi 3, Pi 4 and Pi Zero W have on-board Wi-Fi 802.11n and Bluetooth. [3]

The Broadcom BCM2835 SoC used in the first generation Raspberry Pi includes a 700 MHz ARM1176JZF-S processor, VideoCore IV graphics processing unit (GPU), and RAM. It has a level 1 (L1) cache of 16 KB and a level 2 (L2) cache of 128 KB. The level 2 cache is used primarily by the GPU. The SoC is stacked underneath the RAM chip, so only its edge is visible. The ARM1176JZ(F)-S is the same CPU used in the original iPhone, although at a higher clock rate, and mated with a much faster GPU. The earlier V1.1 model of the Raspberry Pi 2 used a Broadcom BCM2836 SoC with a 900 MHz 32-bit, quad-core ARM Cortex-A7 processor, with 256 KB shared L2 cache.[48] The Raspberry Pi 2 V1.2 was upgraded to a Broadcom BCM2837 SoC with a 1.2 GHz 64-bit quad-core ARM Cortex-A53 processor, the same SoC which is used on the Raspberry Pi 3, but underclocked (by default) to the same 900 MHz CPU clock speed as the V1.1. The BCM2836 SoC is no longer in production as of late 2016. The Raspberry Pi 3 Model B uses a Broadcom BCM2837 SoC with a 1.2 GHz 64-bit quad-core ARM Cortex-A53 processor, with 512 KB shared L2 cache. The Model A+ and B+ are 1.4 GHz. The Raspberry Pi 4 uses a Broadcom BCM2711 SoC with a 1.5 GHz 64-bit quad-core ARM Cortex-A72 processor, with 1 MB shared L2 cache. Unlike previous models, which all used a custom interrupt controller poorly suited for virtualisation, the interrupt controller on this SoC is compatible with the ARM Generic Interrupt Controller (GIC) architecture 2.0, providing hardware support for interrupt distribution when using ARM virtualisation capabilities. The Raspberry Pi Zero and Zero W use the same Broadcom BCM2835 SoC as the first generation Raspberry Pi, although now running at 1 GHz CPU clock speed. The Raspberry Pi Pico uses the RP2040 running at 133 MHz. [3]

Video:

The video controller can generate standard modern TV resolutions, such as HD and Full HD, and higher or lower monitor resolutions as well as older NTSC or PAL standard CRT TV resolutions. As shipped (i.e., without custom overclocking) it can support the following resolutions: 640×350 EGA; 640×480 VGA; 800×600 SVGA; 1024×768 XGA; 1280×720 720p HDTV; 1280×768 WXGA variant; 1280×800 WXGA variant; 1280×1024 SXGA; 1366×768 WXGA variant; 1400×1050 SXGA+; 1600×1200 UXGA; 1680×1050 WXGA+; 1920×1080 1080p HDTV; 1920×1200 WUXGA. [3]

Higher resolutions, up to 2048×1152, may work or even 3840×2160 at 15 Hz (too low a frame rate for convincing video). Allowing the highest resolutions does not imply that the GPU can decode video formats at these resolutions; in fact, the Raspberry Pis are known to not work reliably for H.265 (at those high resolutions), commonly used for very high resolutions (however, most common formats up to Full HD do work). Although the Raspberry Pi 3 does not have H.265 decoding hardware, the CPU is more powerful than its predecessors, potentially fast enough to allow the decoding of H.265-encoded videos in software. The GPU in the Raspberry Pi 3 runs at higher clock frequencies of 300 MHz or 400 MHz, compared to previous versions which ran at 250 MHz. [3]

The Raspberry Pis can also generate 576i and 480i composite video signals, as used on old-style (CRT) TV screens and less-expensive monitors through standard connectors – either RCA or 3.5 mm phono connector depending on model. The television signal standards supported are PAL-B/G/H/I/D, PAL-M, PAL-N, NTSC and NTSC-J. [3]

