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Presented by**: MOHAMMED BASSAM MABEDI**

HICHAM DOUADI

Untitled

PERSONAL PROTECTIVE (PPE) DETECTION USING DEEP LEARNING

Supported in**: 07/06/2022**

Before the Jury

M r. FATIMA AMEUR	MCB	President	UKM	OUARGLA
M r. RACHID CHLAOUA	MCB	Examiner	UKM	OUARGLA
M r. ANOUARESSADATEAOUF	MAA	Supervisor	UKM	OUARGLA

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Thanks

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Dedications

I dedicate this work:

My dear father Ahmed and dear mother Hadja Fatoum.

To my dear brother and sisters.

To my colleague who helped us in this work

To my colleague who was the biggest support in achieving this work Amna

To those who have supported me throughout my studies.

Med Bassam Mabedi

Dedication

To my older brother Hamza

I dedicate this humble work to my brother Hamza, who was my main supporter

To my father, Mr. Douadi Mebarak, my mother, Mrs. Ben Oumhani Fatiha, my brothers, Samir sliman, and my sister, Samia

I owe you all your love, support and encouragement in everything.

I can't finish without you.

Thank you..

Hicham Douadi

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Notations and Symbols

PPE: Personal Protective Equipment.

AI: Artificial Intelligence.

ML: Machine Learning.

CNN: Convolution Neural Network.

YOLO: You Only Look Once.

CV: Computer Vision.

OSHA: Occupational Safety and Health Administration

RNN: Recurrent Neural Network

CE: European Conformity

BIM: Building Information Modelling

AR: Augmented Reality

VR: Virtual Reality

SSD: Signal Shot Detection

Abstract

Machine learning tasks, such as image identification and computer vision, deep learning has shown outstanding results. The availability of high-quality training data consisting of huge numbers of human-annotated examples limits its application to supervised problems To solve this problem, automatically created images or video sequences using realistic photo rendering engines, such as those used in entertainment applications, have recently become more popular in the AI field. Large sets of training photos for deep learning algorithms can be easily constructed this way.

we generated photo-realistic synthetic image sets to train deep learning models to recognize the correct use of personal safety equipment (e.g., worker safety helmets, high visibility vests, ear protection devices) during at-risk work activities. Then, we performed the adaptation of the domain to real-world images using a very small set of real-world images. We demonstrated that training with the synthetic training set generated and the use of the domain adaptation phase is an effective solution for applications where no training set is available.

Keywords: Artificial Intelligence, deep learning, Safety, Automation, YOLO.

ملخص:

حقق التعلم العميق نتائج رائعة في العديد من مهام التعلم الآلي مثل التعرف على الصور ورؤية الكمبيوتر. ومع ذلك، فإن قابلية تطبيقه على المشكلات مقيد بتوافر بيانات تدريب عالية الجودة تتكون من أعداد كبيرة من الأمثلة المشروحة من البشر (مثل الملايين). للتغلب على هذه المشكلة، في الآونة الأخيرة، يستغل عالم الذكاء الاصطناع بشكل متزايد الصور المصطنعة أو تسلسلات الفيديو باستخدام محركات عرض الصور الواقعية مثل تلك المستخدمة في تطبيقات الترفيه. بهذه الطريقة ، يمكن إنشاء مجموعات كبيرة من الصور التدريبية بسهولة لتدريب خوارزميات التعلم العميق. في هذه الورقة، أنشأنا مجموعات صور واقعية اصطناعية لتدريب نماذج التعلم العميق للتعرف على الاستخدام الصحيح لمعدات السلامة الشخصية (على سبيل المثال ، خوذات سلامة العمال ، وسترات عالية الوضوح ، وأجهزة حماية الأذن) أثناء أنشطة العمل المعرضة للخطر. بعد ذلك، أجرينا تكييف المجال مع صور العالم الواقعي باستخدام مجموعة صغيرة جدًا من صور العالم الحقيقي. لقد أظهرنا أن التدريب باستخدام مجموعة التدريب التركيبية التي تم إنشاؤها واستخدام مرحلة تكييف المجال هو حل فعال للتطبيقات التي لا تتوفر فيها مجموعة تدريب.

الكلمات المفتاحية: معدات الوقاية الشخصية ، الذكاء الاصطناعي ، التعلم العميق ، السلامة ، الأتمتة .

Summary

L'apprentissage en profondeur a obtenu des résultats impressionnants dans de nombreuses tâches d'apprentissage automatique telles que la reconnaissance d'images et la vision par ordinateur. Son applicabilité aux problèmes supervisés est cependant limitée par la disponibilité de données d'entraînement de haute qualité constituées d'un grand nombre d'exemples annotés humains . Pour surmonter ce problème, depuis peu, le monde de l'intelligence artificielle (IA) exploite de plus en plus des images ou des séquences vidéo générées artificiellement à l'aide de moteurs de rendu photo réalistes tels que ceux utilisés dans les applications de divertissement. De cette façon, de grands ensembles d'images de formation peuvent être facilement créés pour former des algorithmes d'apprentissage en profondeur. Dans ce mémoire, nous avons généré des ensembles d'images synthétique pour former des modèles d'apprentissage en profondeur afin de reconnaître l'utilisation correcte de l'équipement de sécurité personnel (par exemple, casques de sécurité des travailleurs, gilets haute visibilité, dispositifs de protection auditive) pendant les activités de travail à risque. Ensuite, nous avons effectué l'adaptation du domaine aux images du monde réel en utilisant un très petit ensemble d'images du monde réel. Nous avons démontré que l'entraînement avec l'ensemble d'apprentissage synthétique généré et l'utilisation de la phase d'adaptation de domaine est une solution efficace pour les applications où aucun ensemble d'apprentissage n'est disponible.

Mots clés :EPI, Intelligence Artificielle, L'apprentissage en Profondeur, Sécurité, Automatisation, Yolo .

General introduction

General Introduction

When engineering or management risk control techniques are neither feasible nor able to fully protect workers, the proper use of Personal Protective Equipment (PPE) becomes a last resort to protect workers. The use of personal protective equipment does not eliminate hazardous conditions. Instead, employees using PPE are given a line of defense against hazards and so injuries and illnesses can be reduced through proper use of PPE. If workers find required PPE unacceptable due to discomfort or other factors, they may not wear it or may tamper with it which impairs the last resort method of controlling risks. Studies on PPE vary, and most have been conducted to evaluate some of the issues related to individual types of PPE in laboratory settings. Some studies have been conducted to determine performance. So this study was About, in the use of different types of personal protective equipment and to identify the factors contributing to the “work” of workers. Discomfort while wearing these devices in the workplace.This Work is organized as follows:

- Chapter 1 contains the definitions and terms of deep learning.
- Chapter 2 is information about personal protective equipment.
- Third Chapter is the results of the experiment PPE (use algorithm YOLO).
- General conclusion.

Chapter 1: Deep Learning

1. Introduction

Deep Learning has been a challenge for many to define specialist in the field as it has slowly changed shape over the past decade. A useful definition clarifies that deep learning is a neural network with more than two layers[1]. The problem with this definition is that it echoes the existence of this estate since the 80s of the last century, thus forming a large contradiction since many people think that this field is relatively new, for refute this contradiction, it is necessary to distinguish the moment when the domain appeared and the moment when it was framed and operated.

This chapter is organized as follows:

- Definitions and types of deep learning.
- Objective of deep learning
- What are the differences between artificial intelligence, machine learning and deep learning?
- Neural network.
- Conclusion.

1.1. Definitions and Types of Deep Learning

1.1.1. Définitions

Deep learning is a subset of machine learning or artificial neural networks, algorithms inspired by the human brain, learn from large amounts of dataSimilarly to how we learn from experience, the deep learning system would repeat a task, tweaking it slightly each time to enhance the outcome. Because neural networks include multiple (deep) layers that permit learning, we refer to it as deep learning. Any problem that can be solved through "thinking" is a problem that deep learning can learn to solve. The amount of data we generate every day is amazing – it's presently estimated to be 2.6 quintillion bytes – and it's this resource that enables deep learning. Because deep learning algorithms need a lot of data to learn, they demand a lot of data. [2] Deep learning algorithms benefit from higher processing capacity nowadays, as well as the proliferation of artificial intelligence (AI) as a service, in addition to creating data.

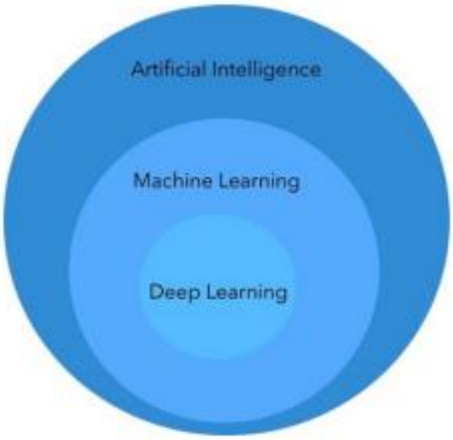


Figure 1:Deep learning.

1.1.2. Types of learning methods

In deep learning, predictive models use various fundamental algorithms to infer relationships

mathematics from training data. There are mainly three types of learning methods**,** to know :

1.1.2.1. Supervised learning

In supervised learning, the model is fed with a set of training data containing both the observations (the inputs) and the corresponding results (the outputs) . The model then infers the mathematical mapping from inputs to outputs, which it can use to classify future test data points.

1.1.2.2. Unsupervised learning

In unsupervised learning, the model is fed with unclassified training data (only the inputs). Then, the model classifies the test data points in different classes by finding commonalities between they.

1.1.2.3. Semi-supervised learning

As its name suggests, semi-supervised learning inherits the properties of supervised learning and unsupervised learning. A semi-supervised dataset contains mostly data points unclassified training materials as well as small amounts of classified data.

