A computer vision-based approach for Safety Management in the Construction Sites

Lidiya Biruk

A Thesis Submitted to The Department of Civil Engineering

School of Civil Engineering and Architecture

Presented in Partial Fulfilment of the Requirement for The Degree of Master's in Civil Engineering (Specialization in Construction Engineering and Management)

Office of Graduate Studies

Adama Science and Technology University

June, 2021

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APPROVAL OF THE BOARD OF EXAMINERS

I, the advisors of the thesis entitled “A computer vision-based approach for Safety Management in the Construction Sites” and developed by Lidiya Biruk, hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

Meseret Getnet (PHD)	________________	________________
Major Advisor	Signature	Date

We, the undersigned, members of the Board of Examiners of the thesis by Lidiya Biruk have read and evaluated the thesis entitled “A computer vision-based approach for Safety Management in the Construction Sites” and examined the candidate during open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in Construction Engineering and Management

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DECLARATION

I hereby declare that this Master Thesis entitled "A computer vision-based approach for Safety Management in the Construction Sites" is my original work. That is, it has not been submitted for the award of any academic degree, diploma or certificate in any other university. All sources of materials that are used for this thesis have been duly acknowledged through Citation.

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Name of the student	Signature	Date

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RECOMMENDATION

I the advisor of this thesis, hereby certify that I have read the revised version of the thesis entitled "A computer vision-based approach for Safety Management in the Construction Sites" prepared under my guidance by Lidiya Biruk submitted in partial fulfilment of the requirements for the degree of Mater's of Science in construction engineering and management. Therefore, I recommend the submission of revised version of the thesis to the department following the applicable procedures.

Meseret Getnet (PHD)	______________________	_______________
Major Advisor	Signature	Date

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ABSTRACT

Personal protective equipment is one of the preventive methods to protect workers from harmful contacts. However, the utilization of this equipment is very poor in developing countries like Ethiopia due to shortage of safety material, lack of training, poor management, and improper utilization. Therefore, to overcome this challenge, local researchers recommend effective safety management. However, they do not include technological solutions on safety management that convert manual into automatic. Thus, this research aims to develop an easy monitoring system through computer vision to detect Personal protective equipment during construction work. Therefore, to achieve the study objective, ground+3 and above building projects are taken as a population, and the sample size is the ongoing projects which are 60 during the data collection period. Data was collected through questionnaires, observation, and interviews from the selected construction companies and analyzed quantitatively and qualitatively to draw results and conclusions. To analyze data IBM SPSS statics and Microsoft Excel were used. This paper also presents a deep learning built on You-Only-Look-Once (YOLO) architecture to verify compliance of workers' safety clothes; if a worker is wearing a helmet, vest, safety shoes, and their combination from images, which is collected from the website and manually to test and train. Several experiments have been conducted, and the obtained detection accuracy 96.97% for helmets, 97.73% for a reflector, and 98.9% for shoes. The obtained results have demonstrated the ability to detect Personal protective equipment with high precision (98%). The findings show that the vision-based method can be used for safety management to detect the presence and absence of personal protective equipment in a construction site.

Keywords: Construction, safety management, personal protective equipment, computer vision, deep learning, YOLO

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LIST OF ACRONYMS

OSHA	Occupational Safety and Health Administration
PPE	Personal Protective Equipment
OHS	Occupational Health and Safety
GPU	Graphics Processing Unit
R-CNN	Region Based Convolutional Neural Networks
CNN	Convolutional Neural Network
HOG	Histogram Oriented Gradient
YOLO	You-Only-Look-Once
CHT	Circle Hough Transform
CAT	Computer Aided Technologies
BLE	Bluetooth Low-Energy
BIM	Building Information Model
LCD	Liquid-Crystal Display
IBM	International Business Machines Corporation
SPSS	Statistical Package for the Social Sciences
CPU	Central Processing Unit
AP	Average Precision
RII	Relative Importance Index
FPS	Frame Per Second
H&S	Health & Safety
SAT	Self-Adversarial-Training
ILO	International Labour Organization
SN	Serial Number
FPN	Feature-Pyramid Network
PAN	Path Aggregation Network

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CHAPTER ONE

INTRODUCTION

1.1 Background of the study

The construction industry is one of the leading industries as a sector of the economy, which plays a significant role in the country's economic development because the construction industry includes a high level of employment or use of many human resources that opens work opportunities for several professional workers, semi-skilled workers, and unskilled labourers. Also, there is a high level of financial movement, raw material and machinery adoption, and large resource consumption (Durdyev & Ismail, 2012). The construction industry covers several areas that are directly and indirectly related to the country's economic growth. However, it faces many challenges that affect project goals and economic development, such as project delay, rising material cost, labour shortage, poor planning, equipment breakdowns, and unexpected accidents during work. Thus from these challenges, safety is one of the most outstanding issues that need special consideration in every construction site. Because it relates directly to human life who works on the site, plus it includes people around the construction area who does not involve in the construction activity. Construction is a highly hazardous industry that widely exposed employees to accidents, and leading the workers to be injured and die through the construction life cycle. According to OSHA, statistics around 90% of fatality occurs from four types of injuries: falling from height when they work on scaffolding or ladders, struck by objects, held between objects, and electrocution (ElSafty et al., 2012).

Currently, the construction industry in Ethiopia growth rapidly due to the governmental movement to improve the country's economic development in every sector from that construction sector takes primary place in economic growth. However, construction safety in Ethiopia is very challenging due to several reasons like absence of safety training, lack of Personal Protective Equipment(PPE) on working site, weak supervision, work more than 48hr per week, and poor safety management (Mersha et al., 2017). Thus to minimize this challenge, different remedial measures need to be adopted. Protective clothing is one of the effective solutions provided to protect workers from contact with any harmful material which may cause injury, disease, or even death. When observing foreign country work culture, PPE used strictly in every construction area, including site visitors, when they come into the site for supervision.

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This kind of trend highly improves the safety culture of the construction environment. Also, the use of personal protective equipment is a universal legal requirement to protect workers against occupational injuries and illnesses in their workplace (Nath et al., 2020).

A study done in Ethiopia among Addis Ababa shows thirty-eight percent of workers have been using at least one PPE material while working. In condominium construction, 96.8% of workers were not using PPE while on duty, but ILO recommendation is 100% safety wear for all industry workers (Alemu et al., 2020). Thus, to increase protective equipment utilization in construction sites, appropriate safety management is required either on the organization or the government side. However, the management system in Ethiopia is inferior due to the tediousness of the management process, careless behaviour of employees and the employer, high level of work responsibility on the manager, and unable to visit continuously by the government side. Thus to overcome challenges in safety management adoption of several types of technological solutions is highly required. System-based technology is one of the automatic safety management solutions with wide application in the construction industry (Gao et al., 2018;Barro-Torres et al., 2012;Fang et al., 2018). Nevertheless, the application of system-based technology is scarcely in developing countries (Khan et al., 2019). Thus this research aims to minimize the technological gap by applying system-based technology on the specific area of safety management by creating an easy monitoring system to control workers' PPE usage on construction sites.

It is a known fact that the primary responsibility falls under the manager to create a safe working environment by controlling how workers use the protective device during construction activity, if the managers fulfil their duty, the number of accidents minimized even though the controlling process each day will be tedious. So this research reduces the complexity and tediousness of the work by utilizing a system-based technology which creates a simple system for the manager to control safety easily without going on the site. Additionally, using this system also helps governmental bodies to monitor the construction firm by using it and recording their safety data. Especially using system-based technology for governmental bodies is very helpful to control the construction company because they have the authority to force the firm and punish the responsible body. Also, it creates a clear understanding, when an accident occurs to judge the contractor and labour by using the recorded data from the system. So the construction sector

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needs to adopt this kind of system as a remedial measure to minimize the challenges and create a safe environment for the next generation by providing a better technological solution.

Generally, this research aims to combine system-based technology in the management field in the specific area of safety management to control PPE utilization on the site, which provides an accessible platform for governmental bodies to manage safety issues. However, past studies in Ethiopia related to safety issues do not include system-based technology (Alemu et al., 2020;Fekele et al., 2016;Tadesse & Israel, 2016a). So, this motivates the researcher to add value by including system-based technology in the construction sites.

1.2 Statement of the problem

An accident is one of the most disastrous things occur in all creature which causes injury and death unexpectedly. The construction job is one of the work sectors with a complex activity that creates life-threatening situations. Nowadays, the accident level increase with the rapid growth of the industry all over the world. Mainly, a country like Ethiopia has been affected by construction accidents due to improper safety culture. In Ethiopia's construction projects, several studies were made related to safety issues. The results show as the main problem in Ethiopia construction is lack of proper safety culture due to the absence of professional training, lack of protective device, lack of workplace regulation, and absence of health and safety training for employees using qualified professionals (Alemu et al., 2020;Lette et al., 2018). Lack of PPE utilization and insignificant safety measures in a construction site is the primary safety challenge resulting in a more worth situation than the site with a good PPE trend. Therefore, the unavailability of PPE during construction had significantly higher risks of work-related injury among construction workers. Poor site management also influences the improper usage of PPE. Thus, an adequate safety management system is needed to improve this situation. However, there is a problem in the management system because of the complexity of the process and less commitment to control safety issues (Bekele, 2019). So to minimize the complexity of the management process, the adoption of technological solutions required (Nath et al., 2020;Barro-Torres et al., 2012). But, in a country like Ethiopia, the adoption of system-based technologies for safety management is not applied.

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1.3 Objective of the study

1.3.1 General objective

- ✓ To utilize a computer vision-based approach for Safety Management in the Construction Sites

1.3.2 Specific objectives

- ✓ To rank personal protective equipment depending on their importance in building construction activity.
- ✓ To detect compliance of personal protective equipment in the construction site using a vision-based method.

1.4 Research questions

To achieve the study objective, and all the efforts were applied to answer the following research questions. So, according to the previous discussion, different research questions raised as follows:

1) Which personal protective equipment is the most important and highly required in building construction project?
2) How computer vision used to detect personal protective equipment for managing construction safety?

1.5 Scope of the study

Construction activity is one of the most complex processes that broadly expose a person to an accident resulting in death and injuries. Thus, to minimize disaster, Personal Protective Equipment (PPE) is provided for the workers. However, in a country like Ethiopia, the use of these materials is lacking. Some research exists in the Ethiopian context related to construction health and safety, but there is not enough specific research related to PPE. Thus, a detailed study in this area is required. It is a known fact that construction safety covers a wide area. So for data collection, a specific city with different construction sites taken as a case to collect data from a construction site. But, before choosing the city, selecting the type of construction project required, then for the selected project, the proper city with the available data taken. Because the availability of the project varies from place to place for road, water, bridge, irrigation, and

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railway project rural area preferable and for building projects urban area is the best choice. Several construction projects exist in the Ethiopian construction industry, such as building projects, road projects, water projects, irrigation projects, bridge projects, and railway projects. However, assessing all of the construction projects in Ethiopia's construction industry will be very hard. Thus due to time and budget limitations, building construction site and Adama city taken. Due to this, the research scope is limited to the Adama building construction site to minimize cost and go with the research schedule.

1.6 Limitation of the study

The researchers have faced limitations when conducting this study. Throughout the data collection period, taking a manual picture is one of the challenging processes because workers were unwilling to offer permission and lack knowledge or understanding about the research. Although respondents believe pictures as evidence for their mistakes and participants think of pictures as unnecessary data. So they choose to answer the question rather than be permitted to take their picture.

1.7 Significance and contribution

The gap that this research tries to identify focused on utilization of system-based techniques by applying a vision-based system to provide a simple platform for controlling workers' on-site wearing to prevent accidents that come from improper usage of PPE. This research contributes directly to the management processes of the construction company by providing an easy management platform. Several kinds of research have existed related to health and safety in the Ethiopian context. However, their study does not focus on applying system-based technologies to monitor workers' outfits on site. So this research use system-based technology that identifies people entering the construction site without and with PPE. In addition, this research is significant because it lays away for future Ethiopian research to include system-based technologies. Because this study shows how much a system can simplify complex problems. Thus this research motivates future Ethiopian researchers to focus on system-based solutions.

Generally, this research contributes to improving the safety of a person entering the site by providing an easy controlling system for managers to overcome the accident that comes from improper usage of safety materials. Also, the system gives an easy regulation system by using

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technology for all of the parties included in each specific project by decreasing the rate of death and injuries on construction activity.

1.8 Organization of the study

This research report has five chapters, and the remainder of this paper is structured as follows. The second chapter focuses on previous research on overall safety issues and management systems, PPE utilization, and technological solutions for safety improvement. The third chapter deals with the research approaches used throughout the data collection process, analysis process, sampling technique, proposed method, and material used for vision based approach. The fourth chapter covers the result and discussion of the study, which presents the study's overall finding, including the primary data finding and detection output. Last but not least, chapter five encompasses a summary of research findings, conclusions, and recommendation part of the study.

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CHAPTER TWO
LITERATURE REVIEW

Safety in construction is one of the crucial things that affect the employees' well-being and productivity to meet the project goal (Jazayeri & Dadi, 2017). Thus, safety in construction is an important thing that needs an effective and efficient management system to keep workers and the organization safe. The following literature shows the researches on safety and health issues.

2.1 General Safety issues

A construction site is a hazardous workplace that results in different injuries and fatalities among workers. To minimize this disastrous situation developing a good safety culture in every construction sector is required. To evolve good safety culture establishing structured safety practice is one of the most convenient ways that includes safety policy, safety training, site supervision, meeting and auditing on safety issues, utilization of PPE, and measuring safety. Thus, to minimize the accident rate in every construction site implementing appropriate safety practices desired, including awareness of employees, efficient training, top management commitment, resource and budget provision, and providing safety booklets in a different language (Keng & Razak, 2014). Identifying hazardous work environments, safety awareness, avoiding exhaustion, and high commitment through employees, inspectors, and managers plays a significant role in creating a safe occupational environment (ElSafty et al., 2012).

The construction site is naturally a very challenging place for going full of safety due to several reasons, resulting in poor safety culture. Organization factors, resource factors, site factors, management factors, and workforce factors are the challenging factors for construction site safety. Under these, causes of construction hazardous are listed, such as the absence of safety awareness, shortage of PPE, lack of knowledgeable managers and technical guidance, ineffective safety policies, and irresponsible acts (Durdyev et al., 2017). In addition to this, there are different types of construction site problems related to safety practices, such as the absence of financial provision for safety management, lack of communication between employees and supervisors, and ignorance of workers (Keng & Razak, 2014).

Injury and death due to construction activity result from several causes or several casual factors related to each other, resulting in hazardous situations. These factors are employee actions, risk

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management, instant supervision, materials or equipment usage, local hazards, employee capacity, and project management. The combination of these factors present in several construction incidents, but their impact differs in every situation. Due to this, the most critical factors which have the highest impact are employee actions, instant supervision, and risk management (Winge, Albrechtsen, & Mostue, 2019). The most critical factors that cause construction accidents are negligence of PPE, improper usage of PPE, poor management and training, and lack of knowledge (Elavarasan & Kamal, 2017). Therefore, to create a safe working environment for the construction workers, the above critical factors need to be reduced.

In Ethiopia's construction site, the major factors that result in poor safety culture are unavailability of strong company Health & Safety (H&S) policy, poor execution of the existing building rules and regulations, and poor safety awareness of the company top management (Fekele et al., 2016). Likewise, working without PPE, lack of H&S training, absence of regular supervision, lack of PPE, working for more than 48hr per week, lack of awareness, employees do not have information that the company has written safety rules & regulations which reflect management concerns are the factors that challenge safety cultures in Ethiopia which related to poor management (Lette et al., 2018;Tadesse & Israel, 2016;Alemu et al., 2020;Mersha et al., 2017). The study done in Addis Ababa road projects shows that the accident is risky work processes, lack of PPE, inappropriate PPE design, incorrectly shielded areas, lack of safety plan, lack of safety training, and ineffectiveness of current safety policy (Bekele, 2019).