3.3 Software

Operating System:

The Raspberry Pi Foundation provides Raspberry Pi OS (formerly called Raspbian), a Debian-based (32-bit) Linux distribution for download, as well as third-party Ubuntu, Windows 10 IoT Core, RISC OS, and LibreELEC (specialised media centre distribution). It promotes Python and Scratch as the main programming languages, with support for many other languages. The default firmware is closed source, while unofficial open source is available. Many other operating systems can also run on the Raspberry Pi. Third-party operating systems available via the official website include Ubuntu MATE, Windows 10 IoT Core, RISC OS and specialised distributions for the Kodi media centre and classroom management. The formally verified microkernel seL4 is also supported. [3]

3.4 Convolutional Neural Network

In deep learning, a convolutional neural network (CNN, or ConvNet) is a class of deep neural network, most commonly applied to analyze visual imagery. They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on the shared-weight architecture of the convolution kernels or filters that slide along input features and provide translation equivariant responses known as feature maps. Counter-intuitively, most convolutional neural networks are only equivariant, as opposed to invariant, to translation. They have applications in image and video recognition, recommender systems, image classification, image segmentation, medical image analysis, natural language processing, brain-computer interfaces, and financial time series. [3]

CNNs are regularized versions of multilayer perceptrons. Multilayer perceptrons usually mean fully connected networks, that is, each neuron in one layer is connected to all neurons in the next layer. The full connectivity of these networks make them prone to over-fitting data. Typical ways of regularization, or preventing over-fitting, include: penalizing parameters during training (such as weight decay) or trimming connectivity (skipped connections, dropout, etc.) CNNs take a different approach towards regularization: they take advantage of the hierarchical pattern in data and assemble patterns of increasing complexity using smaller and simpler patterns embossed in their filters. Therefore, on a scale of connectivity and complexity, CNNs are on the lower extreme. Convolutional networks were inspired by biological processes in that the connectivity pattern between neurons resembles the organization of the animal visual cortex. Individual cortical neurons respond to stimuli only in a restricted region of the visual field known as the receptive field. The receptive fields of different neurons partially overlap such that they cover the entire visual field. CNNs use relatively little pre-processing compared to other image classification algorithms. This means that the network learns to optimize the filters (or kernels) through automated learning, whereas in traditional algorithms these filters are hand-engineered. This independence from prior knowledge and human intervention in feature extraction is a major advantage. [3]

4. INDUSTRY 4.0

Wikipedia defines Industry 4.0 as thus: The Fourth Industrial Revolution (4IR or Industry 4.0) is the ongoing automation of traditional manufacturing and industrial practices, using modern smart technology. Large-scale machine-to-machine communication (M2M) and the internet of things (IoT) are integrated for increased automation, improved communication and self-monitoring, and production of smart machines that can analyze and diagnose issues without the need for human intervention.[4]

Automation under Industry 4.0 has a particular schema or pattern at its outset. Presented below is how automation in the mass production industry as well as consumer level products are built in today's technological era.

The schema presented in Figure 4 has a lot of other components involved but the generic outline of it stands justifiable for all kinds of automation today.

The software automaton of the conventional automation model, which is the status quo, was built by a human expert or a team of human experts till now. With the advent of machine learning technology, the software automaton was not fully directly designed by human experts. The human experts build the machine learning software and give the real world data set as training information. The machine learning software identifies the pattern between the input and the output parameters of the dataset in the form of a mathematical model. This mathematical model can be downloaded as a working software module to other electronic computing devices. This mathematical model is referred to as the 'trained machine learning module'. The software automaton of all the current digital embedded devices is a mathematical model that gives a numerical output for a numerical input based on arithmetic and logical conditions. This software automaton, as explained above can be either directly developed by a set of human experts by means of setting the boundary conditions themselves based on observation and requirement or can be downloaded as an executable module from machine learning training systems that are trained with relevant dataset. In whatever way the software automaton is developed, it can be loaded onto the relevant embedded computing module that can be used for either sensor based closed loop automation or open loop automation.