Semi-supervised models have two important advantages. First, they are significantly more accurate than unsupervised models with the addition of a few classified data points. Second, they are significantly less laborious and time-consuming than supervised learning. Semi-supervised learning can refer either to transductive learning or to inductive learning.[3]

1.2. Objective of deep learning

Deep learning advancement was aided in part by the failure of traditional algorithms, particularly in relation to Big Data and related issues, and the fact that computing machines have emerged as a powerful tool. One of the major differences between Deep Learning and traditional machine learning algorithms is that it adapts effectively; the more information provided, the better the overall performance of a Deep Learning set of rules.

Now and again known as an "overall performance plateau", Deep Learning fashions do now no longer have such Another Difference Between Traditional ML Algorithms and Deep Learning Algorithms In conventional ML algorithms time and calls for an expert withinside the discipline while in Deep Learning this step is carried out.

1.3. What are the differences between artificial intelligence, machine learning and deep learning?

To better understand the difference in approach between these three technologies, let's see how they must proceed to teach a computer to recognize the presence of a cat in images:

• AI requires a programmer to write all the code necessary for the computer to recognize a cat in an image .The programmer creates the learning model.

• Machine learning requires programmers to teach the system what a cat looks like by showing it different images and correcting its analysis until it is correct (or more precise). We talk about supervised learning since human intervention is necessary.

• Deep learning divides the task of recognizing the characteristics of the cat into several layers: one layer of the algorithm learns to recognize the eyes, another the ears, a third the general silhouette, and so on. Once connected, these different layers have a certain ability to recognize cats in order to recognize the animal on each new image submitted Machine learning and deep learning make AI more efficient and more accessible.

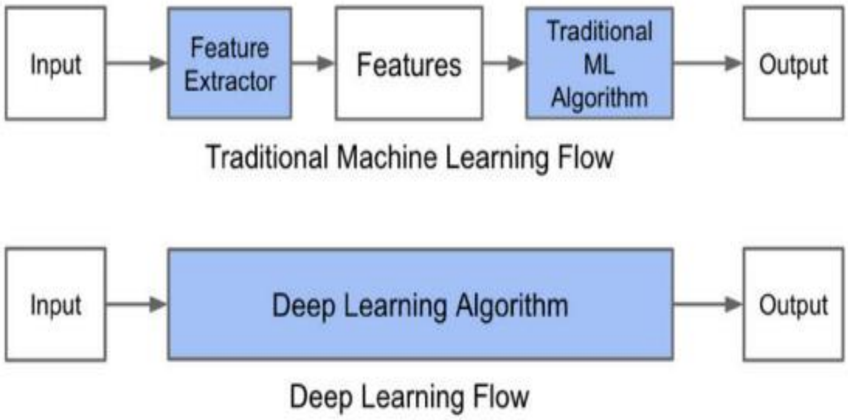


Figure 2: The process of classical ML compared to that of Deep Learning.*[4]*

1.4.Neural networks

Neural networks (Neural Networks) is one of the algorithms maximum famous system gaining knowledge of gear today. Over time, he neural networks had been conclusively demonstrated to outperform othersalgorithms in phrases of accuracy and speed. With numerous variations such as CNN (Convolutional Neural Networks (abbreviated as CNN)), RNN (Convolutional Neural Networks Recurrent Neurons), Auto-Encoders, etc…, neural networks become step by step for scientists or practitioners of system gaining knowledge of, this that linear regression changed into for statisticians Deep Neural Networks (CNNs) have had full-size achievement in reputation and localization of gadgets in images. The fundamental approach which brought about CNNs is to construct synthetic structures primarily based totally on thehuman mind and vision. Yet, in lots of vital respects, skills of CNNs are not as good as the ones of human vision. A line of research promising is to discover similarities and variations with the aid of using filling withinside the gaps, to enhance CNNs. There are numerous Deep Learning algorithms.

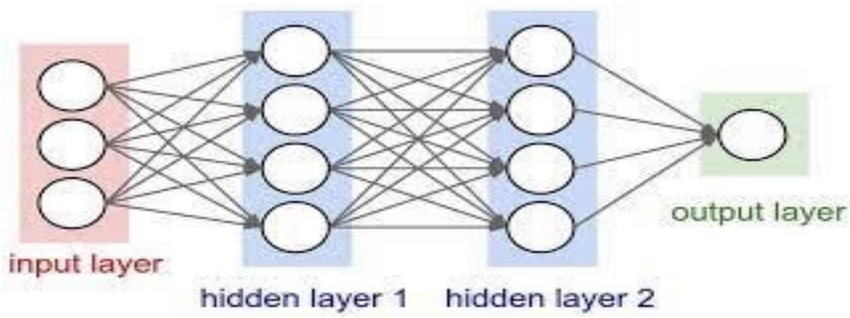


Figure 3: Diagram of an artificial neural network[5]

1.4.1. Convolutional Neural Networks (CNN)

Computer imaginative and prescient is unexpectedly converting day way of means of day. One of the motives is the improvement of deep learning. When we speak approximately imaginative and prescient via way of means of pc, a time period convolutional neural community involves thoughts because hat CNN is closely used here. CNN examples in pc imaginative and prescient areface recognition, picture classification, etc. It is much like the community primary neurons. CNN additionally has learnable parameters, such as than the neural community, specifically the weights, the biases.

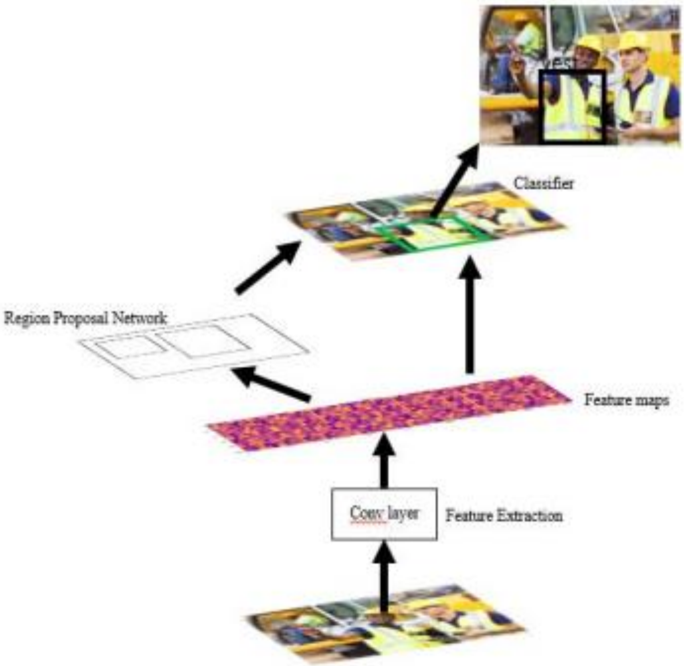


Figure 4: Convolutional neural networks.*[6]*

1.4.2. Layers of convolutional neural networks

There are several different layers in CNN as shown in Figure 1.5:

- ✓ Input layer.
- ✓ Convolution layer (Convo layer: Convolution + ReLU).
- ✓ Pooling layer.
- ✓ Fully connected layer.
- ✓ Softmax/logistics layer.
- ✓ Output layer.

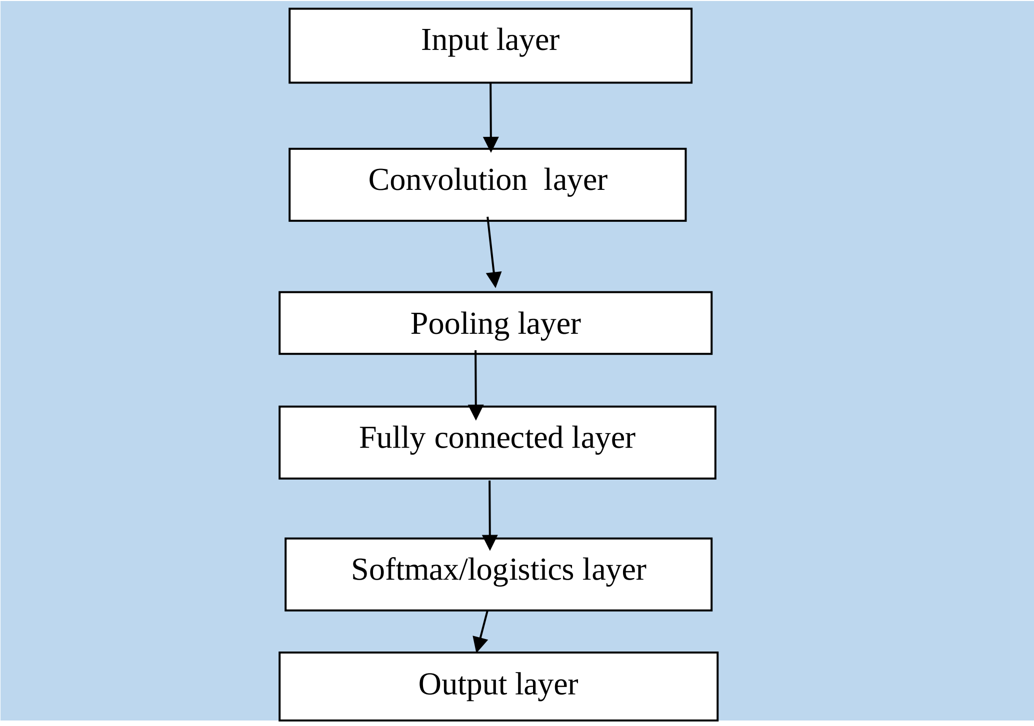


Figure 5:Layers of CNN [7].