Generally, foreign researchers provide several solutions for improving safety in construction projects, which combine several fields of studies such as management, system-based technology, law, material, and medical fields. Likewise, Ethiopian researchers consider all solutions that included in foreign researches except system-based technologies. A study was done in South-eastern Ethiopia state as a solution that the promotion of PPE, provision of safety training, regular supervision, and satisfying their employees to reduce the rate of injuries by the employer side requested (Lette et al., 2018). Considering safety and health policy in the contract document before taking the project is an essential solution, including safety as a pay item and assigning a budget for health and safety (Fekele et al., 2016). On the client-side, develop a good safety culture provision of occupational safety assurance and implement a safety management system. Also, associated factors for utilization of PPE in a proper way are the provision of safety

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training, preparation of safety brief before starting work, and governmental visits (Alemu et al., 2020). Generally, effective regular site supervision, adequate safety training, monitoring hazards in the workplace, and controlling PPE usage are the usually given solutions to create a safe working environment (Tadesse & Israel, 2016b;Alemu et al., 2020).

2.2 Safety management system

Management is a vast discipline that deals with organizing, planning, leading, and controlling. The construction industry is one of the largest industries that apply management in every aspect of the industry. Safety management is one of the management aspects that contain a continuous process to decide risk-related issues. It is an approach that manages safety in a well-organized way that embraces organizational policy, procedure, accountability, and structure. Also, a safety management system is a set of interconnected elements to implement safety and health policy and objectives (Jazayeri & Dadi, 2017). In general safety management system includes safety encouragements, safety guide, safety regulation, and training (Wong et al., 2020). Also, safety management is one of the main factors, which affects construction safety due to less management commitment, lack of knowledgeable managers, and poor management (Keng & Razak, 2014; ElSafty et al., 2012).

A safety management system is a crucial way of management that prevent and control the hazardous situation in construction place, by minimizing the number of injuries, reduce risk of accidents, regulate workplace risk, decrease material and equipment damage, reduce the cost of insurance and legal cost of the accident, minimize loss of expert and experience (Jazayeri & Dadi, 2017). The management team is required to consider safety issues at the planning phase, and higher responsibility falls into top management and governmental authorities for improving safety performance (Durdyev et al., 2017). A variety of safety management factors that helps the construction industry to achieve better safety performance were assessed such as, roles and responsibilities, OHS and project management, education, site management, staff management, and working risk management. The most strongly linked factors to safety performance are site, staff, and operational risk management (Winge, Albrechtsen, & Arnesen, 2019).

Implementing a safety management system in every construction site is used to create a safe working environment and minimize hazardous situations. However, there are some obstacles to implement this system, such as taking safety issues as insignificant, inactive contribution among

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the stakeholder regarding safety issues, tight project schedule, and high-income rate (Yiu et al., 2019).

2.3 Personal Protective Equipment utilization

Personal protective equipment (PPE) is any material utilized to protect workers in any hazardous working environment. The construction industry is a risky industry that requires the utilization of this protective equipment during the construction process to protect workers from harmful chemicals and materials. However, construction workers improperly utilize PPE or refuse it; even the professional workers neglect PPE or wear it improperly. Ignoring PPE during construction activity increases hazards, especially ignoring safety belts, safe clothing, helmet, and safety vest from several types of equipment result in much worse conditions (Aung et al., 2019). The main reason for neglecting PPE during construction activity resulted from several factors like PPE utilization attitude, habituation, risk awareness, safety-related issues, safety awareness, safety management system, time influence, and workplace situations. Also, lack of comfort is one of the challenges when using PPE during work. Because the PPEs designed only by considering the defensive ability of the material and lack of comfort doesn’t get attention by the designers, which highly minimize the usability of the equipment and push the workers to refuse PPE. Thus, to minimize this challenge, designers must design comfortable and easily adaptable PPE (Wong et al., 2020).

The study done in Ethiopia shows that PPE culture is weak in every construction site. The result is expressed statically by different researchers taken from Ethiopia towns. The research done in Addis Ababa shows that PPE is not available on-site, which exposed workers to injury, and death in the construction site. Occupational injuries annually show 847 injuries per 1000 workers, and 74 were hospitalized (Mersha et al., 2017). 38.3% of the employee in Addis Ababa in building construction projects used at least one PPE, and 3/4 of the employees did not use PPE on construction sites (Tadesse & Israel, 2016;Alemu et al., 2020). Also, the study on Addis Ababa road construction projects revealed that 90.32-96% of employees’ on-site value safety but there is no training provided, 42.31% of site workers use PPE not comfortable to use (Bekele, 2019). The study on Robe town revealed that injuries on female workers in construction sites 60% less than male workers. A construction worker who doesn’t use PPE

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during work was 3.6 times more likely to face injury than a worker who uses PPE (Lette et al., 2018).

To improve these challenges inspiring workers and creating awareness required to increase utilization of PPE, which includes the provision of practical training, selecting the right PPE depends on the task and PPE maintenance. Because the effectiveness of PPE depends on the experience, skill, attitude, and acceptance of workers (Amir et al., 2018), and training related to PPE utilization is one of the influencing factors to improve PPE usage culture among the workers (Sehsah et al., 2020). Generally, to enhance PPE culture in the construction industry, a better management system is needed to control workers' PPE usage, give guidance when using PPE, and prepare training related to PPE usage.

Availability of PPE is one of the factors that influence the utilization of protective equipment. Because most construction companies have weaknesses in providing protective equipment for their employees and the common PPEs used in construction sites are helmets, safety shoes, reflectors, protective cloth, gloves, goggle, face shield, dust mask, and earplugs. The availability of this protective equipment differs from site to site. However, providing all of the material will be difficult due to their high-cost requirement. Helmets and safety shoes are provided in most construction sites because the absence of both PPEs results in more damage when compared with the rest PPEs. In the first place, helmet and safety shoes ranked when measured by availability in construction sites, and safety harness, protective clothing, and gloves ranked in third, fourth, and fifth place. The lowest-ranked value given for safety goggle and noes mask is not available in most construction sites (Amir et al., 2018). Thus, PPE should be wear at all construction sites to control the risk of injury and death. Every construction activity requires an employee to wear a helmet, safety shoes, gloves, goggles, eye protection, earplugs, face shield, dust mask, reflector, safety harness, and protective clothing (Bekele, 2019). Description of the commonly used PPEs in construction sites defined in Table 2.1.

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Table 2.1 Description of PPEs

SN	PPE	Description
1	Helmet	To Protect the head against impacts from fixed and falling objects.
2	Goggle	Used to protect the eye when cutting, welding, or nailing construction equipment.
3	Safety shoes	To prevent crushed toes when working around heavy equipment
4	Earplug	hearing protection is used in work areas with high noise levels like crusher sites.
5	Glove	To protect the hand from harmful chemicals by using heavy-duty rubber gloves
6	Reflector	It is utilized when visibility is impaired.
7	Safety harness	It is a fall protection equipment that protects employees when working in height.
8	Face-shield	To protect the wearer's entire face from any harmful materials.
9	Dust-mask	Utilized to prevent any harmful dust during construction and cleaning activities.
10	Protective clothing	Used to protect the body against hazardous liquids and gases

2.4 Technological solution for safety management

2.4.1 Vision-based technology to monitoring Personal Protective Equipment

Personal protective equipment (PPE) usage is one of the crucial factors that affect construction site safety which challenges the managers to monitor the employees during construction activities. Because the only method used to monitor PPE is visual inspection which is a very tedious process (Barro-Torres et al., 2012). To minimize the management challenges and to develop a good safety culture, technological solutions preferable. Foreign researchers include vision-based technology to monitor safety directly related to PPE using different methods.

Computer vision is a part of artificial intelligence that enables the computer to understand the visual world by constantly training using images and videos. Also, it uses Deep learning models for training that able the machine/computer to detect accurately. The health & safety monitoring system that compromise, vision-based methods categorize into three groups, such as object detection, object tracking, and action recognition based on types of information required to evaluate hazardous conditions (Seo et al., 2015). A vision-based method adopts to check employees' wearing ways of PPE like a hardhat, reflector, safety shoes, safety harness, gloves, and goggles during construction works. During this process, on-site Cameras fixed to detect

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workers’ safety cloths to check that they are wearing PPE properly by video frames. Then it identifies automatically and gives signs or alerts depends on the incorrectness ways of wearing (M.-W. Park et al., 2015;Delhi & Thomas, 2020;Nath et al., 2020;Fang et al., 2018).

The vision-based method is a technological method used to detect the PPE of workers to check that the employees wore the protective device properly. This method was applied to detect each protective device separately, such as detecting hard hat, safety harness, hard hat with reflector, and combination of all protective equipment detected using vision-based method during construction work. The model development process classifies into two primary detections; the first one is the detection of the human body and the second one is the detection of protective material. Then by combining both detections finally, the developed model identifies the employees’ usage of PPE. On both conditions for detecting the human body and PPE, the machine used different types of the model such as Faster-Region-Based Convolutional Neural Networks (Faster-R-CNN), Deep Convolutional Neural Networks (Deep CNN), Histogram Oriented Gradient (HOG), Convolutional Neural Network(CNN), You-Only-Look-Once (YOLO), Face Net, colour-based and Circle Hough Transform (CHT).

2.4.1.1 Hard hat detection

Helmet detection is one of the applications of vision-based methods that detect hard hats when workers enter the site. This method detects human bodies and helmets at the beginning by using -site cameras, then the captured helmet and human bodies matching checked using geometric and spatial relationships, then automatically person who doesn’t wear a helmet identified and alert (Park et al., 2015). Thus the system passes two vital processes, first human detection from the given image and second helmet detection by taking color information (Rubaiyat et al., 2017). The system can identify the helmet by detecting the helmet shape or circular shape, and also it can recognize helmets with different colors (Mneymneh et al., 2017).

2.4.1.2 Safety harness detection

Fall from height is one factor contributing mainly to injuries and death when employees work at height. Thus to overcome this challenge, using a protective device that prevents falling is required. Safety harness is a type of protective device utilized to prevent falling from height. Also, a vision-based method can control the workers wearing safety harnesses when they work at the top place (Fang et al., 2018).

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2.4.1.3 Hardhat and reflector

By using the vision-based method, both hardhat and reflector recognize at the same time. The machine checks the presence of helmet(hardhat) and vest (safety jacket or safety vest) on the site, then it identifies in different category such as safe, not safe, no helmet, no vest then it gives alert and reports (Delhi & Thomas, 2020;Nath et al., 2020).

2.4.1.4 Full Personal Protective Equipment detection

Full PPE was also detected using a vision-based method to check that the workers wear all protective devices (Tran et al., 2019). Table 2.2 shows the summary of vision-based PPE detection papers that focused on developing a system-based model to identify several types of PPE such as helmets, safety harnesses, safety shoes, reflectors, and gloves. The data set used for training and test in terms of number listed and the models used to build in each paper listed such as face net, YOLO, CHT, HOG, CNN, Faster-R-CNN, and deep CNN. Also, the result found in each research in terms of mean average precision, recall, and accuracy included.

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Table 2.2 Summary of vision-based paper

Paper title	Type of PPE	Data set	Model used	Result	Limitation
(Fang et al., 2018)	Safety harness	Total of 5770 images, 770 workers wearing a Harness, 5000 workers not wearing a harness	Faster-R-CNN to detect the presence of a worker and deep CNN model to identify the harness	The precision and recall rates for the Faster R-CNN were 99% and 95%, and the CNN models 80% and 98%, respectively	The model developed by Considering only safety harness
(Nath et al., 2020)	Hard hat & vest	Pictor-v3 dataset used which contains, 1,500 annotated images and 4,700 instances of workers wearing various combinations of PPE components, total of 6200 image	YOLO-V3 architecture, single convolutional neural network (CNN) framework, classified by CNN-based classifiers	72.3% mean average precision (map)	The model developed by Considering only hard hat & vest
(Delhi & Thomas, 2020)	Hard hat & vest	A data set of 2,509 images	YOLOv3 deep learning network	average precision and recall rate at 96%	Colour mismatching (especially for hard hats)
(Mneymneh et al., 2017)	Hard hat	datasets of 75 positive and 164 negative images	HOG-based cascade object detector from images captured on many indoor jobsites	Not mentioned	The model developed by Considering only hard hat and other important PPE not included
(Rubaiyat et al., 2017)	Hard hat	To train 354 human and 600 non-human sample images, For testing	Human detection algorithm Histogram of Oriented Gradient (HOG) for construction worker	In detecting helmet 79.1% accuracy	The model developed by Considering only hard hat

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		200 construction images, total of 1154 image	detection, the combination of color-based and Circle Hough Transform (CHT) feature extraction techniques is applied to detect helmet	In detecting construction worker without helmet 84.34% accuracy	other important PPE not included
(Tran et al., 2019)	Helmet, reflector, gloves, belt, pant, shoes	For PPE detection training data set is 12000 and test data set is 1200 For face detection training data set is 4500 and test data set is 500	YOLO-V3, Face Net model	accuracy for 6 main PPEs is up to 98% while that for face detection and recognition is 96%.	It's the best when it compared with others because it includes different equipment but the PPE included in this model is too much for our country condition.
Own source	Helmet, safety shoes, reflector	For PPE detection training data set is 3800 and test data set is 900	YOLO-V4 architecture	Accuracy 96.97% for helmets, 97.73% for a reflector, and 98.9% for shoes. detect PPE with high precision 98%	This research is used the latest version of YOLO (YOLO-V4) and it achieve highest accuracy and precision, however the data used in this research is lesser when it compared to other researches.

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2.4.2 System-based training

Before starting any construction activities provide training for each employee to create enough awareness about the safety issue required. To provide practical training for workers, technological approaches or technical training is essential. Thus, technologies apply to train workers about safety rules, usage of hazardous materials, and building awareness about PPE and its advantages. Computer-aided technologies (CAT) are crucial solutions to support health and safety training compared with traditional training tools as studied in research(Gao et al., 2018). Because the CAT training method represents the workplace's actual situations, it also has good user engagement and provides a text-free interface. CAT training includes serious games, computer-generated simulations, virtual reality, augmented reality, and mixed reality. Traditional training includes lecture, toolbox talk, handout, audio-visual material, computer-based instruction, and hands-on training (Gao et al., 2018;Sacks et al., 2013;Pink et al., 2016; Le et al., 2015;Greuter et al., 2012).

2.4.3 System-based accident identification

In nature, construction is very hazardous by its activity, equipment, and work behaviour. To solve this disastrous situation before resulting any damage to the workers and the company property identifying hazardous areas required to instruct the employee to move carefully in the unsafe area and take appropriate remedial measures to manage risk. In the construction industry, manual observation is used, which is very challenging for safety managers to identify continuously due to the construction environment complexity. Thus to identify the hazardous situation effectively and efficiently using technological approach or methods is desired. Several hazard identification methods developed by different researchers that pass through different process includes hazard recognition, detection of accident area, and reporting of incidents. Bluetooth Low-Energy (BLE)-based location detection technology, Building Information Model (BIM)-based hazard identification, and a cloud-based communication platform develop to identify and analyse hazardous situations in construction (J. Park et al., 2017). Also, LCD information technology is one of the systems used for controlling safety, which displays at the construction site to present updated information about safety matters by using 3D and 4D model views to inform identified unsafe situations (Merivirta et al., 2011). Figure 2.1 shows the summary of system-based safety management approaches used by former researchers for training purposes, hazard identification, and PPE monitoring in construction sites.