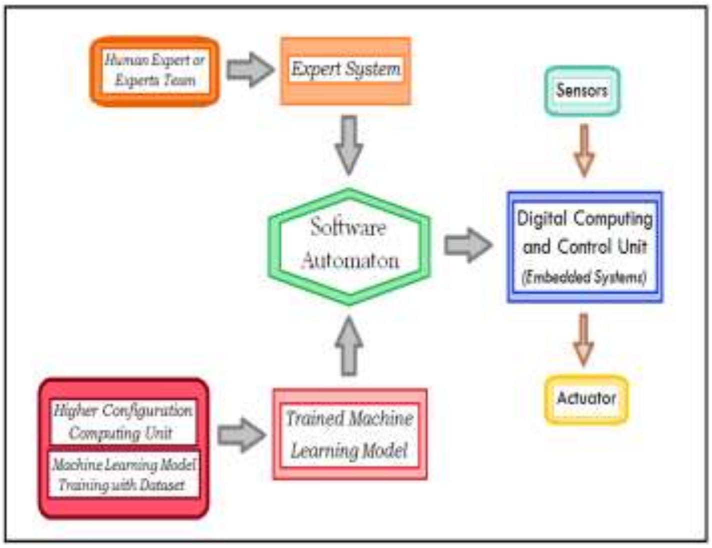

Figure 4. Schema of Automation

The technological components of Industry 4.0 includes IoT, augmented reality, virtual reality, cloud computing, 3D printing, big data analytics, networking, data security, human-machine interaction and others. IoT is a very effective way to collect real world data. Sensors integrated with data acquisition and transmission systems can be placed anywhere and the collected data can be pre-processed if required and used as datasets to train machine learning models.

Cloud computing is employed for optimized utilization of computing resources. There are many third party vendors like Google and Amazon which are very reliable in terms of data security and speed of computation. These services offer companies and organizations a cheap and reliable way to harness the power of artificial intelligence and machine learning.

Big data analytics is the set of technological components involved with collecting, collating and managing large quantities of data for analytics and decision making. When so much data is involved, especially with third party service providers, data security plays an important role.

One of the paramount concerns about Industry 4.0 is the unemployment it can create due to powerful automations. The field of human-machine interactions and co-working has been a very developing field now to mitigate the above mentioned problem.

5. WORKING

Figure 5. Schematic Diagram

Presented above (Figure 5) is a schematic diagram of the system presented in this paper. A camera is placed with such a field of view that it can identify fingers placed before the rotating blade. This image is taken and is sent to the local microcontroller based computing device that has a trained CNN automaton loaded on to it. The CNN module is trained to identify only between two classes: if the fingers are before the blade or if the fingers are not there before the blade. If the fingers are there before the blade then the alarm buzzer is initiated to give a loud alarm.

Figure 6. Example System 1

Figure 7. Example System 2

Presented above are two images (Figure 6 and 7) wherein the system described in this paper can be implemented for avoiding finger cutting accidents.