An example of the CNN architecture is shown in Figure 6

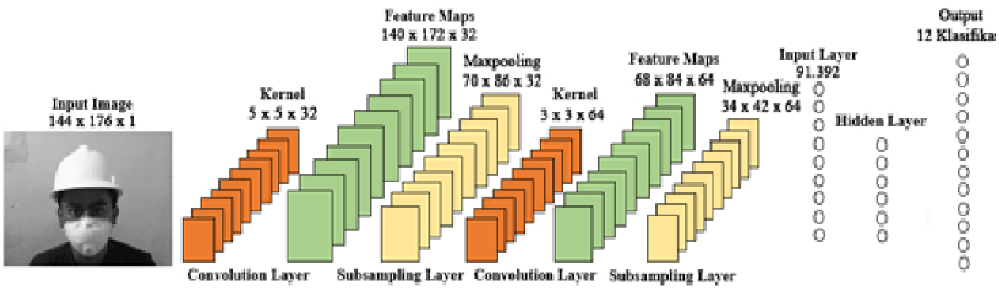


Figure 6:CNN Architecture Example.*[8]*

a) CNN input layer

The enter layer in CNN have to comprise facts describing the picture. The picture facts is represented via way of means of a third-dimensional matrix which in general have to be reshaped right into a unmarried column (vector representation).

b) Convolution layer

Three hyper parameters are used to length the quantity of the convolution layer (additionally referred to as output quantity): depth, pitch and headroom.

1. Layer depth: wide variety of convolution nuclei (or wide variety of neurons related to the identical receptive field).
2. Pitch controls the overlap of receptive fields. The smaller the pitch, the more receptive fields overlap and the better the output quantity .
3. The margin (at 0) or 0 padding: now and again it's miles handy to place zeros at the boundary of the enter quantity. The length of this `0 margin controls the spatial size of the quantity perfect to hold the identical floor as that of the enter quantity.

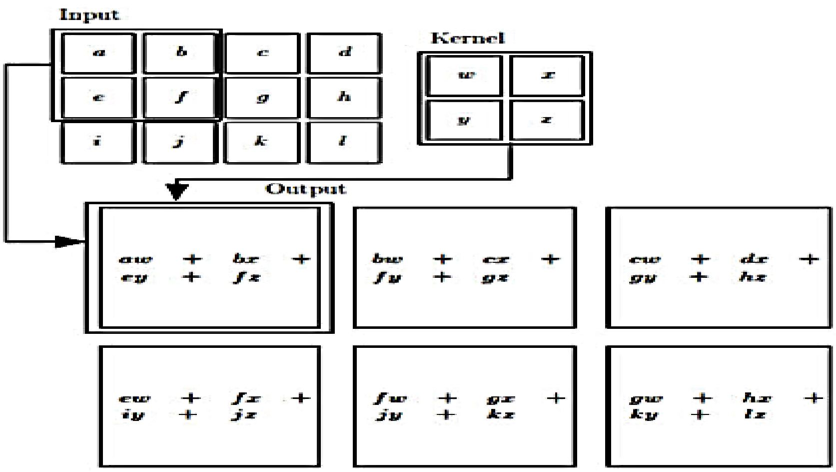


Figure 7: Convolution Example.*[9]*

c) Pooling Layer

Pooling layer is used to reduce the spatial volume of the image input after the convolution. It is used between two convolutional layers. we apply ***fc*** (Fully Connected) after Convolutional layer without applying pooling or maximum pooling, the computation will be expensive. Thus, the maximum pooling

is the only way to reduce the spatial volume of the input image by encoding information.

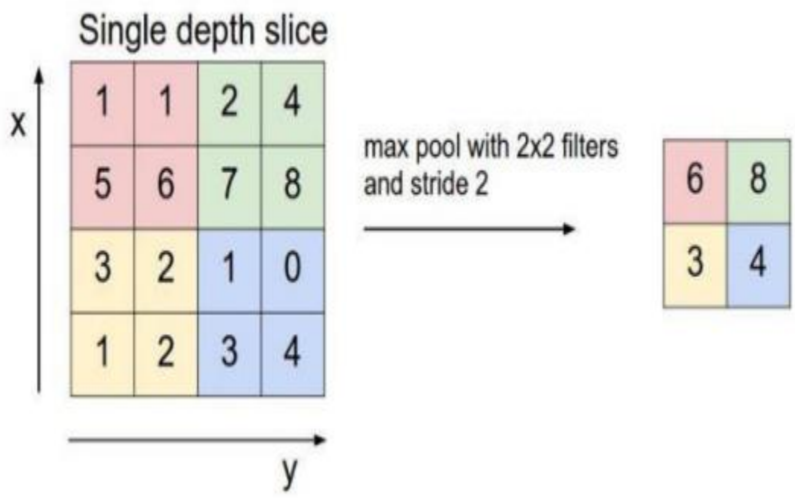


Figure 8:Example of Pooling principle.*[10]*

d) Fully connected layer

A completely linked layer includes weights, biases and neurons. It connects neurons in a single layer to neurons in some other layer. He is used to categories pictures among extraordinary classes via way of means of formation.

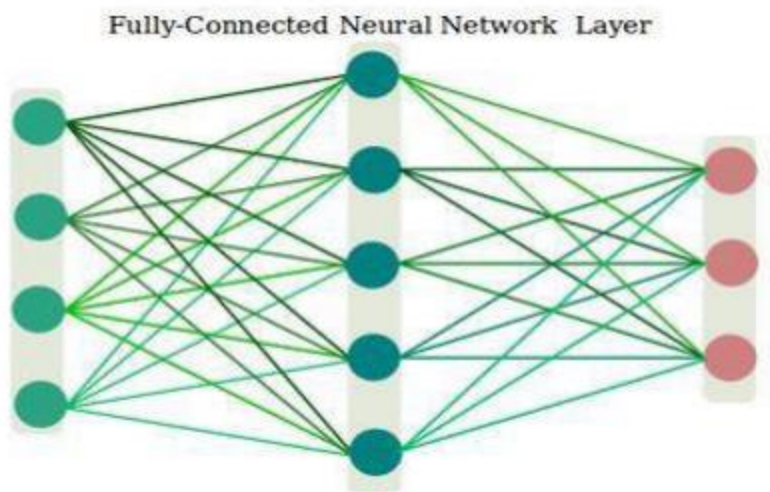


Figure 9:Principle of the fully connected layer (fc).

e) Logistics or Softmax layer

Softmax or logistics layer is the closing layer of CNN. She is living at the cease of the FC layer. Logistics is used for binary category and Softmax is for multi-category.

f) Output layer

The output layer carries the label that is in encoded shape as proven in figure 1.9.

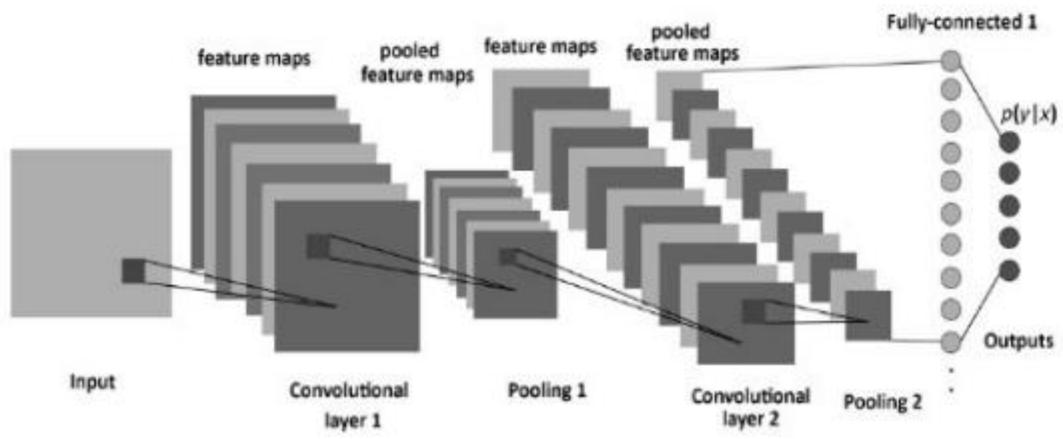


Figure 10:Example showing CNN output layer coded label.[11]

1.5.Conclusion

In this chapter we have introduced deep learning, types of learning methods, cycles and the difference between deep learning, machine learning and artificial intelligence, we have introduced the basic concepts of neural networks, artificial and convolutional neural networks (CNN) and how it works

Chapter 2: Personal Protective Equipment(PPE)

Chapter 2: Personal Protective Equipment(PPE)

1. Introduction

Hazards exist in every workplace in different forms: sharp edges, falling objects, flying sparks, chemicals, noise, and a myriad of other potentially dangerous situations. The Occupational Safety and Health Administration (OSHA) requires employers to protect their employees from workplace hazards that can cause injury. Controlling risk at its source is the best way to protect employees. Depending on the hazard or workplace conditions, the Occupational Safety and Health Administration (OSHA) recommends the use of engineering or work practice controls to manage or eliminate hazards to the extent possible. For example, building a barrier between danger and personnel is an engineering control; Changing the way employees perform their work is a control of work practice. When engineering controls, labor practices, and administrative controls are not feasible or do not provide adequate protection, employers must provide personal protective equipment (PPE) to their employees and ensure their use. Personal protective equipment, commonly referred to as "personal protective equipment", is equipment that is worn to reduce exposure to a variety of hazards. Examples of personal protective equipment include items such as gloves, foot and eye protection, protective hearing devices (earplugs, protective coverings), hard hats, respirators, and full underwear. This guide will help both employers and employees do the following: Understand the types of PPE. Learn the basics of conducting a “risk assessment” in the workplace. Choosing appropriate personal protective equipment for a variety of circumstances. Understand the type of training required in the proper use and care of personal protective equipment.[12]

This chapter contains first the definition of PPE, secondly to Hazard assessment, thirdly to the principles of selection and use of PPE, fourthly to the selection of personal protective equipment, fifth also to Types of personal protective equipment, in addition to Classification Criteria of the Personal Protection Equipment and Computer Vision in Construction Management, and finally Conclusion.

2. Definition

Personal Protective Equipment (PPE) is the equipment that protects the user against health or safety risks. Not wearing PPE dramatically increases the chances of injuries and in many situations also financial losses due to fines for injuries and death of workers as well as contamination caused by not wearing gloves, hairnets, shoe covers, etc. Recent advancements in edge computing hardware coupled with ever more efficient software have enabled novel solutions with the potential to prevent injuries, and save lives as well as money and time. This document describes the world's first edge compute solution for PPE ingress and real-time PPE compliance monitoring[13].