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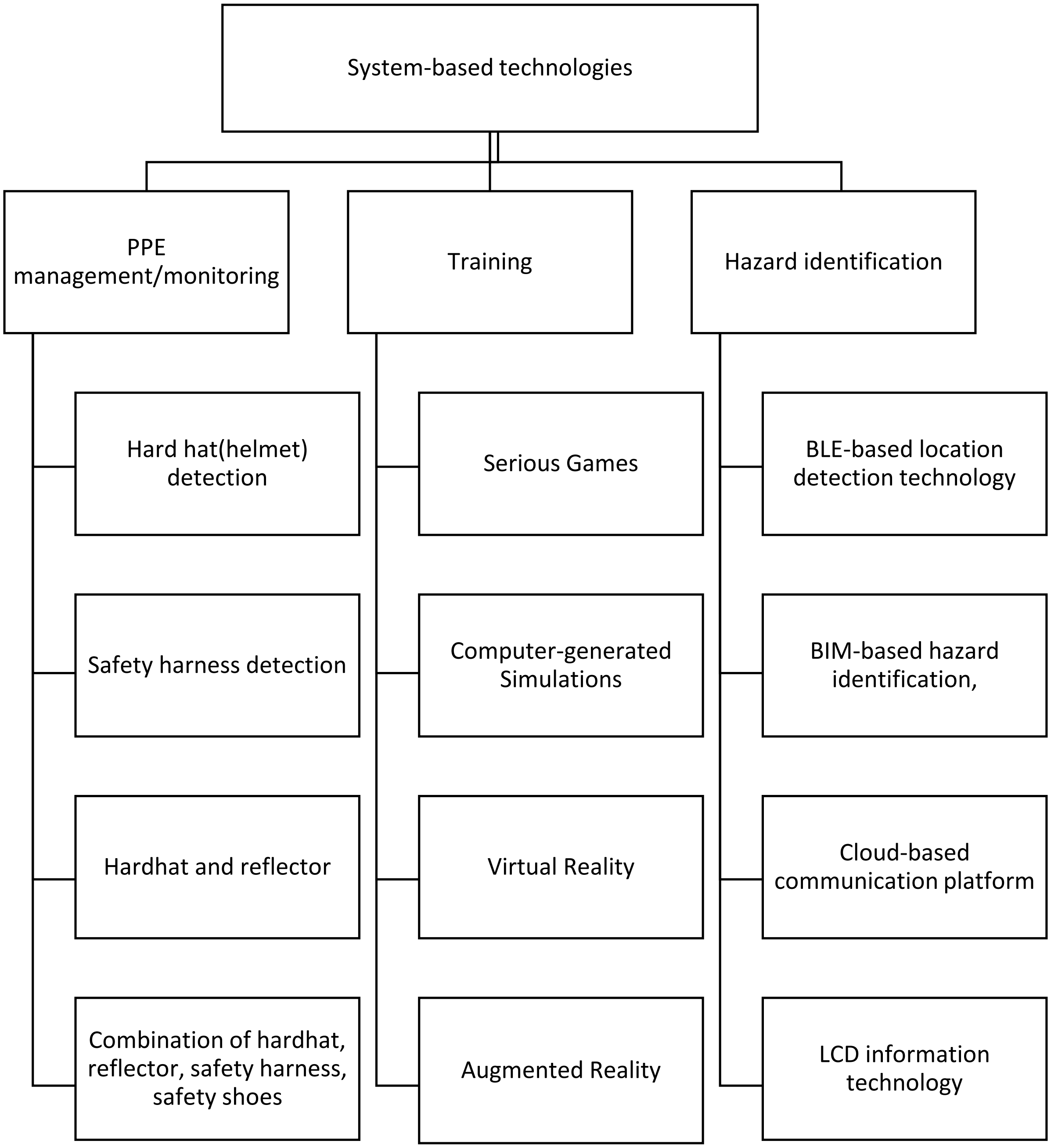

Figure 2.1 Summary of system-based approaches used for construction safety

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2.5 Summary of literature review and research gaps

Safety in the construction industry is one of the most important issues that needs improvement in different aspects, such as the management system, safety investment, and technological adoption. In detail the review describes about general safety issues, factor affect construction site safety, safety management system, PPE utilization among construction workers, solution provided by different researchers, and several technological approaches for providing a safe working environment. Depend on this review the research gaps were identified and during this phase strong base was formed for the research.

In the above review, the most important factor affecting construction safety is the effectiveness of the safety management system on the construction company. Safety management is one of the management aspects which contains organizational policy, procedure, accountability, and structure. The safety management system, is used to minimize the number of injuries, reduce the risk of accidents, regulate workplace risk, decrease material and equipment damage, reduce the cost of insurance and legal cost of an accident, minimize loss of expert and experience (Jazayeri & Dadi, 2017). To achieve more excellent safety performance, several safety management factors were explored, such as roles and responsibilities, OHS and project management, education, site management, staff management, and working risk management (Winge, Albrechtsen, & Mostue, 2019). However, some obstacles limit the implementation of good safety management systems, such as taking safety issues as insignificant, inactive contribution among the stakeholder regarding safety issue, tight project schedule, and high-income rate (Yiu et al., 2019). To overcome the construction challenge adoption of several solutions required. Currently, several solutions by local and foreign researchers offer to solve safety issues. The local researchers mainly focused on policy and strategy development, assessing the core issues, developing management systems, and recommending future work improvement. Local researchers provide several solutions like promotion of PPE, provision of safety training, regular supervision, employee satisfaction, adequate regular site supervision, monitoring hazard in the workplace, and controlling PPE usage (Lette et al., 2018;Tadesse & Israel, 2016;Alemu et al., 2020).

Personal Protective Equipment is one of the most critical solutions suggested by all of the researchers. Effective utilization of PPE results from good safety culture by protecting workers

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from any harmful material and incident. To develop a good safety culture, utilization of PPE plays a vital role in every construction activity, and there are some associated factors to utilize PPE in a proper way, such as the provision of safety training, preparation of safety brief before starting work, and regular governmental visits (Alemu et al., 2020).

On the other hand, foreign researchers, like local researchers, provide strategy and policy, develop the management system. Additionally, foreign researchers include several technological approaches to improve the management system, training system, and identification of hazardous situations. When the technical solutions compare with manual safety solutions, technical solutions are very effective, less time taken, and accurate. Thus, applying these system-based technologies is very useful in construction safety to improve the limitations of manual systems. The technological approaches include system-based technology that used a vision-based method that detects worker usage of PPE and reports to their manager or supervisor. The approach used by past researchers embraces different PPE in the model like the only helmet, only safety harness, helmet & vest, and combination of Hemet, gloves, belt, pant, safety shoes, and vest (Delhi & Thomas, 2020;Nath et al., 2020;Tran et al., 2019). Also, the system-based technology is used to identify a hazardous area and for training purposes. However, technological gaps are observed in local researches because they do not involve any technological solutions. So, the researcher was inspired to minimize the technological gaps by adopting the system-based technology in this research. The system-based technology used in this research focuses on PPE detection using a vision-based method that provides an easy monitoring system and effective control in the construction site. As discussed before, lack of good PPE culture is one of the major sources of an accident in Ethiopia construction sites, so to improve this condition, the adoption of a technological monitoring system is needed.

To sum up the above discussion, this research tries to minimize the technological gap in the safety management area. This research fills the scientific gaps by utilizing a computer vision approach that controls PPE usage during construction activity, detecting worker clothes. Although there is a lack of technological research in Ethiopia, this research inspires future researchers to integrate scientific solutions in the civil engineering field.

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CHAPTER THREE

METHODOLOGY

This chapter discusses the study area description, population and sampling method, sources and tools/ instruments of data collection, and data analysis methods. In general, this chapter presents the research method to achieve the study objective and answer the research questions discussed in the above chapters.

3.1 Description of the study area

In this research, case conduct in building construction companies located in Adama city, Ethiopia. Based on the data acquired from Adama City regulatory office the town has six sub-cities called Aba Gada, Denbela, Lugo, Bole, Dabe, and Roku. Adama is also known as the sparkling city in the rift valley with continuous development for the past ten years. In history, Adama establishes in 1908 E.C at a distance of 99 kilometres southeast of Addis Ababa. The size of the town increases fourfold than it was two decades ago. The urban expansion in Adama city is 34000 hectares in 2010E.C. Adama city grew rapidly in terms of population in the last three consecutive censuses, increasing from 77,237 in 1984 to 373,661 in 2008 whom male 185,107 and female 188,554 (Fufa, 2017).

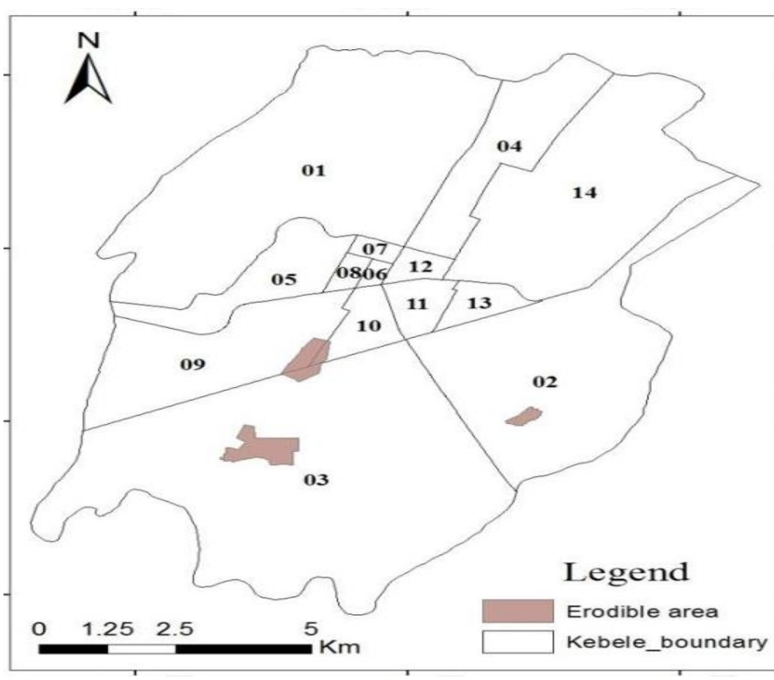

Figure 3.1 Adama city map

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3.2 Population and sampling method

3.2.1 Target population

The total population includes all building construction companies in Ethiopia construction projects. Because building projects are more exposed to construction accidents due to their complex activity, and building projects are searchable to identify and understand problems. The representative companies are taken from G+3 and above ongoing building construction projects in Adama city. The study population obtains based on the data acquired from Adama City Construction Authority office. Hence, the total population consists of 152, G+3, and above building projects. The research narrows the scope to G+3 and above building projects in Adama because the construction projects below G+3 are not expected to fulfil safety matters and also they are not obliged by the regulatory office to provide safety requirements depending on the information acquired from the regulatory office. Because work complexity on these projects is significantly less due to this, the rate of exposure to construction accidents is less when it compared with G+3 and above ongoing projects, so the regulation on safety issues for this kind of project is inferior. Thus, the researcher forces to focus on the projects G+3 and above building projects. The targeted population is the employees who worked in G+3 and above building projects, such as project managers, site engineers, timekeepers, Forman, carpenters, and bar benders of the selected construction companies. In addition to this, pictures manually collected from the construction site, including daily labours.

3.2.2 Sample size

The research sample is ongoing G+3 and above building projects located in different in Adama. The questionnaire distributes to each building project employee, such as office engineers, site engineers, project managers, safety manager/ supervisors, and others available at the construction site during the data collection time. All of the respondents are currently working on each building construction project. Out of the total population-representative samples were taken by selecting randomly ongoing building projects. During the data collection period, ongoing construction projects in Adama city are around 60, located in different sub-city areas because there was a shortage of construction material, especially cement. So to make the research reliable, all of the ongoing building projects were taken as a sample.

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Generally, in building projects, governmental regulation in safety issues is inferior. Most of the time, they raise safety issues only in big projects, so this research focuses on G+3 and above building projects. Additionally, the following expected reasons, like the data availability factor, and the time constraint to complete the project work limited the research to focus only on the case study of these projects and project areas.

3.3 Data collection instrument

In this study, both quantitative and qualitative methods or a mixed-method approach are utilized. Each approach has its limitations and advantages, so it is vital to use both method to find better results from the analysis and investigation. For the quantitative data, questionnaires survey and the qualitative data interviews and field observation used.

3.3.1 Questionnaire

In this research, a questionnaire was used as a data collection instrument to identify the most significant PPEs, and available color of PPE in the Adama building construction site. Moreover, to make it more straightforward for the employees' questions were prepared in English and Amharic language (see: Appendix A). Close-end questions type used in this research such as Dichotomous questions and Likert scale questions. Likewise, the color of PPE was asked in a table format by listing different colors of PPEs to help the respondents memorize the available color then they select in the questionnaire (see: Appendix A4). A dichotomous type of questions is used in this research to assess which type of PPE available in their construction site. In the dichotomous questions, the participants respond yes/no for the availability of protective materials currently on the construction site (see: Appendix A2). Also, Likert scale type of questions is used in this research to evaluate the importance of PPEs. The Likert scale is one of the best approaches used by different researchers to measure importance. Likert scale question is a type of question with five or seven-point options. A seven-point, Likert scale question type is used in this research to assess the importance of each piece of protective equipment. The seven measuring scales are 7-extremely important, 6-very important, 5-important, 4-somewhat -important, 3-not that important, 2-neutral, and 1-unimportant (see: Appendix A3). Thus, the Likert scale questions are used in this study to assess the importance of PPEs then the importance of PPE was ranked using RII methods.

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3.3.2 Interview

Interviewing data collection method is used as an intermediating approach to minimize the gap between the data collected from the questionnaire and observation. To make the data more relevant to the study, questionnaires' supported by the interview and to find why they rank PPEs from extremely important up to unimportant. Also, it helps respondents to understand the question result from lack of knowledge interview method of data collection used. Depends on these reasons, respondents informally interviewed to support the questionnaire.

3.3.3 Observation checklist

An observation checklist is a list of questions that the data collector should answer via observing the actual condition or environment. It is a surveying technique in which the data collector measures the existing situation from a professional insight to determine the fact. An observational checklist is used in this research to evaluate the actual PPE utilization in building construction sites to know the real situation further. Also, observation is used for the data collection to support the result found from the questionnaire and interviews that the workers answered and cross-check that the given answer is believable.

Mainly, the data collected by using a questionnaire to assess and rank PPEs in building construction sites. However, using only the data taken from the questionnaire is not recommended because some of the participants respond to answers that are very far from reality due to that cross-checking the questionnaire result by using the observation method required. The observational method is a valuable method used to assess actual site conditions and evaluate the questionnaire response by presenting on the site. Therefore, an observational method uses to assess PPE availability in Adama building construction sites.

3.4 Primary data analysis techniques

The data gathered from the primary sources using questionnaires were analyzed using IBM SPSS statics 20 and Excel 2016. IBM SPSS statistics 20 used in this research to analyze the descriptive statistics of the primary data. Descriptive statistics is the analysis of data used to summarizes data easily. Also, the output of the analysis presented as percentages and frequency and data export from SPSS to Excel to represent data in graphical and table form. Also, Excel used to rank PPEs by using the RII method of ranking.