6. RESULTS AND DISCUSSION

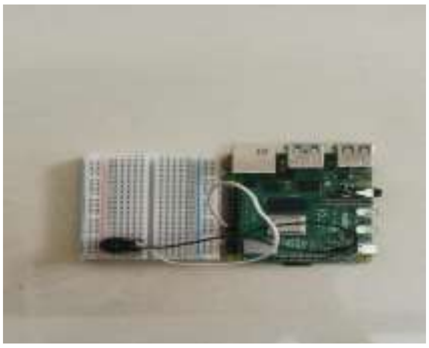

Figure 8. Raspberry Pi Setup

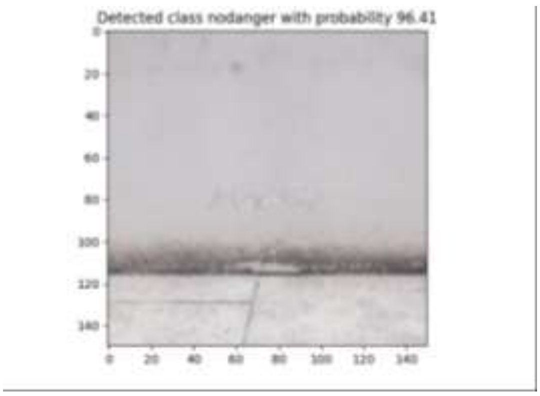

Figure 9. Detected class – No danger

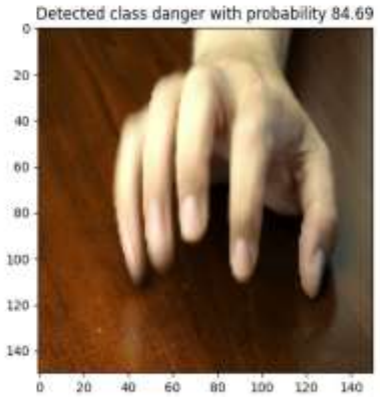

Figure 10. Detected class – Danger

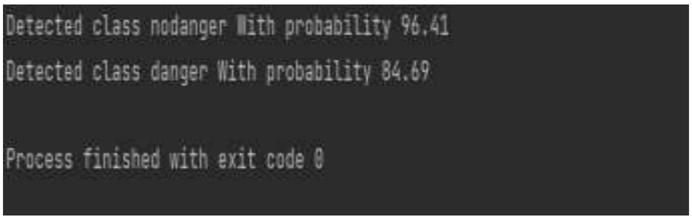

Figure 11. Status Output

As shown in the Figure 8, the circuit of the system consists of a Raspberry Pi, a Pi cam and the corresponding actuator, which in this case is a buzzer. This is an ideation level prototype of the product presented in this paper. The industrial grade prototype of this product will have a very similar setup as above. The difference will be that more industrial grade components will be used. This circuitry along with the image processing CNN algorithm was tested and the performance was satisfactory in terms of validating the proposed method. When the fingers are identified as shown in Figure 10, the buzzer is triggered. Images obtained in this project are continuously sent to a centralized server in the industrial grade unit. Analytics can be performed on the collected, collated and preprocessed image data for obtaining useful inferences of the system and the environment.

7. CONCLUSION AND FUTURE WORK

Computer vision and machine learning are the two fields integrated to achieve this effective technology. Image processing and classification techniques can be used for a lot of very similar requirements. In requirements like this at least 10 to 15 features of the objects to be classified are extracted. Machine learning algorithms including Random Forest, SVM, KNN and ANN can be applied on such requirements. IIoT can be integrated with this project of identifying the dangerously placed finger before the blade. The frequency of how often the fingers are kept before the blade is measured. The number of times the actual cutting process happens and the corresponding number of times the fingers are kept before. These counts can be personalized for workers and the safety level of every worker can be assessed. Workers with more percentage of finger placing before the blade can be warned or reassigned to other works. One all the more effective way of completely eliminating this problem is employing robots assistance in executing such dangerous cutting tasks. To maintain the human employment quotient, semi-automated robotic systems can be used. Biomedical sensors can be used to measure the state of carefulness based on the heartbeat and pressure level indicating to the worker with a gentle buzzer every time a certain degree of callousness is measured.

References

[1]. Varsha Goud and Padmaja Vangala, "Vehicle Accident Automatic Detection and Remote Alarm Device", International Journal of Reconfigurable and Embedded Systems (IJRES), July 2012.

[2]. https://static.raspberrypi.org/files/product-briefs/Raspberry-Pi-4-Product-Brief.pdf

[3]. https://en.wikipedia.org/wiki/Raspberry_Pi

[4]. https://en.wikipedia.org/wiki/Fourth_Industrial_Revolution