3. Hazard assessment

Employers must assess their workplaces to determine if hazards are present, or are likely to be present, which require the use of PPE. A documented and certified walk-through survey (hazard assessment) of each work area must be done. The certification must show the date of assessment, are evaluation, and the name of the person certifying the evaluation. The survey should consider the following potential exposures:

- Impact
- Penetration
- Compression (roll-over)
- Chemicals
- Heat
- Harmful dust
- Light (optical) radiation

After the survey has been completed, the employer must select the proper PPE. Employees who purchase their equipment must follow the same criteria the employer uses.

4. Principles of selection and use of PPE

Making the workplace safe includes providing instructions, procedures, training, and supervision to encourage people to work safely and responsibly. Even where engineering controls and safe systems of work are in place, some hazards might remain. Such hazards may contribute to injuries, including:

- Inhalation of contaminated air harming the lungs,
- Falling materials harming the head or feet,
- Splashes of infectious materials or hazardous chemicals harming the eyes,
- Contact with corrosive materials harming the skin, and
- Extreme heat or cold harming the body.

PPE is needed in these cases to reduce the risk of these events resulting in inconsequences to the personnel. When PPE is still required after implementing risk.

5. Selection of personal protective equipment

Some common selection, use, and maintenance points for PPE : are PPE should be labeled to show what it protects against and is resistant to. Talk to manufacturers and suppliers about the protection offered by their products before buying. Always use PPE according to the manufacturer's instructions. The Personal Protective Equipment Regulations 2002 state that PPE on the market must be supplied with relevant information in the official language(s) of the country of destination on:

• Storage, use, cleaning, maintenance, servicing, and disinfecting.

• The level of protection provided by the PPE.

•Suitable PPE accessories and appropriate spare parts.

• Limitations on use.

• The obsolescence period for the PPE or certain of its components.

• The PPE must be CE marked. Where this is not possible due to the nature of the PPE, for example, Earplugs, the CE marking should be on the packaging.

• Checks need to be carried out to ensure that the PPE fits the workers correctly to ensure an adequate level of protection.[14].

• Workers should be consulted because the PPE is uncomfortable it will not be worn.

The PPE will be CE marked and tested and certified by a notified body. Also, the quality Control system of the manufacturer must be independently checked. The body carrying out This function will be identified by a number, which must appear alongside the CE mark.

Figure 11:CE Mark.

6. Types of personal protective equipment

6.1 Head protection:

Required when employees are in areas where there is a potential for injury to the head from:

- Falling objects.
- Fixed object.
- Protruding material.
- High voltage equipment and work involved.

To protect from that we have:

Industrial safety helmets Protect against falling objects or collisions with stationary objects provide limited flame protection. Helmets that protect against collision at high or low temperatures, electrical shock from brief contact up to 440 V ac, and molten metal splash are also available.

Bump caps –Protect against head bumps (e.g., walking into a fixed item) and scalping, as well as hair becoming entangled in equipment and moving parts. Where there is a risk of falling objects or moving or hanging loads, bump caps are insufficient.

Fire fighters' helmets– These are similar to industrial safety helmets, but cover more of

the head and give greater protection against impact, heat, and flame.

Figure 12:Industrial safety helmet.

Figure 13:Climbing helmet.

6.1.1. Types of head protection

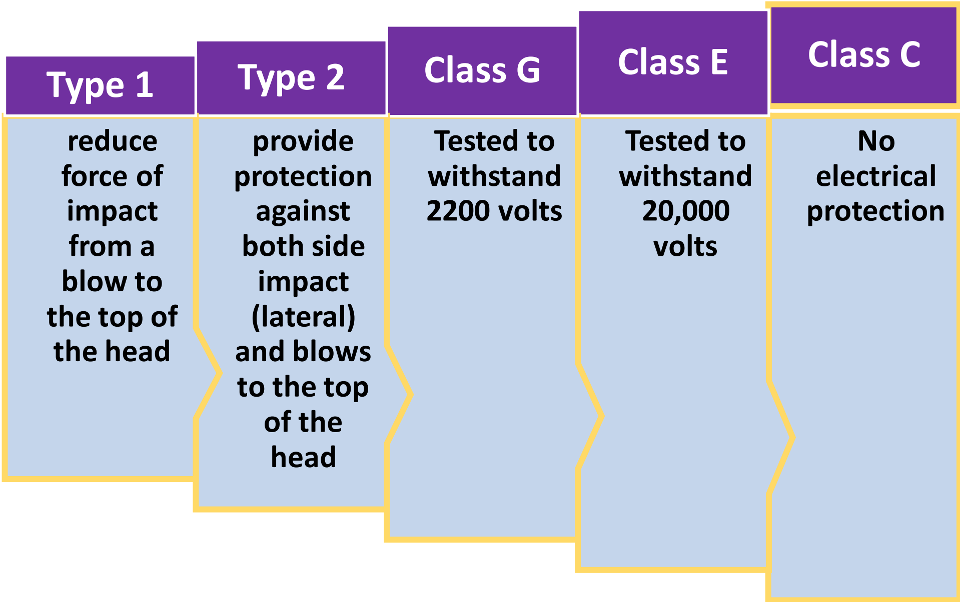


Figure 14: Types of Head Protection.

6.2 Eye and face

Employees can be exposed to a large number of hazards that pose danger to their eyes and face. OSHA requires employers to ensure that employees have appropriate eye or face protection if they are exposed to eye or face hazards from flying particles, molten metal, liquid chemicals, acids or caustic liquids, chemical gases or vapors, potentially infected material or potentially harmful light radiation.

Many occupational eye injuries occur because employees are not wearing any eye protection while others result from wearing improper or poorly fitting eye protection. Employers must be surethat their employees wear appropriate eye and face protection and that the selected form of protection is appropriate to the work being performed and properly fits each employee exposed to the hazard.

Eye and face protection items are intended to protect the employee from the number of hazards determined from the hazard assessment. These hazards include:

- **Impact** – flying objects such as large chips, fragments, particles, sand, and dirt
- **Heat** - anything emitting extreme heat
- **Chemicals** – splash, fumes, vapors, and irritating mists

- **Dust** – harmful dust
- **Optical Radiation** – radiant energy, glare, and intense light

6.2.1. Eye and face protection Safety Spectacles

- Safety spectacles are intended to shield the wearer’s eyes from impact hazards
- You are required to use safety spectacles with side shields when there is a hazard from flying objects.
- Non-side shield safety spectacles are not acceptable eye protection for impact hazards

Figure 15: Safety Spectacles.

Safety Goggles

• Safety goggles are intended to shield the wearer’s eyes from impact hazards

•They fit the face immediately surrounding the eyes and form a protective seal around the eyes.

- Are available in clear lenses
- Are available with removable lenses
- May incorporate prescription lenses
- Do not provide special protection against optical radiation

Figure 16: Safety Goggles.

Face shields

These have one large lens with a frame and adjustable head harness or are mounted on a helmet. Most can be worn with prescription glasses. They protect the face but do not fully enclose the eyes.[15]

- Face shields are intended to protect the entire face or portions of it from impact hazards
- Must use in combination with safety goggles or spectacles
- When worn alone, face shields DO NOT protect employees from impact hazards (flying objects)

Figure 17: Face shields.

6.3.Handprotection

Figure 18:Hand protection.

If a workplace hazard assessment reveals that employees face potential injury to hands and arms that cannot be eliminated through engineering and work practice controls, employers must ensure that employees wear appropriate protection. Potential hazards include skin absorption of harmful substances, chemical or thermal burns, electrical dangers, bruises, abrasions, cuts, punctures, fractures, and amputations. Protective equipment includes gloves, finger guards, and arm coverings or elbow-length gloves.

Employers should explore all possible engineering and work practice controls to eliminate hazards and use PPE to provide additional protection against hazards that cannot be eliminated through other means. For example, machine guards may eliminate a hazard. Installing a barrier to prevent employees from placing their hands at the point of contact between a table saw blade and the item being cut is another method.

6.3.1. Types of protective gloves

Gloves made from a wide variety of materials are designed for many types of workplace hazards. In general, gloves fall into three groups:

- Leather, Canvas, or Metal Mesh Gloves
- Fabric and coated fabric gloves
- Chemical- and liquid-resistant gloves

1) Leather, Canvas, or Metal Mesh Gloves

Sturdy gloves made from metal mesh, leather, or canvas protect against cuts and burns. Leather or canvas gloves also protect against sustained heat.

Figure 19: Leather, Canvas, or Metal Mesh Gloves.

2) Fabric and coated fabric gloves

Coated fabric gloves are normally made from cotton flannel with napping on one side. By coating the unmapped side with plastic, fabric gloves are transformed into general-purpose hand protection offering slip-resistant qualities. These gloves are used for tasks ranging from handling bricks and wire to chemical laboratory containers. When selecting gloves to protect against chemical exposure hazards, always check with the manufacturer or review the manufacturer's product literature to determine the gloves' effectiveness against specific workplace chemicals and conditions**.**

Figure 20:Fabric and coated fabric gloves.

3) Chemical- and liquid-resistant gloves

Butyl gloves are made of synthetic rubber and protect against a wide variety of chemicals, such as peroxide, rocket fuels, highly corrosive acids (nitric acid, sulfuric acid, hydrofluoric acid, and red-fuming nitric acid), strong bases, alcohols, aldehydes , ketones, esters, and nitro compounds. Butyl gloves also resist oxidation, ozone corrosion, and abrasion, and remain flexible at low temperatures .Butyl rubber does not perform well with aliphatic and aromatic hydrocarbons and halogenated solvents.

Figure 21:Chemical- and liquid-resistant gloves.

.

Figure 22:some types of cloves.