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3.4.1 Relative Importance Index method

Data collected using a scale questionnaire can be ranked using different methods, and the scale was measured by using the importance of each PPEs. Thus, the ranking method should be a suitable approach for rating the importance. Relative importance index (RII) is a ranking method commonly used for ranking data collected in terms of importance scale. Thus, in this research relative importance index (RII) method is used to rank which type of PPE is the most important for building construction projects because it is suitable for ranking questions measured by the importance of something. The ranking value taken from Adama building construction sites using Likert scale questions and the questions analyzed using SPSS statics then using an excel spreadsheet the result ranked. The rank of different types of PPE values depends on their importance calculated.

$$RII = \frac{7n_7 + 6n_6 + 5n_5 + 4n_4 + 3n_3 + 2n_2 + 1n_1}{A * N}$$

N= Total number of respondent (114)

A= Highest weight (7)

n1= number of unimportant response

n2= number of neutral response

n3= number of not that response

n4= number of somewhat response

n5= number of important response

n6= number of very important response

n7= number of extremely important response

3.5 Validity of the study

Data validity test is a method used to measure how accurately the collected data measures what it intended to measure. In this research, the validity tested using content validity, face validity, and construct validity. Content validity is used before the actual data collection to evaluate the content of the question if some aspects are missing and irrelevant aspects embrace. Although

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by using face validity suitability of the questionnaire tested and construct validity used to test the method of measurement used in the collection process match with the concept the researcher wants to measure. Thus, the above validity measuring method used in this research to test the questions before using for the actual work by asking some respondents to identify problems on interpretations and detect any doubts. Likewise, in the interview, volunteer bodies asked a couple of questions in the interview form. To test the validity of the interview response of the sample question was recorded and organized as data. Thus, to assure data quality, pre-testing the questionnaire taken from some selected respondents before the real work begins to identify problem areas, unanticipated interpretations, and cultural objections to any questions.

3.6 Reliability of the study

Reliability is a measure of consistency to evaluate the reliability of the result. There are three types of reliability measure such as test-retest reliability, internal consistency, and inter-rater reliability. The test-retest reliability is the reliability of the output or result measured by the result difference when the data collection time varies, thus to avoid this kind of issue, the interview at the same time in different companies was collected. In this research, there is no need for Interrater reliability measures because the data was collected only by the researcher, so no variation occurs in the interpretation of the responses. The internal consistency was measured by using Cronbach's Alpha α (or coefficient alpha), developed by Lee Cronbach in 1951, which measures internal consistency, which shows how closely related a set of items, to measure the scale of reliability. This method of testing reliability is used for dichotomous and continuously scored variables to indicates consistency. The Cronbach's Alpha is a coefficient that ranges from 0 to 1; if the answer is 0, there is no consistency in the measurement in another way if the answer is 1, perfect reliability, and if the answer is 0.7 means the score is reliable variance and its more realistic. Thus, the reliability in this research was tested by using Cronbach's Alpha (coefficient Alpha) in IBM SPSS statics 20 to measure internal consistency.

The formula for Cronbach's Alpha is:

$$\alpha = \frac{N.\bar{C}}{\bar{V} + \left((N-1)\right).\bar{C}}$$

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Where:

N = the number of items.

c̄ = average covariance between item-pairs.

v̄ = average variance.

In this research, several threats that bias the reliability eliminated like participant error, participant bias, researcher error, and researcher bias. Participant error is an error that occurs if the participant response affects by time variation. However, this research is done in different places at a fixed time in the morning to get more energetic respondents, so this research is free from participant error. Participant bias is a condition that forces the participant to give a false result. Although the interview individually is done to prevent bias in this research, when the respondent is free and the questionnaires collected confidentially, to respond their opinion without the influence of their managers. Also, this research is free from any researcher error because the interview was taken in the data collection stage for two weeks without getting tired through a repetitive process so, this explains the interview taken from the participant when the researcher is fully energetic. The last one is the researcher biases is any factor that adds a bias in the researchers when recording responses in the interview and interprets subjectively. However, in this research, the researcher made all of the interview objective rather than subjective. So, depending on the above factor, this research is reliable because it avoids any factors that influence the reliability of this research.

3.7 Computer vision-based approaches development tools and technique

This section deals with the method, procedure, tools, and techniques used in vision-based method. The methods used to achieve the general objective of the study discussed in detail in the sections below.

3.7.1 Model development procedure

In this research, a vision-based method to monitor safety automatically was used, and for implementation YOLO-V4 architecture was used. The YOLO architecture allows for end-to-end training and real-time performance while retaining high average precision. The input image is divided into S S grid by the device. If the core of an object lies inside a grid cell, the grid cell

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is in charge of detecting the object. Each grid cell predicts bounding boxes and their confidence scores. These confidence scores show the assumption that the box holds an item and how correct it believes it is that it forecasts. Figure3.2 shows the research method for this study is depicted, which represents the standard method for deep learning. The main processes involved include developing the algorithm, preparing data sets, training, and validation, and the following pages describe these processes in detail.

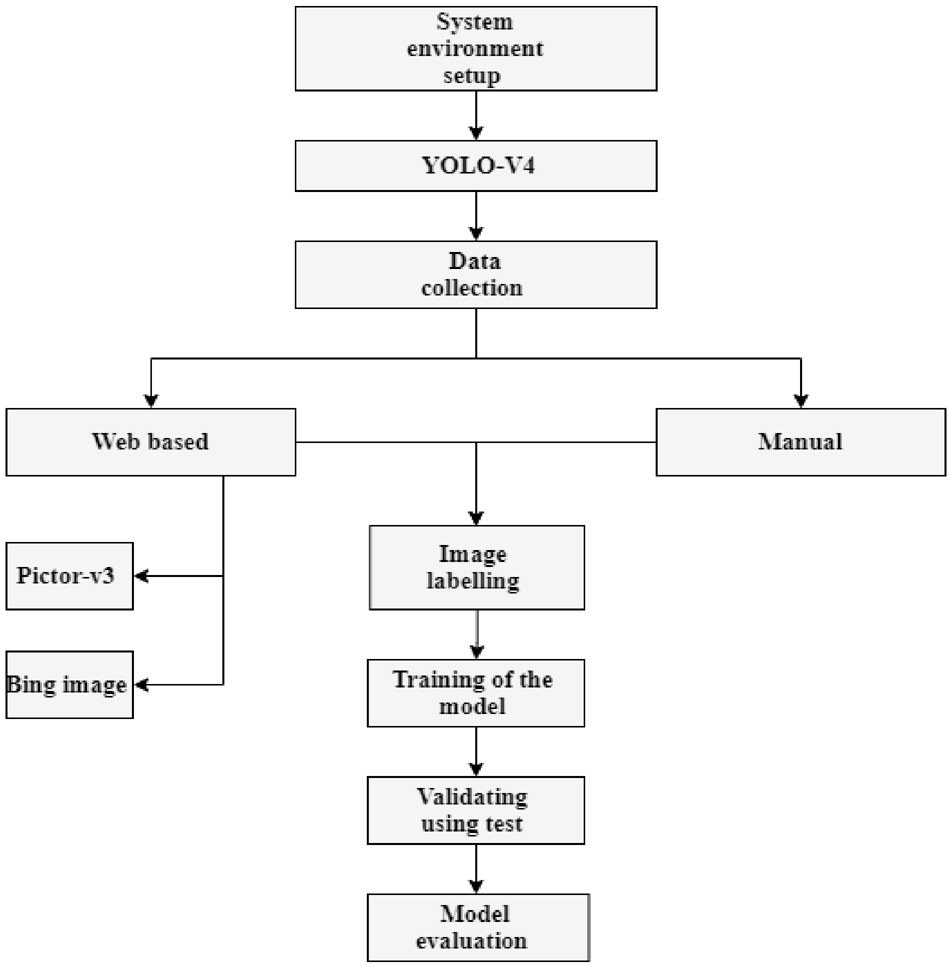

Figure 3.2 Standard method for deep learning models

3.7.2 Development Tools and packages

In this research Python programming language used to write the program. Python programming language commonly builds, compares, evaluates, graphical representation, and data processing using a python programming language. Python is beneficial because its interactive, interpreted, Consistent, Beginners' Language, and straightforward. Also, it reduces development time because it contains many libraries and frameworks for machine learning and

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deep learning architectures. Python often uses English keywords, which makes it very understandable, and it has few syntactical constructions compare with other programming languages and the Python-3 version used in this research.

3.7.3 Environment Setup

The environment used in this research is Google colab, colab is a short form of colaboratory produced by Google Research that permits anyone to compose and execute arbitrary python code through the browser, and it is particularly well suited to machine learning data analysis and instruction. Colab is a hosted Jupyter notebook service that needs no setup, and colab provides free access to computing resources, including GPUs. Google Colab notebooks are shared easily in colab; everyone with a Google account can copy the notebook on his own Google Drive account. In this research, the development is done in a colab environment because colab provides free GPU without requiring internal graphics of the pc, and there is no need to install libraries in your pc. In other words, when working with google colab, space does not require running and install any package. However, there are some limitations on colab, such as space and time limitations. Google Colab platform stores file with a free space of 15GB in Google Drive, but it is challenging to execute when working on a larger dataset due to space limitations. However, for this research, the space provided by Google Colab is enough.

3.7.4 Libraries and frameworks for the proposed approach

In this research, YOLO-V4 was used for the implementation. The new YOLO-V4 architecture uses CSPDarknet54 as a backbone, which enhances CNN's learning capabilities. Weighted-Residual-Connections(WRC), Cross-Stage-Partial-Connections (CSP), Cross-Mini-Batch Normalization (CmBN), Self-Adversarial-Training (SAT), and Mish-activation support in the implementation of universal features included. Alexey Bochkovskiy, Chien-Yao Wang, and Hong-Yuan Mark Liao created YOLO-V4 and announced it in April 2020 as one of the most advanced real-time object detectors available. YOLO proposes to address the problem of target detection speed in deep machine learning. When YOLO compares with the traditional frameworks such as RCNNN, fast-RCNN, and faster-RCNN solves object detection as a regression problem. YOLO-V4 is an updated version of YOLO-V1, YOLO-V2 and YOLO-V3, with a fast target detection system designed for applied working environments. From YOLO-V1 to YOLO-V4, detection accuracy and object localization continuously improved. Small

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object recognition has enhanced to reach the cutting edge of current detection systems in speed and accuracy. According to the report, in comparison to YOLO-V3, YOLO-V4 is 12 percent faster and 10% more accurate. The new YOLO-V4 architecture uses CSPDarknet54 as a backbone, which enhances CNN's learning capabilities (Wang et al., 2020). Like most target detection systems, the structure of the YOLO-V4 system divides into four central parts: Input, Backbone, Neck, and Prediction. Figure 3.3 shows that the YOLO-V4 system structure.

Figure 3.3 Flow Chart (Wang et al., 2020)

The YOLO-V4 is used in this research for transfer learning in the Keras framework. The final output layer to output classes modified, namely – helmet: accuracy in % (only helmet), reflector: accuracy in % (only vest), shoes: accuracy in % (only safety shoes), helmet: accuracy in %, reflector: accuracy in %, shoes: accuracy in % (combination of helmet, vest, safety shoes). The trained weights of YOLO-V4 uses as an initial set of weights for the CNN network, and the convolutional and fully connected layers are all opened up for training with the data from construction sites and to generate reports in case of non-compliance of PPEs code developed to increase the utilization of the algorithm on construction sites.

3.7.4.1 Input

The input primarily uses Mosaic data enhancement, CmBN, and SAT. The Mosaic data enhancement is executed by randomly scaling, collecting, and ordering the four images to improve the strength of the neural network, thus enriching the data set and reducing the GPU, which enables a single GPU to achieve good training results.

3.7.4.2 BackBone

BackBone uses the Mish activation function, the CSPDarknet 53, and Dropblock. Generally, BackBone holds five CSP modules, so the graphics can be reduced 32 times after BackBone to get a feature map, reducing the computational bottleneck. CSPDarknet53 allows the system to be lightweight while maintaining accuracy. On the other hand, Mish enables some advancement in network accuracy for CSPDarknet53 compared with leaky_relu; thus, YOLO-V4 changed

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the Leaky version of a Rectified Linear Unit (Leaky_ReLU) in BackBone to Mish. Although, Dropblock censors localized areas of the image, which draws on Cut out data enhancement. Although Cut out only works on the input side, Dropblock applies to every feature map, and the chance of culling changed at any time.

3.7.4.3 Neck

Neck mainly uses Spatial Pyramid Pooling (SPP) modules, and FPN+PAN. Generally, convolutional neural networks need fixed-size data as input. However, in many cases, the aspect ratio of the data is not fixed because significant data will likely be missing if the image is in a fixed size. But, SPP uses to divide the convolutional feature maps into several copies, pools them, and convert them into one-dimensional matrices. Thus, data enter appropriately. Likewise, FPN fuses top-level features by up-sampling and low-level features in a top-down direction, and YOLO-V4 adds a reverse direction feature pyramid containing two PAN structures after FPN. FPN is responsible for communicating semantic solid features, and feature pyramids responsible for communicating strong positional features. Both perform feature aggregation on the detection layer from opposite directions, improving the feature extraction capability of YOLO-V4. Table 3.1 discusses the functions of YOLO-V4 features presented in subsection 3.7.4.

3.7.4.4 Prediction

In the prediction, CIOU loss takes the aspect ratio into account and the overlap area and the distance from the centroid, compared to the normal objective box regression function.

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Table 3.1 YOLO-V4 features function

SN	YOLO-V4 features	Function
1	Spatial Pyramid Pooling (SPP) modules	To map any size input to a fixed size output
2	Feature-Pyramid Network (FPN)	Generates multiple feature map layers with better quality information
3	Path Aggregation Network (PAN)	Increase information flow in a proposal-based instance segmentation framework
4	CSPDarknet53	To partition the feature map of the base layer into two parts and then merges them through a cross-stage hierarchy
5	Cross Stage Partial Network, CSPNet	Improve the capabilities of CNN while reducing the amount of calculation by 20%
6	Mish	It has a better performance when compared with ReLU and swish because Mish has smooth, non-monotonic, upper-bounded, and lower bounded characteristics.
7	Mosaic data enhancement	Allows the model to detect more objects by Combining four pictures at one time than Cut Mix which, combines only two and reduced dependence on large batch size.
8	Self-Adversarial Training (SAT)SAT	Adjusts the input image instead of the weight to deceive that there is no expected target in the network image, then the network detects the target in the adjusted picture in a normal way.
9	Dropblock	Gradually increasing the number of dropped units during training and leads to better accuracy and more robust hyperparameter choices.
10	Convolutional Neural Network(CNN)	A deep learning algorithm takes an image as an input to differentiate objects automatically without any human supervision.

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3.7.5 Data collection tools for vision-based approach

This research aims to develop system-based technology to manage safety by using a vision-based method that detects worker outfits when the employees enter the site. The computer vision approach used in this research forecasts the workers' safety by taking the image from the onsite camera. However, before this, the machine should be trained and evaluated by uploading several pictures in the system used to give the machine information to make it familiar with PPE images. Total of 4700 images were taken from online sources such as the Bing image trend and Pictor v3 data set. Also, some actual site image data collected using a mobile camera to evaluate the machine.

3.7.5.1 Bing image trend

Bing Image trend is a feature in Microsoft Office documents that allows you to fastlly search online pictures and insert them directly into a document without bouncing between browser and download windows. It is a web search engine for collecting images from online sources owned and operated by Microsoft. Microsoft provides Bing images for collecting pictures simply by using only keywords or related images and explore images from endless online sources. Then the picture from Bing's image trend was collected using zip in google chrome to collect all images easily. The Bing image trend is used in this research to collect data from online sources.

3.7.5.2 Pictor v3 data set

Pictor v3 is a data set founded in GitHub, which contains 774 crowd-sourced and 698 web-mined pictures. GitHub is an advanced development platform that millions of developers and companies build and maintain their software worldwide. Pictor v3 data set embraces web-mined pictures contain 2,230 and Crowd-sourced contain 2,496 instances of laborers, respectively.

3.7.5.3 Manual image

A variety of image sources is used in this research to collect images required. The source used in this study is online sources such as the pictorv3 data set and Bing image trend. Additionally, to prove the applicable to the Ethiopian construction site, the approach was evaluated by manual pictures. Using a manual site picture is significant to convert to the Ethiopian context. Also, it is a warranty to approve that it can be applicable in Ethiopia. The manual picture was collected only from Adama building construction sites using a mobile camera. The rest of the construction

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sites do not include because assessing all construction projects is impossible due to time and budget limitations.

3.7.6 Data/image labeling

Labeling is a process of structuring data by using software, or it is a process of organizing data in a variety of groups. In this research, labeling was done using Labellmg software. Labellmg is a software used to label each image individually to interpreting the label name in the form of text data or converting a specific point/ part of the picture into numbers. The labeling number contains the ID number of each label, height, width, XY coordinate of the picture for each image.

Lablellmg software is a labeling software used to select labels using a box with a different color manually. Because there is no existing labeled image online for safety shoes but helmet and reflector labeled image data founded from online sources. However, this does not fit the requirement because safety shoes need labeled data for training, so manual labeling for each image is required.

3.7.7 Model validity

In general, the main contribution of this research is to develop system-based technology for managing safety in construction site using machine learning through a vision-based method. To check the validity of the model evaluation of matrices method, which is the most frequently used in different researches, whether to test the model can validate to achieve the project aim. Several matrix methods to check validation are used, such as accuracy, precision, recall, and F-measure. Precision quantifies the number of positive class predictions that belong to the positive class. Recall quantifies the number of positive class predictions made out of all positive examples in the dataset. Through these several validation measures, the result found from the image process was tested with the research question and objective. Accuracy and precision methods of evaluation are used in this research for evaluation.

3.7.7.1 Accuracy

Accuracy is one metric for evaluating the classification of models, which is the fraction of predictions that the model got correct. It is a percentage of correct predictions which assesses the performance of the model when the data tested. Although, by dividing the number of correct predictions, the total number of predictions calculated.

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$$Accuracy = \frac{correct\ predictions}{All\ predictions}$$

3.7.7.2 Validation loss and mean average precision (mAP)

The mean Average Precision (mAP), also known as AP, is a metric used to measure the performance for object detection tasks, and the Loss value shows how poorly or well it detects after each iteration calculated on training and validation, and it is the sum of errors occur for each validation set.

$$precision = \frac{true\ positives}{true\ positives\ +\ false\ positives}$$

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CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Introduction

In this chapter, the primary data collected from the questionnaire, interview, and observation are analysed and discussed. The data is collected from G+3 and above building projects. A total of 114 questionnaires in the selected construction company distribute to a manager, supervisor, foreman, bar bender, and carpenter workers, who are available during the data collection period, and respondents fill all questions adequately. The questionnaire in English and the Amharic language prepared. The primary data/ questionnaire and manual picture collected from April-5 up to April-20 for two consecutive weeks. Also, the result included in this chapter that obtained from the detection output. This chapter classified into different sections that reflects the output of two main findings, the first section discussed the primary data result acquire from a questionnaire, interview, and observation. The detection result is discussed in the second section. The first section includes general information about the respondent, PPE availability in building construction sites, and the ranking of PPE depends on their importance. The second section embraces data description, data labelling, application/ experiment result, and evaluation of the vision-based approach.

4.2 Respondent and project profile

In this research, the descriptive statistics are obtained based on questionnaires response of workers such as managers, supervisors, foremen, carpenters, bar-benders, and contractors in Adama construction sites. The questions are generally about PPE availability in the selected construction site and ranking by their importance for protecting employees in building construction site condition. Data are presented as percentages and frequency using IBM SPSS statistics 20 and Excel used to represent data in graphical and table form. The analysis output in graph and table representation present in the next sub-chapters.

4.2.1 Respondents profile

This section presents the demographic characteristics of the respondents who participated in this study. In the first section of the questionnaire, the demographic characteristics of the respondent responses explain their personal information. Respond background information is

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an optional question that depends on the participants' interest to respond or not. However, most of the respondents share their personal information, and eight respondents hide their personal information from the total 114 respondents, and the rest of 106 respondents gives the entire information asked in the first part of the questionnaire. The question includes gender, age, experience, educational background, employment condition, and work position. A total of 114 Construction workers participate in this study. A complete response (100%) obtain from all respondents, and the result obtained from the questionnaire shows that the majority of the respondents (47 or 41.2%) have BSC degrees who work in a project management position and a site engineer position. Experience of the majority of respondents, 48(42.1%) and 49(43%) are between 1-5 and 6-10. The employment condition of the majority of the respondent, 60(52.6%), is permanent in the selected company. Table 4.1 shows the demographic character of respondents in detail.

Table 4.1 Demographic characteristics of Construction workers

Variables		Frequency	Percentage
Educational back-ground	Illiterate	3	2.6
	Elementary	14	12.3
	high school	22	19.3
	Diploma	28	24.6
	BSC	47	41.2
Work experience	1-5 year	49	43
	6-10 year	48	42.1
	>10 year	17	14.9
Employment condition	Permanent	60	52.6
	Contract	54	47.4

It is a known fact that safety issues concerned all of the construction workers involved in construction activity. As observed from the data collection process, all of the construction workers have an understanding of safety matters. Project managers, site engineers, office engineers, supervisors, and Forman have advanced knowledge about safety concerns. On the other hand, bar benders, carpenters, and timekeepers have lesser knowledge in safety matters. However, in this research, all of the workers in the above position included because to find

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selected respondents like project managers and site engineers will be hard because most construction sites, especially privately-owned sites constructed by general Forman. Also, carpenters and bar benders are available on every construction site. Thus when the managers, site engineers, and office engineers are absent in the selected construction company Forman, carpenters, and bar benders participated in the data collection process. The result shows that most of the respondents work in Forman position (30%), and the minority of respondents were supervisors and timekeepers. Also, project managers and carpenters follow Forman in second and third place. The work position of employees presents in detail in Table 4.2.

Table 4.2 Work position of respondents

Title of respondent position	Percent
Project manager	13.2
Office engineer	5.3
Site engineer	22.8
Forman	29.8
Carpenter	18.4
Supervisor	1.8
Bar bender	7
Time keeper	1.8
Total	100

4.2.2 Project background

The data acquired from G+3 and above building projects, which locates in Adama city. The project background classifies into two groups in work progress and ownership type in the selected construction firms. Depend on project progress, classified construction projects as substructure and superstructure. The result shows the majority of construction progress (73.7%) is in the superstructure process, and 26.3% of construction progress is in the sub-structure progress. Although, it depends on ownership type buildings classified into private and governmental building projects. Most building projects (83.3%) construct by private owners/clients (83.3%), and the rest, 16.7%, owned by the government as a client to meet the public interest. The minority of the respondent participated from the government, but safety conditions and availability of professionals like managers, site engineers, and office engineers

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are better than privately owned construction projects. Governmental project work structure organizes in a structured manner with better human resource management. Several professionals, such as project managers, site engineers, supervisors, and office engineers, are presented in governmental projects. Nevertheless, in private projects, lesser human resource management observes, due to that most of the time professional is not available. In private projects, most of the time Forman's, are available and manages all of the site activity, and in some big privately-owned projects, better professional employees' availability is observed.

4.3 Reliability test result

Testing the reliability of the data is one way of evaluating the responses to prove the consistency of the data collected from primary sources. Several types of reliability testing methods exist from that Cronbach alpha is one of reliability testing method to measure the internal consistency of the data collected through questionnaire. In this study, the data collected from the questionnaire using the Likert scale question type tested by using the Cronbach alpha method to check that the data are internally consistent. The reliability tested by using Cronbach's Alpha (coefficient Alpha) in IBM SPSS Statics 20, and the result is 0.779, which shows the data is reliable. Because the answer is greater than 0.7, which proves the data is reliable, in the Cronbach alpha method principle. Table 4.3 shows the Cronbach alpha value founded from SPSS result.

Table 4.3 Cronbach's Alpha value for the primary data

Reliability of the data using SPSS		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	Number of Items
0.779	0.734	10

4.4 Result of importance level of personal protective equipment

The above sub-section discussed the collective result of the study and the reliability of the data tested and passes the reliability requirement point. In this section, the data collected from the Likert scale question ranked using the best ranking method. The ranking value is given by participants' perspectives and knowledge about the protective equipment, in the form of

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importance measured on the Likert scale (see Appendix A3). The participants believe safety shoes and helmets are significant materials for all building construction site activities. Especially safety shoes are required in every stage of construction activity and required for all types of workers. So workers think wearing safety shoes is the first thing to keep workers from several hazardous. However, helmet utilization is very poor because it's not comfortable during construction work. Mainly in a place like, Adama the utilization of helmets is very challenging due to the hotness of the weather. However, depending on its high protection helmet ranked in the second place due to absence of this equipment causes a high level of injury and death. In third and fourth place, goggle and gloves ranked because most participants were familiar with this equipment because they provided in every construction site due to their cheap cost requirement. So they experience the importance of both equipment due to its availability on the construction site. The safety harness is one of the most significant protective materials that every construction site must provide. However, in the Adama construction site, safety harness availability is less because most participants think it is slightly significant because they work in height without it. Thus, due to poor utilization of a safety harness, most participants conclude as less important PPE in building construction sites. Also, protective clothing and reflector have come in sixth and seventh place in the ranking order because the respondent uses both types of equipment as a uniform to differentiate workers from other peoples. A reflector is significant when working on the night shift and when less visibility exists. However, this condition is not regular, so less ranking weight is given for the reflector by participants. Likewise, most participants have a vague understanding of the significance of protective cloths, even though most participants don't think protective cloth is one type of PPE material. Earplug, face shield, and dust mask ranked lastly with a quite different, and most respondents believe this three equipment is unimportant or less important. A face mask and a dust mask are protective materials provided in any construction firm due to their minimum cost requirement. However, most of the participants rank Face masks and dust masks as unimportant equipment for their work due to their lack of comfort during construction work because it limits employees' respiration process. Also, earplugs in a high sound place are required. But, most construction firms refuse earplugs in building construction activities, and earplugs provide for regular employees with high exposure to this kind of disturbance. Depends on the above reason majority of the participant doesn't have experience of using earplugs. Therefore, they conclude it as

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unimportant equipment, and the ranked result shows it's in the last place or the tenth place of the ranking list. Table 4.4 shows the ranking result of PPEs analyzed using an Excel spreadsheet. The RII method of ranking used in excel to rank PPEs depends on their importance for building construction sites.

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Table 4.4 Ranking result using RII method

Types of PPE	(7) Extremely important	(6) very important	(5) important	(4) Somewhat important	(3) not that important	(2) neutral	(1) unimportant	total	total number of respondent (N)	A	A*N	RII	RANK
Helmet	700	54	15	0	3	0	1	773	114	7	798	0.968672	2
Shoes	742	42	0	0	0	0	1	785	114	7	798	0.983709	1
Vest	14	180	200	108	12	0	11	525	114	7	798	0.657895	7
Harness	259	204	115	16	0	2	15	611	114	7	798	0.765664	5
Cloth	28	198	245	68	12	4	5	560	114	7	798	0.701754	6
Glove	91	342	135	28	15	0	5	616	114	7	798	0.77193	4
Goggle	217	300	115	20	3	0	4	659	114	7	798	0.825815	3
Face	14	84	205	104	24	0	23	454	114	7	798	0.568922	8
Dust	14	78	195	92	24	0	29	432	114	7	798	0.541353	9
Ear	14	18	85	76	57	0	54	304	114	7	798	0.380952	10

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4.5 Observational result on utilization of safety equipment

The observational result showed a gap when it cross-checked with the questionnaire result. This gap occurs due to several reasons like protective material requirements for that working stage, participant tries to hide their weakness, and respondents afraid of the data acquired for governmental evaluation create a vast difference in the questionnaire and observational result. Fear of governmental supervision and hiding the weakness of their firm are the challenging things that limit the researcher to accept the answer founded only from the questionnaire. Thus, using the observational method was the best option to eliminate this kind of issue covering the actual data, affecting the output founded from primary data. The observational result shows the most construction companies don't provide PPE for their workers, and some of the construction firms provide PPE, but workers don't use it properly. Thus, the result shows there is a lack of PPE utilization and provision exist. PPEs utilization culture in Adama building construction site generalized into three categories. First, construction companies that provide PPE and the employees use it during construction activity. Second, construction companies supply PPE, but their employees neglect it during work then, third construction companies do not provide PPE for their employees. Also some of the materials, such as safety harnesses, gloves, goggles, and earplugs, are utilized for specific work stages. On this condition, the materials provided, when required for selected activities as an example in concreting level glove required. If the site isn't at that stage, the result in the questionnaire will differ from the observational result. To fill this gap interviewing method is proper as an intermediate approach to get reliable results and conclusions.

4.6 Interview result

As discussed in the above section, the data collected using questionnaires and observation is somewhat different due to several reasons like fear of workers and working stage. Fear of workers is one factor that limits information provision when they are afraid of managers and governmental supervisors. Also working stage is the other factor that creates a difference between the result because the providing of PPE differs depending on the construction stage. Thus to fill this gap or misunderstanding, using an interview is the best solution. When

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observing the site during data collection glove, and goggles provide by the company or employee. Due to this, both types of equipment not utilized due to their working stage. So to eliminate this, interviewing the participant why their response and actual work varies, therefore the occurrence of misconception was removed due to the data collection approaches using the interview method.

During the data collection time, causes for poor PPE culture informally interviewed from the respondent, especially participants who worked in the management area. Several reasons result from poor utilization of PPE, such as uncomfortable behaviour of PPE, lack of PPE, high-cost requirement of PPE provision, and unstable employment condition of workers. The cause for poor PPE culture is employee negligence because PPE is not comfortable for work, especially in a place like Adama the weather is too hot, so the employees choose to neglect it. Also, using PPE limits the flexible movements of the worker by its challenging behaviour. Also, the unavailability of PPE is one of the factors because PPE is expensive, and it requires the construction companies additional cost. So most construction companies give priority to their benefit. Unstable employment condition is also the other factor that results from poor PPE culture. Because in the construction industry, there is a high level of human resource utilization and unstable employment condition. Chiefly, daily labour changed day today due to this provide PPE for temporally employed workers is not possible. Budget is one of the factors that limits the majority of the construction companies to supply PPE. Chiefly, in private companies' provision of PPE is less when compared to governmental projects. Because financial benefit comes first in privately-owned projects, to minimize cost, owners choose to neglect PPE rather than providing.

4.7 Experiments

4.7.1 Dataset description for vision-based approach

This subsection deals with the description of the data used for utilizing vision-based approach, which is images and different sources used for collecting images. Several types of data used in machine learning from that vision-based method is a part of machine learning which processes

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images and videos to provide object detection system. In this research, Images are used as input for training and evaluation which collected manually and web-based. The image was collected manually from the Adama building construction site using a mobile camera (Samsung S7). However, web-based data collected from online sources such as Bing image trends and Pictor v3 data sets. Other researchers collected Helmet images from Pictor v3 data set and Bing image trends pictures of reflector, shoes, and helmet collected. Images from a different angle were taken, which helps to identify when the view changed. So, the data collected by considering the colours of protective equipment. If the machine trained with several colours, it can be flexible in identifying PPE when the colour and angle of the picture changed.