6.4.Body Protection

- Select and use the right type of protective clothing for the right job
- Protective clothing must fit and be used properly, else they will become a hazard to the user
- Inspect protective clothing before use
- Store in a clean, cool, dry, and ventilated area

6.5.Protective clothing

Protective clothing must offer some specific protection – if it does not, it is classified as 'work wear'. There are three main types of protective clothing:

(a) **Separates** – jackets, trousers, etc. that only cover part of the body.

(b) **Aprons** – that only cover part of the body.

(c) **Overalls, coveralls, and bodysuits** – which cover the whole body.

6.5.1. High visibility clothing:

Most high visibility clothing has a fluorescent yellow or orange background, made from materials impregnated with fluorescent pigments, with bands of shiny retroflected material. It is designed to make the wearer easy to see under any light conditions during the day and illumination, for example by vehicle headlights in the dark.

6.5.2. Types of high visibility clothing:

88 There are three classes of high visibility clothing. Each has minimum areas for the background and retrore flective bands:

- **Class 1** – the least conspicuous (waistcoats and most trousers).
- **Class 2** – more conspicuous than Class 1 (waistcoats, jackets, and some trousers).
- **Class 3** – the most conspicuous (jackets and coveralls). [16]

Figure 23:High visibility waterproof jacket.

7. Classification Criteria of the Personal Protection Equipment

Security and health requirements must be taken into account in the design, location, and use of individual protective gear. The intricacy of the protective equipment area necessitates a more comprehensive classification.[17]

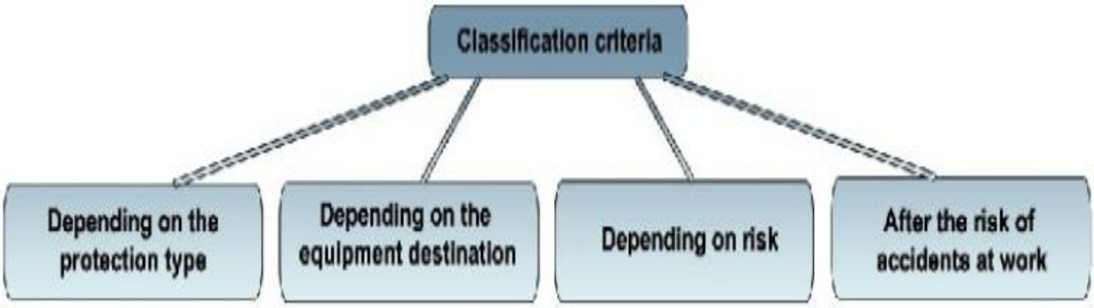


Figure 24:Classification criteria for the personal protection equipment

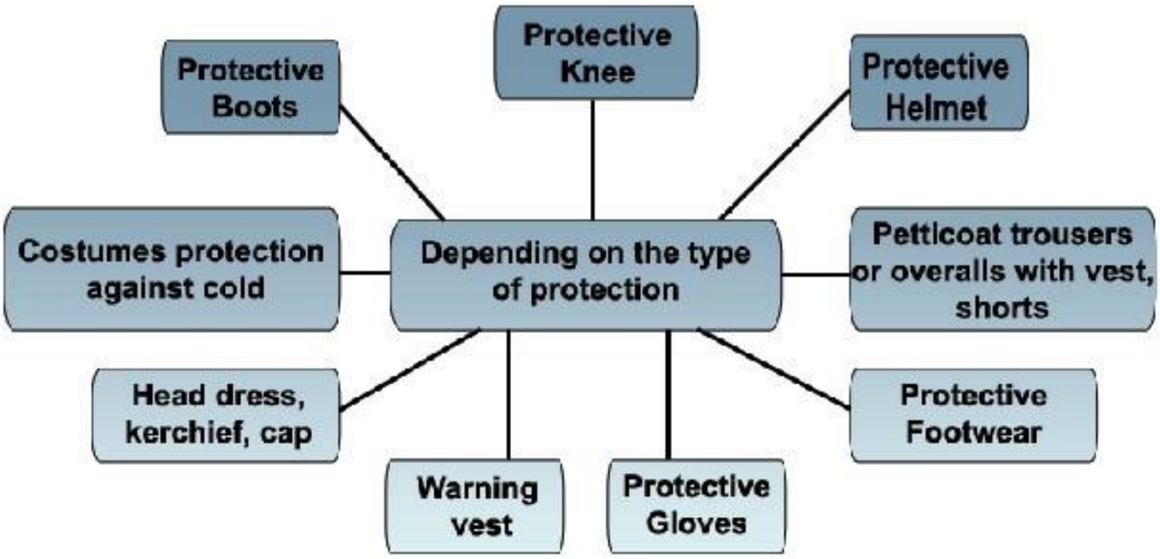


Figure 25: Classification of the personal protection equipment by the type of the protection element.

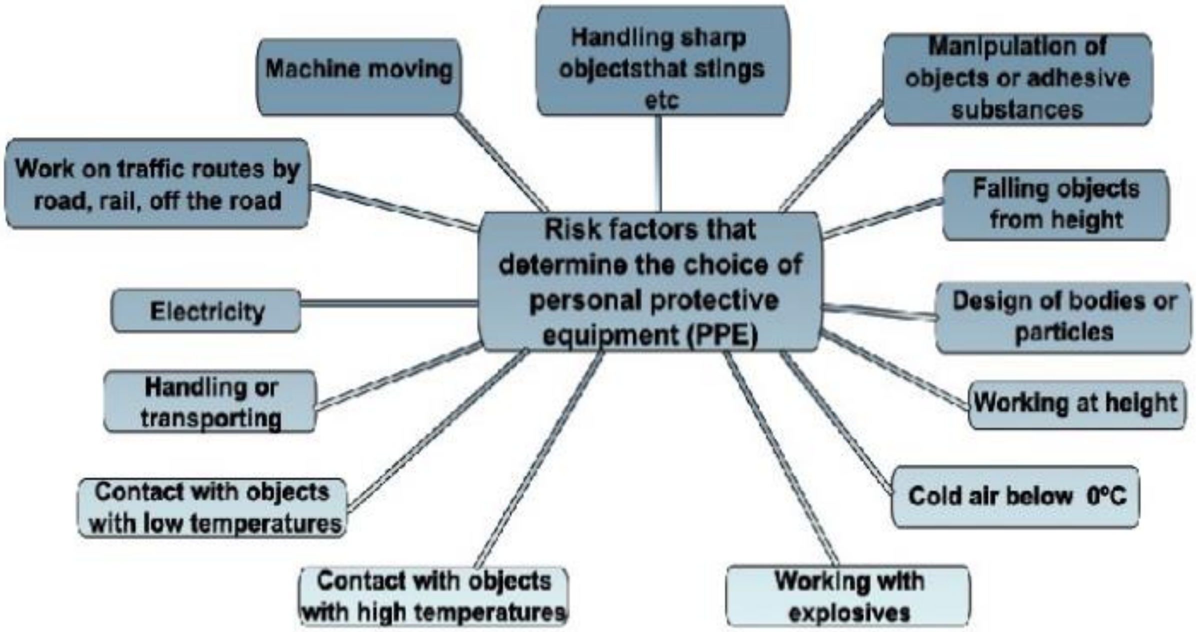


Figure 26: personal protection equipment by the risk factors.

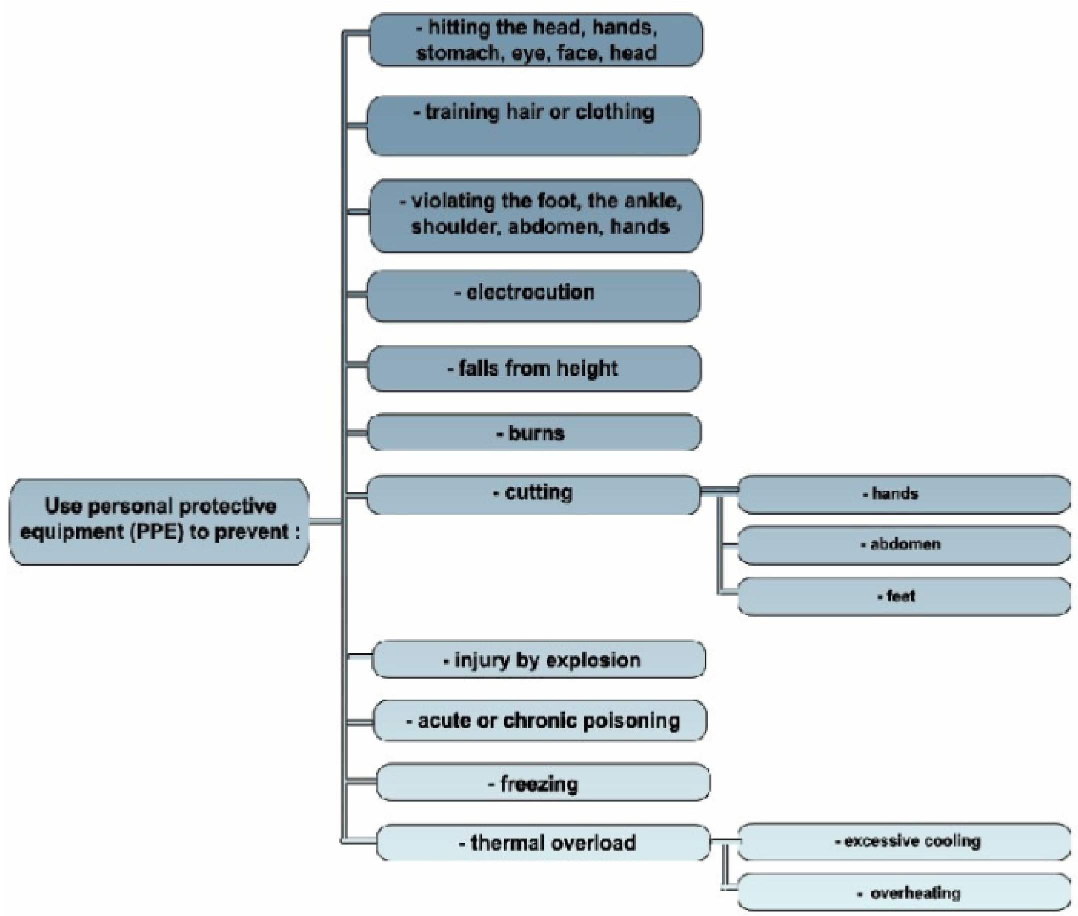


Figure 27: Classification of personal protective equipment by the type of injury threat at work.