Table 4.5 Total number of image from different sources

Type of PPE	Number image from Bing	manual image	Pictor v3	Total number of image
helmet	600	100	790	1490
reflector	500	50		550
shoes	300	80		380
helmet and reflector	1000	130		1130
helmet, reflector and shoes	400	100		500
reflector and shoes	350	60		410
helmet and shoes	200	40		240
Sum				4700

Table 4.5 shows the total number of PPE images used in this research. The number of PPE used in this study classified depends on the labels used. The label classified as helmet, reflector, shoes, and their combination. Thus the image was collected by considering these given classes.

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The numbers of collected images vary by the availability of the pictures in online sources and in building construction sites.

4.7.1.1 Bing image trend dataset description

The Bing image trend is used in this research to collect data from online sources. The data collected from Bing's image depends on the labels used in this research, such as helmet, helmet reflector, helmet reflector and shoes, reflector, and helmet. After the collection process, images were organized in a group then the picture was labelled using labelling software. The data collected from Bing image trend contain all of the labels such as helmet (600), reflector (500) and safety shoes (300), helmet and reflector (1000), helmet, reflector and shoes (400), reflector and shoes (350), helmet and shoes (200) which taken from different angles by different colors and persons. Taking different people and different colors of PPE is significant because it increases the detection ability to identify accurately when various types of data are entered. Table 4.6 shows in detail the number of images collected only by using the Bing image trend.

Table 4.6 Total number of image from Bing image

Types of PPE	**Number image**
Helmet	600
Reflector	500
Shoes	300
helmet and reflector	1000
helmet, reflector and shoes	400
reflector and shoes	350
helmet and shoes	200

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4.7.1.2 Pictor v3 data set description

Pictor v3 dataset is a large dataset contain several types of images that use to develop various types of object detection models. In this research, the Pictor v3 data set used for training and around 791 helmet images were found from this data set.

4.7.1.3 Manual image dataset description

Manual images were used in this research to test the detection capacity and its applicability in Ethiopia's condition. The manual picture was collected only from Adama building construction sites using a mobile camera. Due to time and budget limitations, the rest of the construction sites do not include because assessing all construction projects is impossible. During the data, collection process managers and educated employees permit to take pictures while they are working. But uneducated workers were unwilling earlier. However, after explaining the research works, they are willing to capture an image. Thus, to eliminate this challenge researcher tries to creates awareness among the respondents, and after that, they asked their willingness with great humbleness. The manual image sample presented in Figure 4.1 shows the images collected manually from the Adama building construction site. The data contain all labels/ classes such as helmet (100), reflector (50), shoes (80), helmet reflector shoes (100), helmet reflector (130), helmet shoes (40), and reflector shoes (60).

Figure 4.1 Manual picture from Adama construction site

4.7.2 Labels/ classes

Labels selected depends upon the actual building site condition located in Adama. The data gathered from the questionnaire analysis and observational results. Likert scale question analysis was used to rank the most critical equipment by using the RII method. The ranking result shows safety shoes and helmets ranked at the top level. However, in this research, reflectors were also included depending upon the observational output. During observation, most construction workers use a helmet, safety shoes, and safety vest in every stage of construction work. Thus, depending on the result of analysis taken from the primary sources, helmet, safety shoes, and reflector use as a label for this research. So, the inputs required decide by combining the ranking value of the participants and the observational result from the actual site. Generally, the primary data used to classify the label in the Ethiopian context. Thus in this research, three protective equipment selected, such as helmets, reflectors, and safety shoes.

In this research, labeling was done using labellmg software. As requirements during the coding process, ID number recommended passing between 0-2 or 0,1,2. ID number of each label given

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by researcher, for helmet 0, for reflector 1, and shoes 2 in this research. Then the machine able to predict images using numbers given for each picture by its ID number, number of XY coordinates, height and width. Figure 4.2 shows manual image labeling using labellmg software. As observed from the figure, the box color is different for each PPE. The box color for the helmet dark blue, for reflector light blue, and orange colors for the shoes used in this researches. The box measures the points this material exists like XY coordinate, height, and width for each label, and also each label has its ID numbers that start from 0 up to 2. After drawing each box label of each selected part shown by choosing their label from the list. Then the file converted from a jpg file to a text file which means the text file shows only the labeled point, and the jpg file shows a complete picture collected from different sources. However, collection of both files to read the label from the jpg file by using numbers gained from the labeled image or text file.

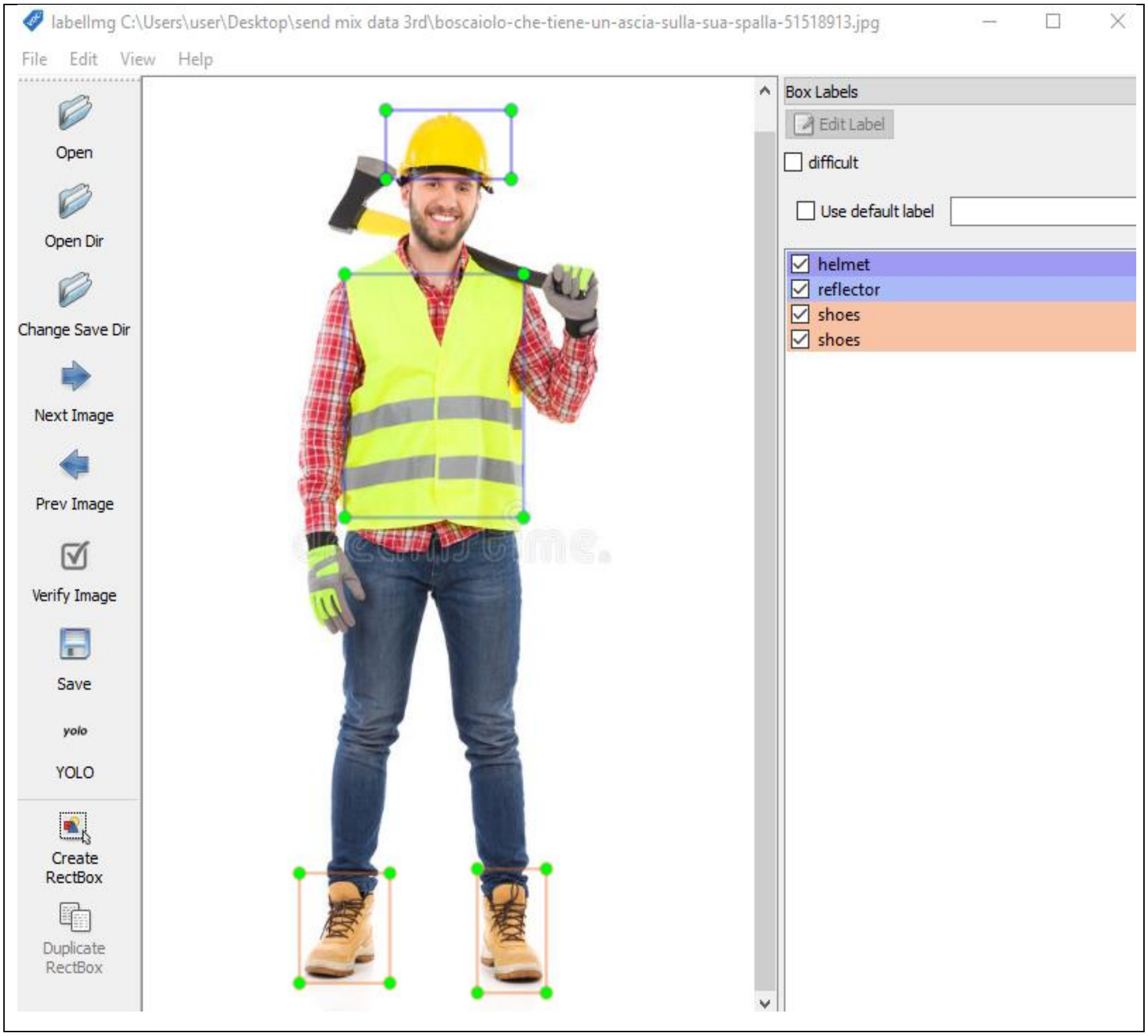

Figure 4.2 Manual labeling using labellmg software

As discussed in the previous sections, this research aims to adopt vision-based approach that can detect PPE. Thus, to detect PPE from the given image first, the machine needs to be trained by selecting the PPE from the picture. But, before training, the machine needs to be learned first what is helmet, reflector, or shoes. In machine learning, the machine understands each item in number, so the labeling stage is required. Thus, by using labeling software text file was generated from the jpg file, but both jpg and text files required. The machine selects specific points which helmet, shoes, and reflector are found by using the coding number from the total picture.

```
File  Edit  Format  View  Help
0 0.494167 0.100000 0.201667 0.071111
1 0.468333 0.361667 0.290000 0.250000
2 0.326667 0.908333 0.146667 0.112222
2 0.596667 0.911667 0.113333 0.127778
```

Figure 4.3 Text file from labellmg software in notepad

Figure 4.3 shows the text file created or generated using labellmg software for the previous jpg file analyzed on labellmg software. The first column four ID numbers 0,1,2,2 in other words, these four numbers explain the presence of helmet (0), reflector (1), and shoes (2) in one picture. Number 2 is repeated in Figure 4.2 because two shoes or shoes in different legs exist in the picture. The rest four-column shows the x coordinate, y coordinate, width, and height of each ID or for each label. Each row explains that one type of PPE in number form. As an example, the first row expresses the presence of a helmet in the jpg file. The first column in the first row shows the ID of a helmet which is 0, and the second and the third column in the first row show the XY coordinates which the helmet or selection box of the helmet located in the jpg file and the last two columns shows the width and the height of the helmet or selection box of the helmet in the jpg file. Then this text file combines with its jpg file (Jpg file is the original data or image collected from the above image sources) for training. Both data are required to learn the computer which part of the picture is helmet, reflector, or shoes from the jpg file using the number given for each PPEs. Because computers read or learn everything in the form of a number.

4.7.3 Experiment of proposed model

4.7.3.1 Initialize GPU

To build the model Creating and initialize NVIDIA GPU on google colab with CUDA Version: 11.2 done. Nvidia GPUs frequently in deep learning used. They have faster analytics due to Nvidia's API CUDA, which allows programmers to use a higher number of cores that exist in GPUs. Because GPUs parallelize programs to increase the training speed of machine learning algorithms due to their extensive use of matrix and vector operations. Researchers, laboratories, tech companies, and enterprise companies use GPUs to create Deep Neural Networks capable of machine learning. Google Brain used Nvidia GPUs because it could increase the speed of deep-learning systems by about 100 times. CUDA is a programming and parallel computing platform developed by Nvidia for general computing on its GPUs (graphics processing units). By attaching the power of GPUs for the parallelizable part of the computation, CUDA allows developers to speed up compute-intensive applications. The following commands are used to check if GPU is running or not by running the command, Nvidia-smi. Then the output becomes the picture presented under this section.

```
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 465.19.01    Driver Version: 460.32.03    CUDA Version: 11.2     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|                               |                      |               MIG M. |
|===============================+======================+======================|
|   0  Tesla P4            Off  | 00000000:00:04.0 Off |                    0 |
| N/A   35C    P8     7W /  75W |      0MiB /  7611MiB |      0%      Default |
|                               |                      |                  N/A |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                                  |
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory |
|        ID   ID                                                   Usage      |
|=============================================================================|
|  No running processes found                                                 |
+-----------------------------------------------------------------------------+
```

Figure 4.4 GPU initialization

Figure 4.4 shows the working of GPU. If the output like this, it means GPUs and Cuda are working. In other words, this figure shows GPUs request is accepted, and the developer can start building in the provided graphics.

`

4.7.3.2 Training of the YOLO-v4 model

In the YOLO-V4 model, all layers except the last three output layers contain pre-determined weights obtained by pre-training the models on a Custom dataset. These pre-trained weights can extract helpful features like colors and edges. The training process using YOLO-V4 pass through several stages, such as creating and initializing GPU on google colab, then link google drive with google colab, then create a folder in google drive, which is named YOLO-V4 in this research, upload labeled data in google drive in the YOLO-V4 folder, then the uploaded data grouped into two such as train and test data, both train and test data must contain obj.jpg and obj text file. In all machine learning data, split into train and test data and most commonly 70% data classified for training and 30% of data used for a test then file generated to colab, after that the machine starts training for continuous 6 hours. In the following sections, each process is discussed in detail.

4.7.3.3 Proposed PPE detection model configuration

Configuration files allow the isolation of the code from the parameters of the machine learning pipeline to help produce repeatable outcomes. Configuration files clarify how to read the data, what model to use, how to learn the model, and how to evaluate model performance – without interaction with the operator. Table 4.7 shows the Configuration of the developed YOLO-V4 models.

Table 4.7 Configuration of yolo-v4 to develop the model

Configurations	Configuration Value	Description
max_batches	6000	max_batches=classes*2000 our class=3 3* 2000 = 6000
Steps	4800 and 5400	change line steps to 80% and 90% of max_batches 0.8*6000 = 4800 0.9*6000 = 5400
Number of classes	3	Number of classes = 3 (Helmet, Reflector, Shoes)
Filters	255	filters= (classes + 5) x3 in the 3 [convolutional] before each [yolo] layer
batch to batch	64	
Subdivisions	16	
Width	416	
Height	416	

Yolo-V4 has different network architecture and configuration parameters. In this research Yolo-V4 OBJ.CFG used the specification on 416 * 416 input image configurations to initialize training parameters on our custom detection YOLO-V4 PPE detection model. Different attributes and Frames Per Second (FPS) parameters with various representations of CFG attributes are listed in Table 4.8.

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Table 4.8 Different attributes with different frame per second (FPS)

Width in cfg	Height in cfg	mAP	AP	FPS(R)	FPS(V)	BFlops
608	608	65.7% mAP@0.5	43.5% AP@0.5:0.95	34	62	128.5
512	512	64.9% mAP@0.5	43.0% AP@0.5:0.95	45	91.1	91.1
416	416	62.8% mAP@0.5	41.2% AP@0.5:0.95	55	96	60.1
320	320	60% mAP@0.5	38% AP@0.5:0.95	63	123	35.5

4.7.3.4 Model detection

Object detection is an automated method grouped under computer vision used for tracking objects in an image concerning the background. Although, deep learning is a part of machine learning used to perform object detection. In this research, an object detection system developed using YOLO-V4 architecture, and the code attached in the Appendix:C step by step.

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Figure 4.5 Model detection output

The test images in Figure 4.5 shows download and locally captured images, miss classified and not detect by PPE detector on Yolo-V4. All of the labels are classified in the bounding box with different colors. The green color represents safety shoes, the reflector represented by yellow, pink represents the helmet, and the red color represents miss-classified and not detectable labels. At the top of each box, the label of PPE written as an output, which is shoes for safety shoes, reflector for reflector or safety vest, and helmet for helmet or hardhat and near to each label probability of classified PPE to be the written label expressed in the form of the number. Thus as it seen from Figure 4.6, the output is presented in word to express a type of label in number to express the probability of that point to be the attached label and box with different colors to represent labels of PPE.

In the above section number of data and description of the manual data set are discussed. In this section, detection of the manual data set present in the form of the figure. Detection of manual pictures observed, but more misclassification occurs when compared with online images because the quality of the image, color or brightness, and the number of data used for training is less than web-based pictures and the output of the web-based and manually collected pictures present in Figure 4.6.

Manual Data Set Detection	**Bing images Data Set Detection**

Figure 4.6 Manual dataset detection sample vs Bing image dataset detection sample

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4.7.3.5 Accuracy

In this research, the accuracy is very close for each label. Accuracy for helmet 96.97%, for reflector 97.73%, and shoes 98.9%. The accuracy for each label presented graphically in Figure 4.8.

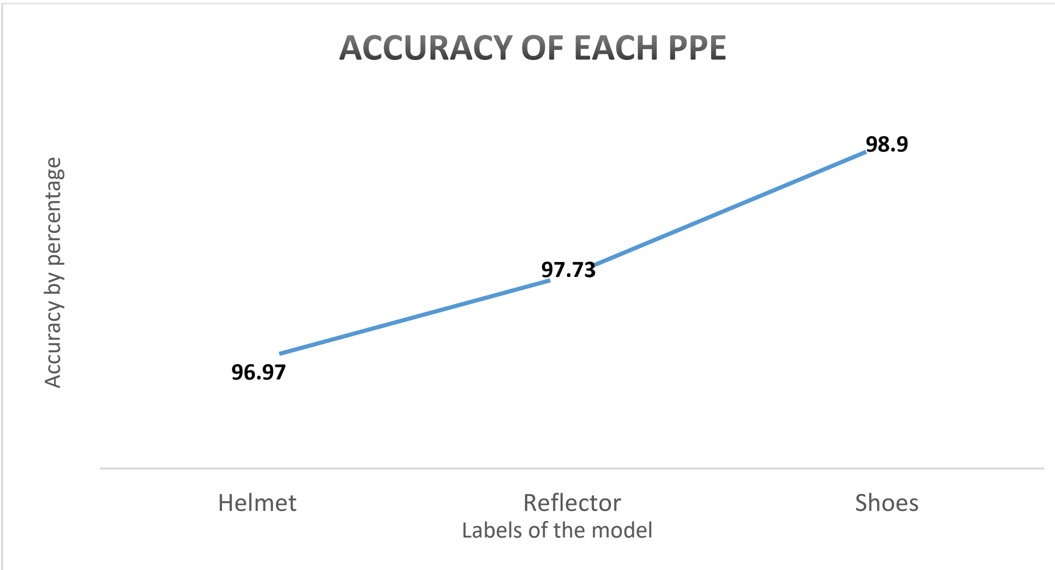

Figure 4.7 Accuracy for each PPE

4.7.3.6 validation loss and mean average precision (mAP)

The mAP of the YOLO-v4 model was achieved (98%). This result target classes (i.e., Helmet, Reflector, and Shoes) are visually very similar (i.e., all contain humans). Moreover, target classes by subtle attributes classified (e.g., based on a Helmet, Reflector, Shoes). As seen from Figure 4.9, the red color shows mAP value that increases and decrease or unstable result in the first iterations from 600 up to 3000 iterations. After 3600 iterations the mAP show a stable value, which is 98%, and the iteration continuous up to 6000 in this experiment. But, the iteration where 98% (mAP) start can be used as the overall iteration, which is between 3000-3600. The mAP result shows that the rest iteration above 3600 is excess. Loss has the opposite output, as seen from the chart because a loss at the beginning was very high, then after several iterations, it decreases. Generally, when the iteration increases map increases, and the loss decreases.

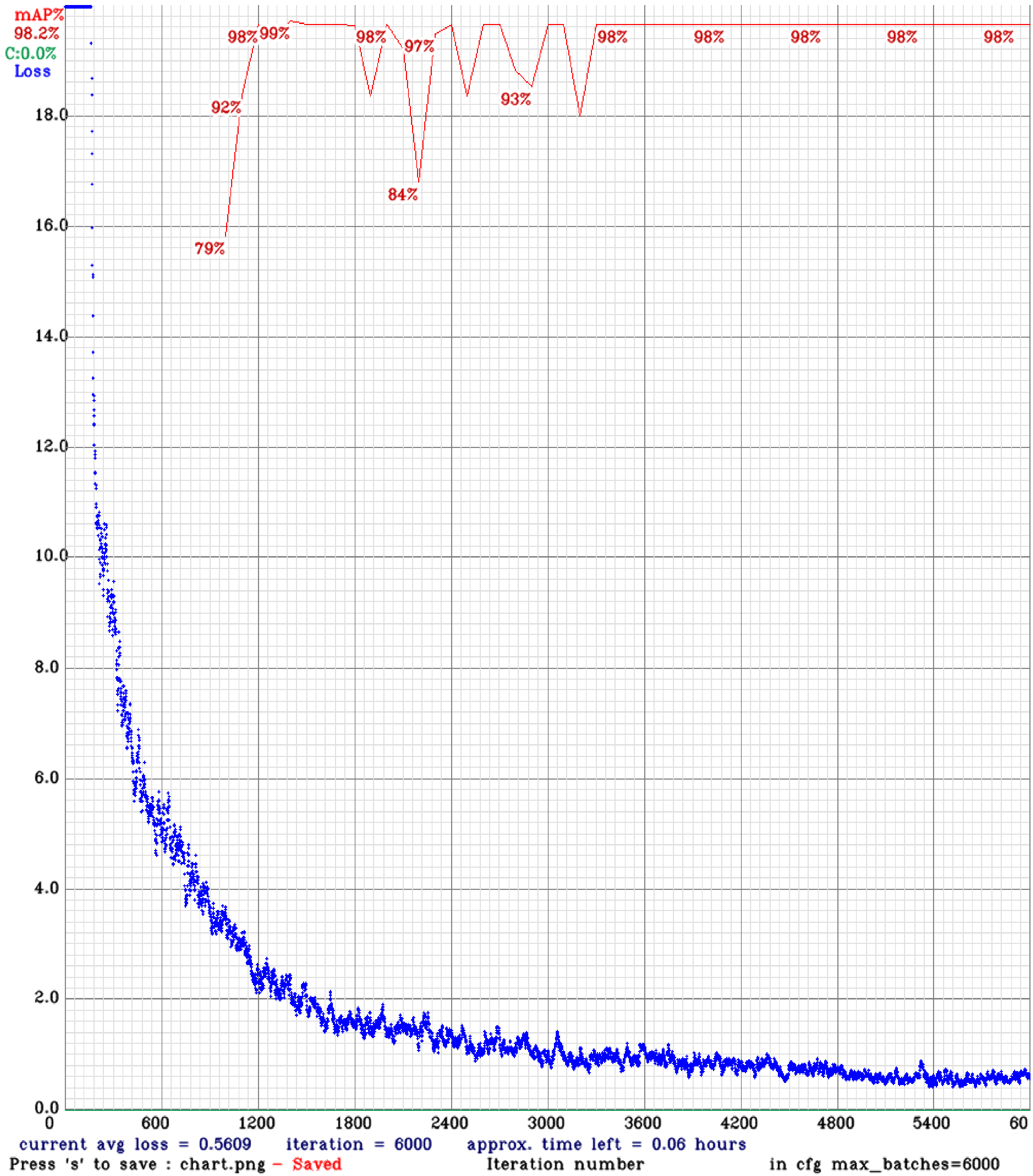

Figure 4.8 Validation loss and macro average precision graph

`

4.8 Discussion and implication of the study

Safety in the construction industry is one of the most important and challenging things observed worldwide. To minimize this challenge, the researcher and all involved parties in the construction industry create several solutions. The utilization of personal protective equipment (PPE) is one of the best approaches that keep workers from any harmful contact. The absence of PPE in construction sites increases the probability of the occurrence of a hazard. As discussed in the above chapters, this study aims to utilize a computer vision approach that detects the presence or absence of PPE in a construction site. Also, this study investigates the available and colors of protective material in the Adama building construction site and ranks PPEs depends on their importance for building construction projects then by using the output founded from the construction site label/ class for detection chosen. Thus the first three objectives use as an input for the last objective. The output of the fourth objective is used as a backbone for all over the research. The fourth objective is directly related to the general aim of the research.

PPE availability in construction sites using different data collection methods assessed, such as questionnaire, interviews, and observation. The result founded from these various methods differs somehow because the existing fact in the actual site differs from the questionnaire result. However, to minimize the gaps interviewing method of data collection are used. Finally, in the end, the combination of these three methods gives better output and leads to a clear conclusion. The questionnaire result reveals that most building construction sites located in Adama provide PPE for their workers; on the other hand, as observed from the site, the availability of PPE during work is less. During the interview, some of the site managers and project managers respond that the company provides PPE but lacks comfort, and its unfitting size for employees' forces workers to refuse it. This result is consistent with data obtained from the studies conducted among construction workers (Onyebeke et al., 2016;Mulyowa, 2019;Amir et al., 2018).

In this research, ten types of PPEs to assess PPE availability listed, and the result shows that safety shoes are the most available protective material in building construction sites. This finding is similar to studies conducted in Kampala, Uganda, among construction workers

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(Mulyowa, 2019), and this finding differs from the study findings ranked on the availability in the construction site, which is helmet ranked first then safety shoes placed in the second place (Amir et al., 2018). Glove and goggle are available in building construction sites that following the availability of safety shoes because of their cheapest cost in most construction companies glove and goggle provided. Also, helmets and reflectors are available in most building construction sites, but they are lesser available when compared with shoes, gloves, and goggle.

A seven-point Likert scale questionnaire was used to measure the importance of PPE utilized in building construction sites. The output of the Likert scale question is used as an input to rank PPEs by their importance using the relative importance index (RII). The result founded from the RII method shows that safety shoes ranked first then helmet ranked second, third place goggles, glove in fourth place then Safety harness in fifth place, protective cloth in sixth place and safety vest in seventh place, face mask and dust mask in the eightieths and ninths place finally earplug ranked in the last place. There is no recently published research online that ranked PPEs depending on their importance for construction projects; thus, this shows the uniqueness of the finding.

The main finding of this study is utilizing a vision-based approach that detects the PPE of workers on construction sites. The finding of this approach is recognizes the helmets, reflectors, and safety shoes of workers on the construction site. The three labels used depend on the result founded using the RII method, which is safety shoes in the first place, helmet in the second place, and reflector used without considering the ranking value. The safety vest/ reflector is available in most construction sites during the data collection and also color and size of the vest are easily visible and detectable, so this makes the research use it as a label. Glove and goggle also follow shoes and helmets in the ranking order. However, they included in the labeling the because utilization of both types of equipment varies from employee to employee and varies by construction phase. Gloves are utilized only in concreting stage and bar bending process; likewise, goggle utilization by stage of construction and work task limited. Thus researcher labeling falls into a helmet, reflector, and safety shoes. The labeling used in this research differs from the research done by using the only helmet (Park et al., 2015;Rubaiyat et al.,

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2017;Mneymneh et al., 2017) and also, it differs from research that uses harness as a label (Fang et al., 2018), a combination of reflector and helmet (Delhi & Thomas, 2020;Nath et al., 2020) and helmet, vest, shoes, and harness combination (Tran et al., 2019). Thus, the comparison of different papers shows the label used in this research differs from past research and the labeling done based on Ethiopia building construction site condition, making this research unique and applicable locally.

A computer vision approach used in this research to increases the efficiency of the safety supervision process and reduces the number of incidents that occur due to the absence of PPEs. This paper demonstrated that YOLO is used to accurately detect if helmets, safety vests, and safety shoes utilize on construction sites. YOLO-V4 was used to ensure a high degree of detection accuracy. YOLO-V4 is the fastest and updated version of YOLO-V3, which is different from, Faster R-CNN used in harness detection (Fang et al., 2018), and differs from the research utilize YOLO-V3 to detect whole safety cloth detection (Tran et al., 2019). In general, YOLO proposes to solve target detection speed problems observed in the previous object detection models such as CNN, R CNN, and Faster R CNN. Although YOLO upgraded from YOLO-V1 up to YOLO-V4, YOLO-V4 is 12 percent faster and 10% more accurate than YOLO-V3. Thus in this research, the upgraded version of YOLO (YOLO-V4) used in PPE detection makes the study unique because past researchers used the previous version of object detection.

The approach used in this research evaluated by two primary metrics accuracy and precision. Accuracy is one of the primary metrics used to evaluate, which measures the percentage of correct predictions. The experiment result shows PPEs detected with the accuracy of 98.4% helmet, 99% shoes, and 96% reflector. The accuracy is approximate for each label, and the higher accuracy result shows the correct prediction. The mAP of is 98% when the iteration is between 3000-3600 and it was stable up to 6000 iterations; that shows there is no variation if the iteration value increased above there is no variation occur in the mAP result. Thus the in this research achieved 98%, which differ from mAP observed in PPE detection papers, 85.6% mAP for hardhat and vest detection (Nath et al., 2020), 80% mAP for harness detection (Fang

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et al., 2018), and similar mAP (98%) result observed in 4000 iterations (Tran et al., 2019). The above comparison shows that the output of this research achieved a good mAP result.

The finding of this research is significant because this research gives new insight for local researchers to combines construction management with technology. It is a known fact that the usage of technology simplifies the complex problem faced in everything worldwide. Likewise, the utilization of technology solutions is significant in every aspect of the construction industry. However, the researcher observes poor utilization of technological solutions in the Ethiopian construction industry and local researches. Somehow this research tries to minimize the technological gap in local research using a vision-based method for managing safety. Also, this research inspires future Ethiopian researchers to adopt a technology-based solution in the Ethiopian construction industry. Therefore, this research opens a way to use a vision-based approach in safety management systems in local research. Additionally, PPEs ranked depending on their importance in building construction works, and there is no existing research published online recently that ranks PPE by their significance. Thus the ranking measurement used in this research makes the finding unique.

Despite the novelty of the research presented, several limitations exist. As discussed in the previous section, this research aims to utilize a computer vision-approach that requires image or video. In this research, images are inputs which collected from online sources and manual pictures from the Adama building construction site. However, taking a manual picture one of the challenging things during the data collection period due to a lack of understanding by the participant to get their permission for taking pictures. Usage of manual images is significant to adapt to the actual condition. However, in this research manually collected image is minimum due to that they used only to test the data, on the other hand, online data used for training purpose. So for the future, it is better to use a manual image when utilizing a vision-based technique. The output was slightly affected by the lack of manual images in the training process. In addition to this for future studies, an increasing number of data or images used in this research will give a better result or output.

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In some instances, the output could not detect PPEs due to the sample size and the color, which directly impacted the detection ability. Because machine learning requires several data to achieve good testing results, if not, overfitting may rise. In the experiment, picture property limited the training quality of the networks, which resulted in some PPEs pictures being unrecognized. Thus this decreases the network's ability to learn and recognize the PPEs. Therefore, future research is required to increase the data used for training purposes to increase the detection ability. Also, due to time and budget limitations, the research is obliged to focus only on building projects when collecting data and the importance of PPEs ranked by building construction context. So, further studies are required to assess other construction projects, especially road projects. Because some of the PPEs have lesser importance in a building project will be ranked in the first place in road project like earplugs and reflector. Therefore, future research must assess road projects and other construction projects and develop an automatic monitoring system that can recognize unsafe acts and areas on construction sites. Additionally, during the primary data collection using the questionnaire, some participants give untruthful responses to keep their company; due to this, some of the results were interrupted by the incorrect answer. If the above limitations are improved, it can be used for practical implications in building construction sites. For practical purposes, it requires a site camera that is fixed on the construction area to capture images of the working environment and workers, after that, the picture is delivered then the presence of PPE detected from the captured image. Finally, the output/prediction is delivered to the manager. Thus the manager supervises workers' PPE usage during work without manual assessment.

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CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

Generally, this study aims to utilize a computer vision approach to manage safety in the Ethiopian construction industry. Specifically, the study has four objectives intended to achieve the general objective of the study. The four objectives are assessing the most available PPE in building construction sites, ranking PPE depending on the importance of PPEs for building projects, identifying the available PPE colour, and utilizing vision based method that detects PPE in construction sites. To achieve the study objective, primary data collected by using questionnaire, observation, and interview, to accomplish the first objectives. The result of the three objectives and manually taken picture used as input for the second objective. Also, image/data collected from online sources like Bing image trend and Pictor v3 data set. The output of primary data analysis uses to decide the types of PPE included as a label. The analysis was done using descriptive statics of frequency and percentage. The RII method of ranking is used to rank the most important PPE in building construction sites. The following significant ideas from the analysis result and experiment result concluded.