8. Conclusion

In this chapiter, we provide a detailed explanation of Personal Protective Equipment is the equipment that protects the user from health or safety hazards. Failure to wear PPE significantly increases the chances of injuries and in many cases also financial losses due to fines for injuries and deaths of workers as well as pollution caused by not wearing gloves, hair nets, shoe covers, etc. PPE may include items such as Gloves, goggles, protective shoes, earplugs or head coverings, hard hats, respirators, or coats, jackets, and full body suits.

Chapter 3: Running detection of Personal protective equipment

Chapter 3: Running detection of Personal protective equipment

1. Introduction

The researchers found that workers' injuries increased significantly due to non-compliance with prevention conditions Immediate monitoring is not possible .But it turns out that nowadays it is possible to monitor by artificial intelligence.After covering the theoretical aspect in the previous chapters, we chose one of the types of personal protective equipment, which is the head helmet . Next we move on to designing and implementing our system that detects helmet wear. This is to protect the safety of workers.

This chapter is orgnised as follows:

- Computer vision in construction management.
- Implementation.
- Run interface with trained weights.
- Validation results.
- Results analysis.
- Conclusion.

2. Computer Vision in Construction Management

Management Parallel discoveries in the field of computer science, particularly those connected to information management and processing, have greatly aided construction management research. Paradigms such as Building Information Modelling (BIM), which aims to provide a unified information management approach for the construction process, have revolutionized the way construction is managed around the world. When paired with BIM, breakthroughs in interface technologies such as Augmented Reality (AR) and Virtual Reality (VR) promise accurate visualization and virtualization of construction management processes. These advancements in the realm of machine learning open up new possibilities for effectively analyzing data, especially when combined with BIM to give managers timely business intelligence. To develop any significant intelligence, such systems typically rely on accurate and enormous amounts of data. This necessitates the employment of various data-gathering devices (e.g., Radio Frequency IDs or RFID technologies). While many types of data from the field are required, video feeds and photos provide rich visual records of activities on-site, and computer vision-based approaches to aid in the understanding of such visual data. In essence, computer vision (CV) seeks to tackle the problem of deciphering information from visual data points, such as an image or video sequence, from a human perspective. Advances in the fields of computer vision and deep learning have influenced research and the application of vision-based strategies in construction management.[18]

2.1.Computer Vision in Construction Safety Management

Identifying objects on a building site is a crucial step in conducting CV-based construction safety research. Workers, equipment, impediments, and any other thing of interest to safety researchers are examples of these objects. To do so, a vast amount of trustworthy visual data is required. Other studies in the past have included the collection of data using site videos, to identify and track objects like workers and equipment on site[19], As the data becomes available, the CV-based algorithms should accurately identify the objects in a given image or video frame. Early research in this area was directed at extracting the right features from a visual data point to identify relevant objects on a construction site. Consequently, studies concentrated on sets of features to distinguish certain classes of objects from one another. However, studies using classic computer vision techniques have some key limitations the first limitation involves in-context identification. Context identification would involve recognizing what is happening on a construction site [20], Traditional computer vision techniques performed poorly, especially when it came to detecting objects in various environments. To categorize and detect objects and activities based on specified sets of discovered features, this research typically used trained machine learning classifier algorithms - multiclass classifiers or big margin classifiers like Support Vector Machines. Having the correct set of features to detect an object, on the other hand, can be difficult. Furthermore, object detection algorithm training necessitates the processing of large amounts of data. Deep learning breakthroughs in the field of computer vision can be used to handle the enormous data requirements of

construction safety management research[21].

2.2.Convolutional neural networks

Recent developments in this field have also identified the use of deep learning CV algorithms such as Convolutional Neural Networks (CNN) as particularly beneficial Object detection, such as hard helmets and safety jackets, is a significant step forward in monitoring the process of encouraging workers to comply with PPE automatically. In the domains of machine learning and artificial intelligence, this discovery creates categorization issues. A classification problem is represented by the function: $Rn \rightarrow \{1 \ldots, k\}$, in which the algorithm divides the data into k classes or categories. The classification problem is at the heart of Convolutional Neural Networks (CNNs), which are designed to learn to recognize images to detect and classify specific objects in images. Around 1989, CNNs were first introduced. Face recognition was one of CNN's first applications, Large, deep neural networks with numerous convolutional and fully connected layers followed by a classifier layer are known as convolutional neural networks. For supervised learning, CNNs have proven to be particularly efficient at processing big image collections. The availability of larger datasets, increasing computer power, and improved regularization techniques have all contributed to CNNs' success[22], CNN's are very useful for detecting PPE and are critical in safety studies. To detect PPE, researchers researched and evaluated various Neural Network Architectures, including faster R-CNN and Single Shot Detection (SSD) methods. A Faster R-CNN was also utilized to recognize workers and equipment on construction sites and forecast the likelihood of collisions. The effectiveness of applying deep learning algorithms and knowledge-based systems to progress toward real-time, automated, and intelligent safety and hazard detection platforms has been demonstrated in research like these[23]

This research adds to and enhances the previous research mentioned. We tested YOLO (You Only Look Once), a strong CNN-based algorithm that is equivalent to Faster R-CNN and SSD methods. Because YOLO has a higher prediction rate, it is a strong option for real-time safety hazard prediction on building sites[24]

2.3..YOLO

The You Only Look Once (YOLO) algorithm is a cutting-edge object identification system that uses CNN principles. It is designed for real-time processing. The input image is divided into an S grid by YOLO. Only one object and a set number of border boxes are predicted in each grid cell. It predicts B boundary boxes for each grid cell, with one box confidence score for each box. Then, regardless of the number of boxes B, it detects only one item. Finally, it forecasts the probabilities of C conditional classes (one per class for the likeliness of the object class). Each boundary box has five elements: (x, y, w, h) and a confidence score for the box. The confidence score is based on the likelihood of the box containing an object, objectless in terms of YOLO authors, and the accuracy of the bounding box[25]. The picture .

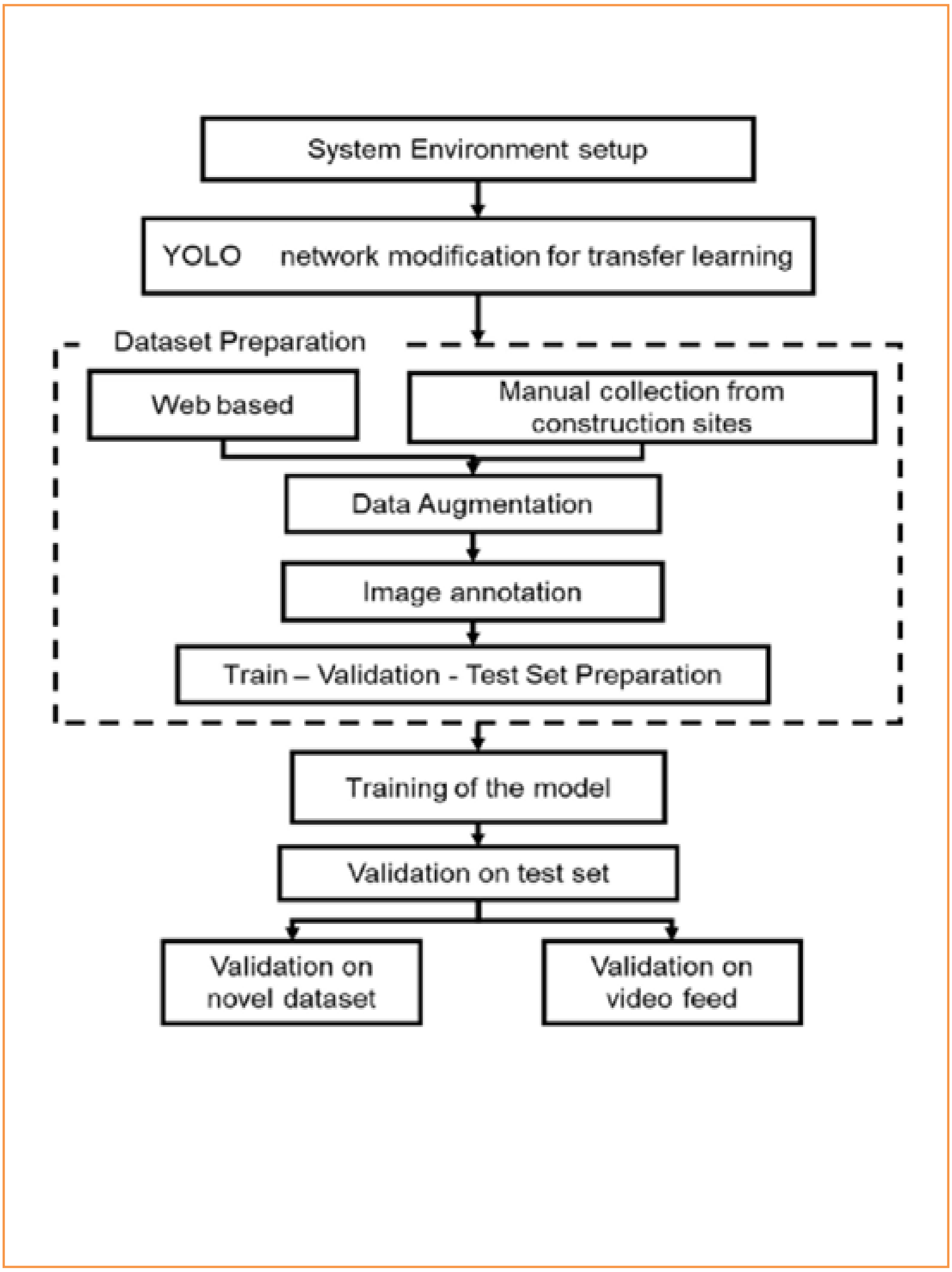


Figure 28:Research methods used for the study.

width and height were used to normalize the enclosing box width w and height h. The offsets to the relevant cell are x and y.

W and h are between 0 and 1. The class confidence score for each prediction box is computed as:

Class confidence score = box confidence score×

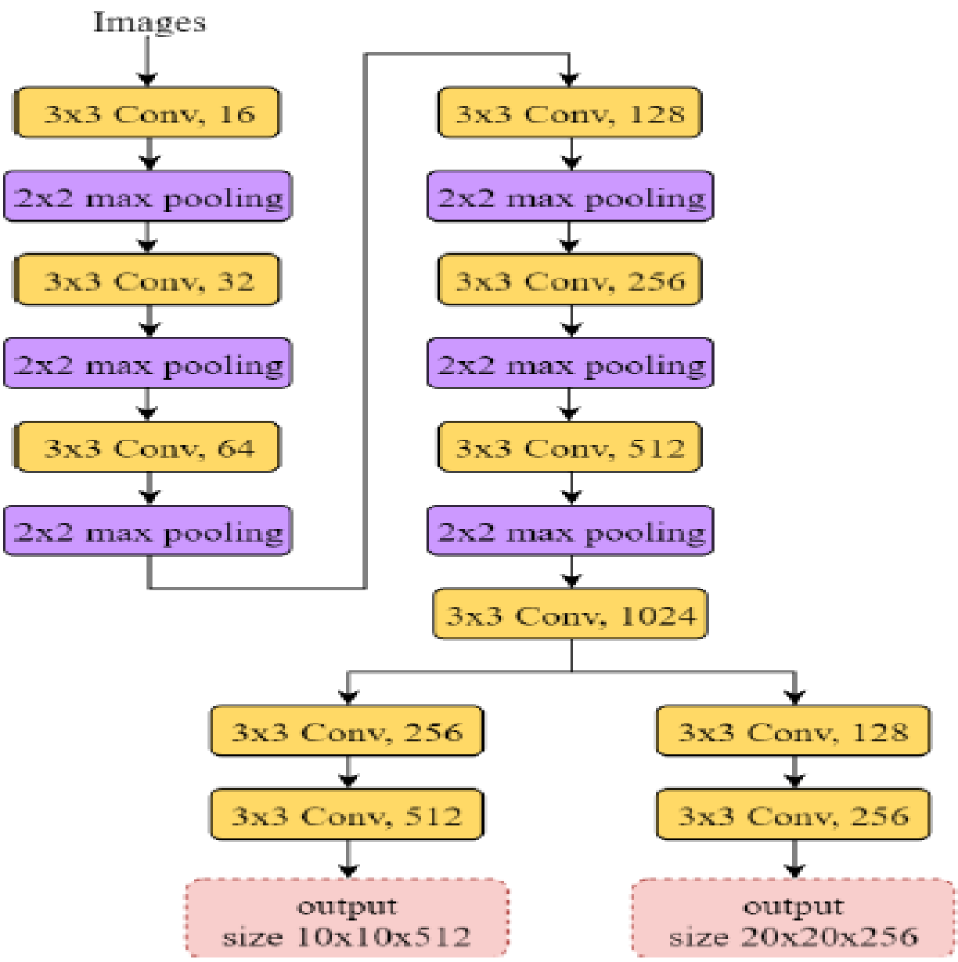


Figure 29: The YOLO model for helmet and safety classification.

3. Implementation

We have used Google Colab GPU Python 3.7 and tensorboard. For the implementation of YOLO, the deep learning library of tensorboard is used, and the training and the testing procedures are done in the Google Colab platform.

Chapter 3: Running detection of Personal protective equipment

3.1.Custom Training with YOLOv5

In this tutorial, we collect a dataset and train a custom YOLOv5 model for helmet recognition in our dataset. To do this we will take the following steps:

- Gather a dataset of images and label our dataset
- Export our dataset to YOLOv5
- Train YOLOv5 to the objects in our dataset
- Run test inference to view our model at work

Step 1 : Install Requirements

First of all, you must download all the requirements as shown in the figure

YOLOv5 requirements :

----

matplotlib>=3.2.2

numpy>=1.18.5

opencv-python>=4.1.1

Pillow>=7.1.2

PyYAML>=5.3.1

requests>=2.23.0

scipy>=1.4.1 # Google Colab version

torch>=1.7.0

torchvision>=0.8.1

tqdm>=4.41.0

protobuf<=3.20.1

----

to download all requirements we use :

```
#clone YOLOv5 and
!git clone https://github.com/ultralytics/yolov5  # clone rep
o
%cd yolov5
%pip install -qr requirements.txt # install dependencies
%pip install -q roboflow

import torch
import os
from IPython.display import Image, clear_output  # to display
 images

print(f"Setup complete. Using torch {torch.__version__} ({tor
ch.cuda.get_device_properties(0).name if torch.cuda.is_availa
ble() else 'CPU'})")
```

Figure 30:Importing library.

To train our custom model, we collected a dataset of representative images with bounding box annotations about the target we want to detect. In Roboflow we upload raw images and annotate them in Roboflow using Roboflow Annotate.Then we call our data from Roboflaw, as shown in the figure 31.

```
!pip install roboflow

from roboflow import Roboflow
rf = Roboflow(api_key="GM7mpLIbw59ENrrXtBsD")
project = rf.workspace("hichamdouadi").project("hich
am")
dataset = project.version(1).download("yolov5")
```

Figure 31:Load data set to google colab from roboflow.

then use this instruction to set up environment to google colab :

```
# set up environment
os.environ["DATASET_DIRECTORY"] = "/content/datasets"
```

Figure 32:set up environment.

Step 3: Train Our Custom YOLOv5 model

Here, we are able to pass a number of arguments:

- **img:** define input image size
- **batch:** determine batch size
- **epochs:** define the number of training epochs.
- **data:** Our dataset locaiton is saved in the dataset.location
- **cache:** cache images for faster trainin

This is where the training process begins :

```
!python train.py --img 416 --batch 16 --epochs 150 --
data {dataset.location}/data.yaml --weights yolov5s.pt --cache
```

Figure 33:Training the model YOLOv5.

3.2.Evaluate Custom YOLOv5 Detector Performance

Here is where training losses and performance metrics are saved in Tensorboard as well as in the log file.

```
# Start tensorboard

# Launch after you have started training
# logs save in the folder "runs"
%load_ext tensorboard
%tensorboard --logdir runs
```

Figure 34: Use TensorBoard to load the entire training process saved in runs folder.

Tensorboard

The Scalars dashboard shows how loss and information change in each period. It shows tracking of training speed, learning rate, and other errors.

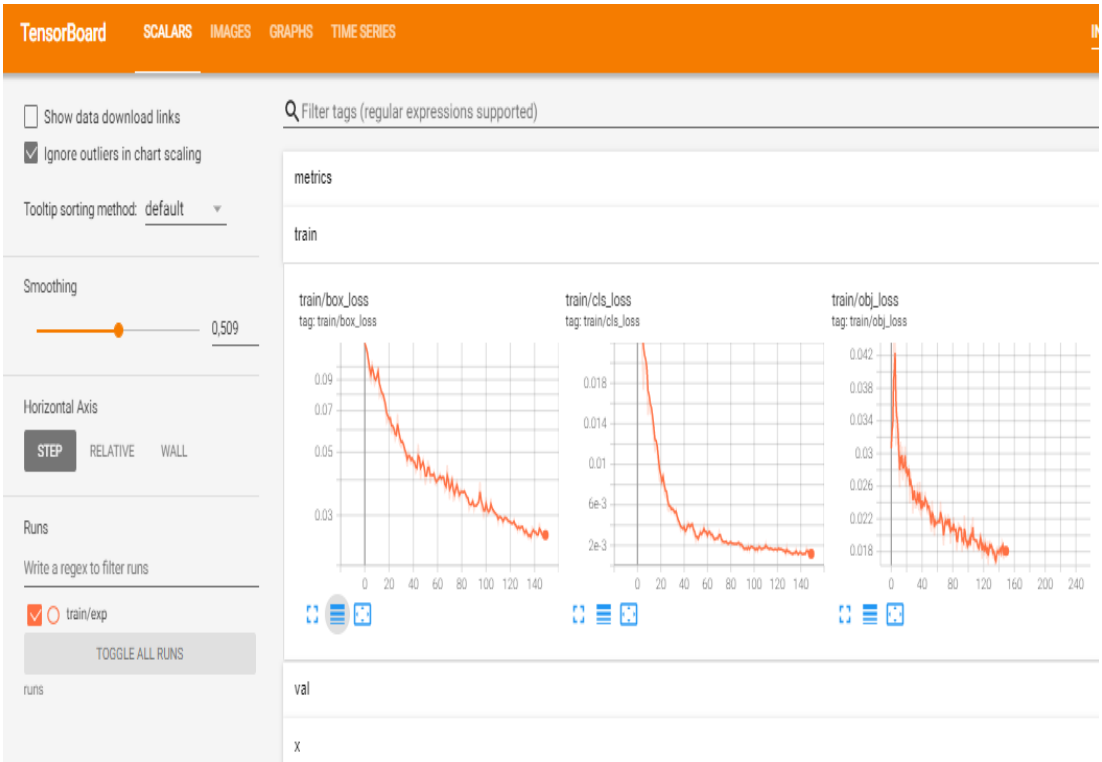
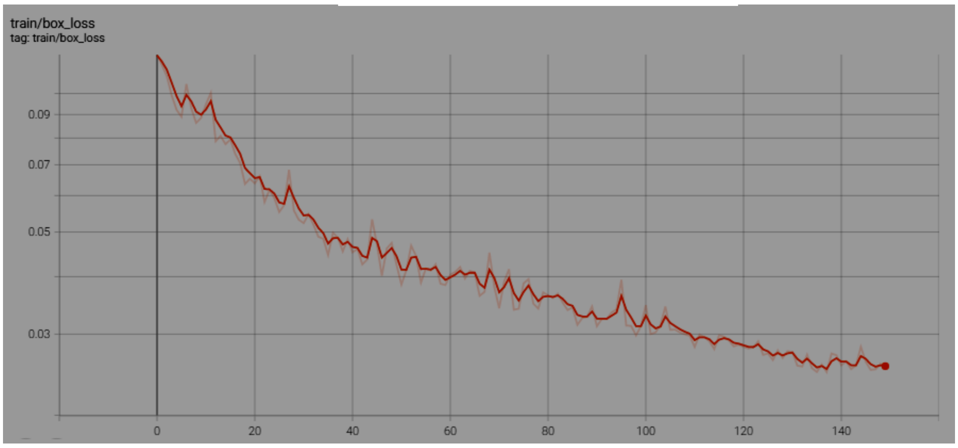


Figure 35:A brief overview of the displayed Scalars of Train .

Box



Classification loss.

Objectness

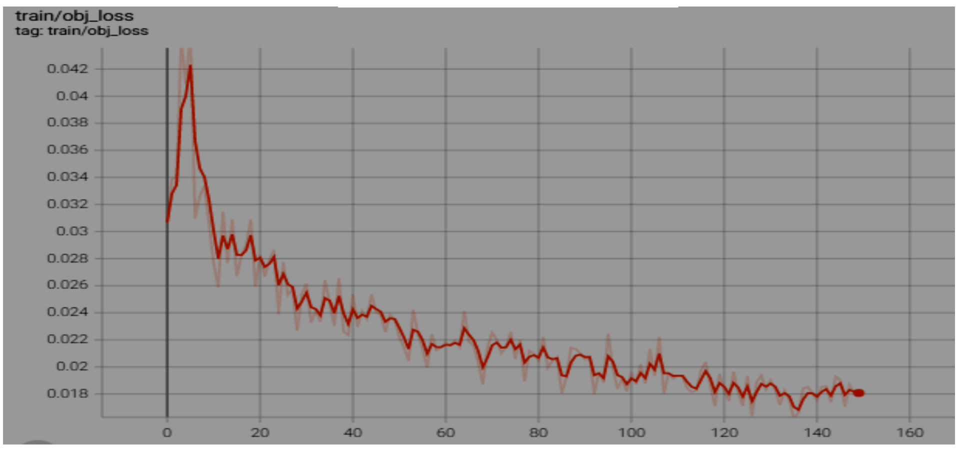


Figure 36:Loss Function.

The loss obtained from the experiment is shown in figure 36.

Generally, in the training process of the model, the smaller the value of the loss function, the better the model is, and the expected value is 0. From figure 36, the horizontal axis represents the iteration epoch, and the vertical axis represents the loss value. As iteration epochs increase, the localization loss, confidence loss and classification loss are basically close to 0.

4. Run inference with trained weights

To run inference to data we trained on:

```
!python detect.py --
weights runs/train/exp/weights/best.pt --img 416 --
conf 0.1 --source {dataset.location}/test/images
```

Figure 37 *:* Run inference to data we trained on

.

Then run to test :

```
import glob
from IPython.display import Image, display

for imageName in glob.glob('/content/yolov5/runs/detect/exp/*.jpg'): #assu
ming JPG
    display(Image(filename=imageName))
    print("\n")
```

Figure 39: Display Inference on ALL test images.

5. Validation results

The proposed automatic detection method based on deep learning to detect safety helmets worn by workers provides an effective opportunity to improve safety management on construction sites. Previous studies have demonstrated the effectiveness of locating the safety helmets and workers and detecting the helmets. However, most of the studies have limitations in practical application. Sensor-based detection methods have a limited read range of readers and cannot be able to confirm the position relationship between the helmets and the workers.

Figure 40: Some Picture of Results .

After running we export the model weights for future use

```
from google.colab import files
files.download('./runs/train/exp/weights/best.pt')
```

Figure 41:export our model's weights for future use.

after download trained Weights we run directly with webcam (source 0)

```
python detect.py --weights C:\Users\PC\Desktop\yolov5\best.pt --img 416 --conf 0.4 --source 0
```

Figure 42: Display inference on live video by webcam.

6. Result Analysis

It is clear from the experimental results that the faster CNN has the highest mAP value And the improved YOLO v5 algorithm map value in detection accuracy. It can also be seen that the improved YOLO v5 takes into account both detection and detection accuracy speed, and can be better applied in the actual environment of Accomplish the task of detecting the wearing of the helmet. In addition, in order to feel intuitively detected The differences between the different algorithms, Figure 46 is the impact of the detection algorithm on the actual construction site environment. In this figure, the orange square indicates the person wearing the helmet and the red square indicates the person without a helmet. That can be seen there YOLO v5 It has good detection effect and high confidence.

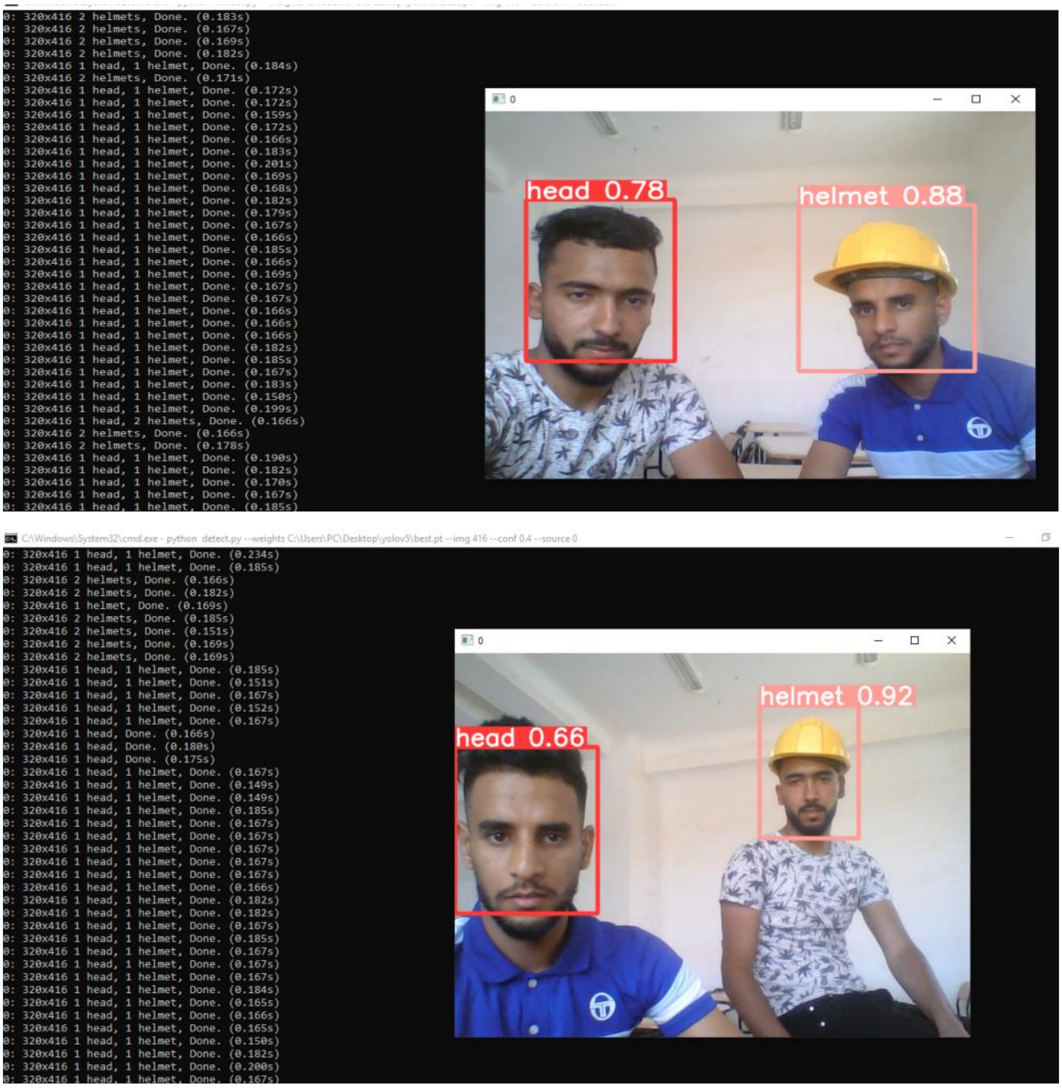


Figure 43:Test Scene

7. Conclusion

This study used computer vision-based deep learning algorithms to automatically detect key processes that keep workers safe on site. Using YOLOv5, a state-of-the-art equipment detection algorithm, this study demonstrates how safety can be complied with and is automatically detected using a trained model to verify data from worker locations. The study showed that the deployment of such algorithms on workers' websites to aid in the near-real detection of safety violations. A real-time dashboard can be created. The model developed in this study can be used in frameworks to regularly report non-compliant safety regulations.

Chapter 3: Running detection of Personal protective equipment

General Conclusion

As discussed before, the detection and treatment of personal protective equipment by deep learning and Less cost and equipment are essential steps to reduce injuries and risks.

In the near future, with the integration of deep learning algorithms and hardware into work centers, it will be possible to achieve faster, cheaper and safer results.

This model gives perfect results comparing with other prominent works in the field and can be improved further with multi-class classification and availability of the larger dataset.

Finally, **Yolo** has great prospects in discovering PPE with a very limited time, resources and costs. However, with such high accuracy the proposed model can It certainly plays an important role in the early and rapid detection of personal protective equipment and thus the reduction Test time and cost.

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