- Safety shoes, helmets, reflector, glove, and goggle are chiefly available protective equipment in the Adama building construction site. Protective clothing is in the middle of the most available and not available equipment; it is placed in 6th place. Although, some other equipment had not been used often or always, such as earplugs, dust masks, face shields, and safety harnesses.
- Helmet and safety shoes used as label depend on ranking result safety shoes ranked in the first place and helmet in the second place and reflector used by its suitability for detection.
- The main finding of this research is utilizing a vision-based method for PPE detection and the first objective used as an input to label the data/image, then depend on the

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findings, the data labelled by selecting three PPE from the total PPE such as helmet, safety shoes, and reflector.

- To ensure high speed of detection and accuracy, YOLO-V4 was used. The experiment result shows PPE prediction with an accuracy of 98.4% for helmets, 99% for shoes, and 96% for the reflector. The mAP of is 98% when the iteration is between 3000-3600, and it was stable up to 6000.
- Despite not recognizing the selected protective equipment with 100% accuracy, the finding of this research provide automatic site management with several benefits to their everyday practice. Firstly, it enables supervision of safety without disturbing work while they are working. Secondly, a wide range of working areas monitored simultaneously and reducing the costs and time associated with inspections.

5.2 Recommendations

5.2.1 Recommendation for practice

For the construction industry:

- ✓ The construction industry must increase utilization of software to change manual work into automatic to create an easy management platform.

For construction companies:

- ✓ Prepare training to increases employee awareness about PPE importance and utilization system.
- ✓ Adopt technological solutions on the safety management systems to manage easily without presenting on the site.

For the governmental regulatory office:

- ✓ Adopt safety management software to manage regularly the construction site.
- ✓ Check the availability of PPE in all construction sites.

For Ethiopian university:

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- ✓ Including software courses in different fields to make the student aware of how to utilize software.
- ✓ Provide short-term training on software courses to increase the ability of students to understand and develop software.

5.2.2 Recommendation for further research work

- ✓ To increase the detection ability, increasing the number of data used for training purposes required.
- ✓ Using large manual data set for training and utilize images taken from onsite video cameras.
- ✓ Assessing PPE availability and ranking its importance in road projects and other construction projects.
- ✓ Utilize other automatic monitoring systems for safety management to recognize unsafe acts and areas on construction sites.

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APPENDIX

Appendix A: Questionnaire

RESEARCH TOPIC “A computer vision-based approach for Safety Management in the Construction Sites”

Dear Sir/Madam,

This research survey is designed to fulfill an academic requirement for MSc program in Construction engineering and Management at the Adama science and technology university. Those who involved in the building construction project G+3 and above are kindly requested to contribute to this research work. The objective of this study is to utilize a computer vision approach for PPE detection in construction site for safety management. Thus before using vision-based method first identifying and ranking currently used protective equipment in your site are required. Also manual site image needed as an input. So your contribution on this study is very important to get appropriate output at the end of the research.

The result of this survey is intended to serve only for academic purpose and will be treated with strict confidentiality. The name of institutions participated will be recorded confidentially. Thank you in advance for your willingness to fill the questionnaires and returning them back on time. Your open response is highly appreciated.

Thank you for your invaluable time and cooperation in advance.

Regards, Lidiya Biruk

Tel: 0961201231

E-mail: lidyabiruk123@gmail.com

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Appendix A1: Respondent profile

Work place/ sub city ____________

Name of the company ____________

Type of project

A) Governmental B) Private

Work progress

A) Sub structure B) Super structure

Sex:

A) Male B) Female

Age:

a) below 20yrs b)20-29yrs c) 30-39yrs d) 40-49yrs e) 50 -55yrs f) 56yrs and above

Educational level

a) Illiterate b) elementary (1-8) c) high school (9-12) d) Certificate & Diploma e) BSc/BA degree and above

Service time/ experience in this organization?

A. less than one year b. 1-5 years c. 6-10 yrs. d. above 10 years

Your employment condition:

A) Permanent B) Contract/ temporary

Title of your current position ____

`

Appendix A2: Availability of PPEs

→ Which of the following personal protective equipment (PPE) provided at workplace?

SN	PPE	Yes	No
1	Helmet		
2	Safety boots		
3	safety vest		
4	Safety Harness		
5	Protective Clothing		
6	Gloves		
7	Goggles		
8	Face shield		
9	Dust mask		
10	Ear plug		

`

Appendix A3: Likert scale question

→ Rate the importance for the type of PPEs available in your site?

SN	Type of Personal protective equipment	Extremely important	Very Important	Important	Somewhat Important	Not That Important	neutral	unimportant
1	Helmet							
2	Safety boots							
3	safety vest/ reflector							
4	Safety Harness							
5	Protective Clothing							
6	Gloves							
7	Goggles							
8	Face shield							
9	Dust mask							
10	Ear plug							

`

Appendix A4: Color of available PPEs in construction sites

→ Mark the color of the PPE equipment available in your site?

SN	Personal protective equipment	yellow	red	orange	Whit e	green	black	brown	blu e	lemon	Others
1	Helmet										
2	Safety boots										
3	safety vest										
4	Safety Harness										
5	Protective Clothing										
6	Gloves										
7	Goggles										
8	Face shield										
9	Dust mask										
10	Ear plug										

`

Appendix B: Type of project VS availability of PPE by frequency

Type of project		governmental	private	Total
helmet	yes	19	75	94
	no	0	20	20
safety shoes	yes	17	82	99
	no	2	13	15
safety vest	yes	19	71	90
	no	0	24	24
safety harness	yes	15	41	56
	no	4	54	58
protective clothing	yes	10	65	75
	no	9	30	39
glove	yes	19	80	99
	no	0	15	15
goggle	yes	19	71	90
	no	0	24	24
face shield	yes	13	35	48
	no	6	60	66
dust mask	yes	15	30	45
	no	4	65	69
ear plug	yes	0	6	6
	no	19	89	108

`

Appendix C: Codes

Appendix C1: GPU initializing

```
! nvidia-smi
```

```
Sun Jun 27 09:31:44  2021
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 465.27       Driver Version: 460.32.03    CUDA Version: 11.2     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|                               |                      |               MIG M. |
|===============================+======================+======================|
|   0  Tesla T4            Off  | 00000000:00:04.0 Off |                    0 |
| N/A   35C    P8     9W /  70W |      0MiB / 15109MiB |      0%      Default |
|                               |                      |                  N/A |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                                  |
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory |
|        ID   ID                                                   Usage      |
|=============================================================================|
|  No running processes found                                                 |
+-----------------------------------------------------------------------------+
```

`

Appendix C2.2: build darknet

```
# clone darknet repo
!git clone https://github.com/AlexeyAB/darknet
```

```
Cloning into 'darknet'...
remote: Enumerating objects: 15150, done.
remote: Counting objects: 100% (77/77), done.
```


```
# clone darknet repo
!git clone https://github.com/AlexeyAB/darknet
```


```
Cloning into 'darknet'...
remote: Enumerating objects: 15150, done.
remote: Counting objects: 100% (77/77), done.
remote: Compressing objects: 100% (43/43), done.
remote: Total 15150 (delta 37), reused 61 (delta 31),
pack-reused 15073 Receiving objects: 100%
(15150/15150), 13.50 MiB | 16.74 MiB/s, done.
Resolving deltas: 100% (10283/10283), done.
```

```
# change makefile to have GPU and OPENCV enabled
%cd darknet
!sed –i 's/OPENCV=0/OPENCV=1/' Makefile
!sed –i 's/GPU=0/GPU=1/' Makefile
```

```
/content/darknet
```

```
# verify CUDA
!/usr/local/cuda/bin/nvcc --version
```

```
# make darknet (builds darknet so that you can then use the darknet executable file to run or
!make
```

`

```
# define helper
functions def
imShow(path):

    import cv2

    import matplotlib.pyplot as plt

    %matplotlib inline

    image = cv2.imread(path)

    height, width = image.shape[:2]

    resized_image = cv2.resize(image,(3*width, 3*height), interpolation = cv2.INTER_CUBIC)

    fig = plt.gcf()

    fig.set_size_inches(18,
    10) plt.axis("off")

    plt.imshow(cv2.cvtColor(resized_image, cv2.COLOR_BGR2RGB)) plt.show()

# use this to upload files
def upload():
```

e

```
def download(path):
    from google.colab import files
    files.download(path)
```

```
!ls
```

3rdparty	DarknetConfig.cmake.in	json_mjpeg_streams.sh	scripts
backup	darknet_images.py	LICENSE	src
build	darknet.py	Makefile	vcpkg.json
build.ps1	darknet_video.py	net_cam_v3.sh	video_yolov3.sh
cfg	data	net_cam_v4.sh	video_yolov4.sh
cmake	image_yolov3.sh	obj	yolov4.weights
CMakeLists.txt	image_yolov4.sh	README.md	
darknet	include	results	

`

Appendix C2.2: mount drive

```
%cd

from google.colab import drive
```

/content

Go to this URL in a browser:

h ttps://accounts.google.com/o/oauth2/auth?client_id=947318

Enter your authorization code: 4/1AX4XfWgDFUDDoCO51p8OrV6Z Mounted at /content/gdrive

```
# this creates a symbolic link so that now the path /content/gdrive/My\ Drive/ is equal to /m
!ln -s /content/gdrive/My\ Drive/ /mydrive
!ls /mydrive
```

coc	Pic
'Colab Notebooks'	proj_implementation
'Copy of obj.data'	Requirents-For-Darknet-master
'Copy of obj.names'	TensorFlow-2.x-YOLOv3 'Copy of yolov4
shoes.ipynb'	thesis
darknet	'thesis all.tar.gz'
diplomat	'Thesis project'
images	yolov3
I	yolov4
'My Drive'	yolov48
PAPERS	

```
# cd back into the darknet folder to run detections

%cd darknet/
```

```
# this is where my datasets are stored within my Google Drive (I created a yolov4 folder to
s
```

backup	generate_test.py	obj.data	test.zip
backup1	generate_train.py	obj.names	yolov4-obj.cfg
backupsec	images	obj.zip	

`

Appendix C2.3: upload data set and cfg file from google drive

```
# copy over both datasets into the root directory of the Colab VM (comment out test.zip.zip i

# upload the custom .cfg back to cloud VM from Google Drive

!cp /mydrive/yolov4/yolov4-obj.cfg ./cfg

# upload the obj.names and obj.data files to cloud VM from Google Drive

!cp /mydrive/yolov4/obj.names ./data

!cp /mydrie/yolov4/obj.data ./data

# upload the generate_train.py and generate_test.py script to cloud VM from Google Drive

!cp /mydrive/yolov4/generate_train.py ./

!cp /mydrive/yolov4/generate_test.py ./
```

Now simply run both scripts to do the work for you of generating the two txt files.

```
!python generate_train.py

!python generate_test.py

# verify that the newly generated train.txt and test.txt can be seen in

!ls data/
```

9k.tree	giraffe.jpg	labels	person.jpg	voc.names
coco9k.map	goal.txt	obj	scream.jpg	
coco.names	horses.jpg	obj.data	test	
dog.jpg	imagenet.labels.list	obj.names	test.txt	
eagle.jpg	imagenet.shortnames.list	openimages.names	train.txt	

`

Appendix C 2.4: start training

```
#this is transfer learning.
!wget https://github.com/AlexeyAB/darknet/releases/download/darknet_yolo_v3_optimal/yolov4.co
```

```
# # train your custom detector! (uncomment %%capture below if you run into memory issues or y      #
%%capture

GPU=1
CUDNN=1

CUDNN_HALF=1
```

```
Tensor Cores are disabled until the first 3000 iterations are reached.
(next mAP calculation at 1000 iterations)
787: 3.788856, 3.481377 avg loss, 0.000384 rate, 7.783142 seconds, 50368 images, 6.1
Loaded: 0.000085 seconds
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 139 Avg (IOU: 0.58
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 150 Avg (IOU: 0.68
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 161 Avg (IOU: 0.68
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 150 Avg (IOU: 0.70
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 161 Avg (IOU: 0.67
total_bbox = 893113, rewritten_bbox = 0.240731 %
total_bbox = 893349, rewritten_bbox = 0.240667 %
infer label file name (check image extension is supported): data/obj/924_75
```

```
# kick off training from where it last saved
!./darknet detector train data/obj.data cfg/yolov4-obj.cfg /
```

```
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 150 Avg
v3 (iou loss, Normalizer: (iou: 0.07, obj: 1.00, cls: 1.00) Region 161 Avg (IOU:
0.89 total_bbox = 60997, rewritten_bbox = 0.268866 %
```

```
# need to set our custom cfg to test mode %cd cfg
!sed -i 's/batch=64/batch=1/' yolov4-obj.cfg
!sed -i 's/subdivisions=32/subdivisions=1/' yolov4-obj.cfg
%cd ..
```

```
/content/darknet/cfg
/content/darknet
```

`

Appendix C 2.5: Test

```
# run your custom detector with this command (upload an image to your google dri
ve to test, t
!./darknet detector test data/obj.data cfg/yolov4-obj.cfg /mydrive/yolov4/backup/yolov4-obj_b
imShow('predictions.jpg')
```

```
[yolo] params: iou loss: ciou (4), iou_norm: 0.07, obj_norm: 1.00, cls_norm:
1.00, delt
nms_kind: greedynms (1), beta = 0.600000
 151 route   147                                            ->   26 x
             26 x 256
 152 conv     512        3 x 3/ 2     26 x   26 x 256 ->    13 x   13 x 512
 0.399 BF
 153 route   152 116                                  ->    13 x   13 x1024
 154 conv     512        1 x 1/ 1     13     13 x1024 ->    13 x   13 x 512   0.177 BF
 155 conv    1024        3 x 3/ 1     13     13 x 512 ->    13 x   13 x1024   1.595 BF
 156 conv     512        1 x 1/ 1     13     13 x1024 ->    13 x   13 x 512   0.177 BF
 157 conv    1024        3 x 3/ 1     13     13 x 512 ->    13 x   13 x1024   1.595 BF
 158 conv     512        1 x 1/ 1     13     13 x1024 ->    13 x   13 x 512   0.177 BF
 159 conv    1024        3 x 3/ 1     13     13 x 512 ->    13 x   13 x1024   1.595 BF
 160 conv      24        1 x 1/ 1     13     13 x1024 ->    13 x   13 x  24   0.008 BF
 161 yolo

[yolo] params: iou loss: ciou (4), iou_norm: 0.07, obj_norm: 1.00, cls_norm: 1.00,
delt nms_kind: greedynms (1), beta = 0.600000
Total BFLOPS 59.578
avg_outputs = 490041
 Allocate additional workspace_size = 52.43 MB
Loading weights from /mydrive/yolov4/backup/yolov4-
 obj_best.weights... seen 64, trained: 22 K-images (0 Kilo-
 batches_64)
Done! Loaded 162 layers from
 weights-file Detection layer: 139 -
 type = 28
 Detection layer: 150 - type = 28
```

`

Detection layer: 161 type =28

/mydrive/images/10.jpg: Predicted in 32.587000 milli seconds. reflector: 98%

helmet: 84%

helmet: 94%

reflector: 94%

reflector: 98%

Unable to init server: Could not connect: Connection refused

(predictions:1723): Gtk-WARNING **: 09:53:58.848: cannot open display: