**Final Year Project Report**

**Full Unit – Final Report**

**Helmet Detection for Construction Workers Using Deep learning in Somalia**

Dahir Shueyb Ahmed

Suheib Mukhtar Nur

A report submitted in partial fulfillment of the

degree of

**BSc in Information Technology**

**Supervisor:** Ubaid Mohamed Dahir



Department of **Information**

**Technology** Faculty of Computing,

SIMAD University

August 2025

**DECLARATION. A**

We declare that the following is our own work and does not contain any

unacknowledged work from any other sources. This project was undertaken to fulfill

the requirements of the bachelor’s degree program in Information

Technology at SIMAD University.

Name :Dahir Shueyb Ahmed

Signature :………………………………….

Name :Suheib Mukhtar Nur

Signature :………………………………….

Date : ……………………

### DECLARATION. B

I hereby declare that the thesis entitled *“Helmet Detection for Construction Workers using Deep Learning in Somalia”*was carried out under my supervision at SIMAD University, Faculty of Computing. This work meets the academic and scientific integrity standards set by the institution.

The thesis presents a significant and innovative contribution to the field of computer vision by applying modern deep learning techniques to address a real-world problem enhancing workplace safety in Somalia’s construction sector. Using YOLOv8 (You Only Look Once, Version 8), a cutting-edge object detection algorithm, the research offers a practical system to automatically detect whether construction workers are wearing helmets on site.

The students have demonstrated strong technical skills, creativity, and a clear commitment to using artificial intelligence to solve critical societal challenges. The research methodology is robust, the outcomes are relevant and impactful, and the developed system holds genuine potential for real-world implementation.

I fully endorse this thesis for academic submission. To the best of my knowledge, this is an original piece of work and has not been submitted for any other academic or professional qualification

Supervisor : Ubaid Mohamed Dahir

Signature :………………………………….

**ACKNOWLEDGEMENTS**

**Student One:** Dahir Shueyb Ahmed

I would like to express my heartfelt gratitude to my supervisor, Mr. Ubaid Mohamed Dahir, for his continuous guidance, support, and insightful advice throughout the development of this thesis. His mentorship not only deepened my understanding of deep learning and its real-world applications particularly in the field of workplace safety but also inspired me to approach the subject with both curiosity and purpose.

I am also thankful to the Faculty of Computing at SIMAD University for providing a supportive academic environment, as well as to my teachers and fellow students, whose input and encouragement contributed meaningfully to the success of this project

**Student Two:** Sueib Mukhtar Nur

I am deeply grateful to my supervisor, Mr. Ubaid Mohamed Dahir, from the Faculty of Computing at SIMAD University, for his patience, constructive feedback, and unwavering mentorship throughout the course of this research. His expertise in artificial intelligence laid a strong foundation for my work on using YOLOv8 for helmet detection on construction sites.

I would also like to thank my fellow students and faculty members for their support and contributions, which made this research journey both meaningful and enriching

**ABSTRACT**

This thesis presents a deep learning-based system specifically developed to address the critical issue of enforcing helmet compliance among construction workers in Somalia. The main objective of this study was to develop a sophisticated, real-time helmet detection program that could determine whether employees were wearing protective helmets while on the job. Utilizing the capabilities of a state-of-the-art object detection algorithm called YOLOv8 (You Only Look Once, Version 8), the system examines visual input from cameras to reliably differentiate between people wearing and not wearing helmets.

A customized dataset suited to Somalia's typical construction conditions was created and trained as part of the project. This involved gathering and annotating pictures of workers wearing and not wearing helmets, then adjusting the YOLOv8 model to guarantee high accuracy in practical settings. Real-time performance and dependability were prioritized, especially in demanding outdoor settings where conventional safety enforcement techniques are insufficient.

The final model achieved an accuracy of 95%, with a precision of 93% and a recall of 94%, demonstrating reliable real-time performance. This work contributes a locally adapted dataset and a real-time AI-based monitoring system for helmet detection, tailored to Somalia’s construction context.

This research contributes both a locally adapted helmet detection dataset and a practical real-time AI-based monitoring system, making it one of the first context-specific safety solutions tailored for Somalia’s construction sector. By combining modern deep learning techniques with real-world constraints, this project offers a scalable solution that not only improves worker safety but also sets a foundation for future AI-driven safety applications in underrepresented regions.

**Table of Contents**

DECLARATION. A..............................................................................................ii

DECLARATION. B.........................................................................................…iii

ACKNOWLEDGEMENTS..........................................................................................iv

ABSTRACT...................................................................................................................v

Table of Contents..........................................................................................................vi

LIST OF TABLES .....................................................................................................viii

LIST OF FIGURES.......................................................................................................ix

LIST OF ABBREVIATIONS AND SYMBOLS.......................................................…x

CHAPTER ONE...........................................…......................................................…...1

INTRODUCTION..........................................................................................................1

1.1 INTRODUCTION....................................................................................................1

1.2 BACKGROUND OF THE PROJECT.....................................................................2

1.3 STATEMENT OF THE PROBLEM........................................................................4

1.4 OBJECTIVES OF THE PROJECT..........................................................................6

1.5 BENEFITS OF THE PROJECT......................................….....................................6

1.6 RESEARCH QUESTIONS......................................................................................7

1.7 THE SCOPE OF THE SYSTEM.............................................................................8

1.8 CHAPTER SUMMERY...........................................................................................8

1.9 PROJECT ORGANIZATION .................................................................................9

CHAPTER TWO..........................................................................................................10

LITERATURE REVIEW.............................................................................................10

2.1 INTRODUCTION..................................................................................................10

2.2 RELATED WORK………………….............................................................…...10

2.3 SYNTHESIS AND IDENTIFICATION OF RESEARCH GAPS........................13

2.4 DIRECTION OF THE PROJECT.........................................................................14

2.5 CHAPTER SUMMERY........................................................................................14

CHAPTER THREE......................................................................................................15

METHODOLOGY.......................................................................................................15

3.1 INTRODUCTION..................................................................................................15

3.2 DATA COLLECTION...........................................................................................17

3.3 DATA PREPROCESSING....................................................................................18

3.4 MODEL TRAINING.............................................................................................20

3.5 DEPLOY REAL TIME DETECTION SYSTEM..…............................................21

3.6 SYSTEM EVALUATION…………….................................................................22

3.7 SYSTEM CLASSIFICATION…………………………………………………...23

3.8 CHAPTER SUMMERY........................................................................................23

CHAPTER FOUR........................................................................................................24

RESULTS AND DISCUSSION…………………......................................................24

4.1 INTRODUCTION..................................................................................................24

4.2 EXPERIMENTAL PROGRESSION AND RESULTS...................................…...24

4.3 DISCUSSION AND FINAL MODEL SELECTION…....................................... 28

4.6 CHAPTER SUMMERY................................................................................….....29

CHAPTER FIVE..........................................................................................................30

CONCLUSION AND LESSON LEARNED……………….......................................30

5.1 INTRODUCTION................................................................................................. 30

5.2 SUMMERY OF ACCOMPLISHMENT OBJECTIVES......................................30

5.3 CHALENGES:.......................................................................;............................................31

5.4 FUTURE WORKS..............................................................................................................32

5.5 LESSONS LEARNED........................................................................................................32

5.6 CHAPTER SUMMERY.....................................................................................................33

REFERENCE............................................................................................................................34

APPENDIX A...........................................................................................................................46

**LIST OF TABLES**

Table 2.2.1: Summary of literature review……………………………….…………11

Table 4.2.1: Performance Metrics for Experiment One………………….….………25

Table 4.2.2: Performance Trend for Experiment Two……………………………….27

Table 4.3.1: Comparative Summary of All Experiments………..…………………..30

**LIST OF FIGURES**

Figure 1.1.1 Workers on construction sites without helmets………………………….1

Figure 1.2.1 No helmet workers……………………………………………………….2

Figure 1.2.2 Helmet workers &No helmet workers…………………………………...3

Figure 1.3.1 head injury at work………………………………………………………5

Figure 1.5.1 Project’s main benefits……………………………………….…………..5

Figure 3.1: Project Framework……………………………………………………….16

Figure 3.3.2.1 Construction workers a)Wearing Helmets b) Not Wearing Helmets...18

Figure 4.2.1: Confusion Matrix for Experiment Three………………………………20

Figure 4.3.2.1 Experiment Two 30 epochs………………………………….……….26

Figure 4.3.2.1 Experiment Two test…………………………………………………26

Figure 4.3.3.1 Experiment Three 50 Epochs………………………………..………27

Figure 4.3.3.2 experimental configuration…………………………………………..28

**LIST OF ABBREVIATIONS AND SYMBOLS**

YOLOv8: You Only Look Once version 8

SSD: Single Shot Multibox Detector

R-CNN: Region-based Convolutional Neural Network

PPE: Personal Protective Equipment

mAP: maen Average Precision

FPS: Frames Per Seconds

CWH: Construction Worker Helmets

SHWD: Safety Helmet Wearing Datasets

GUI: Graphical User Interface

IP-cameras: Internet Protocol cameras

GPU: Graphics Processing Units

CHV: Construction Hardhat Video

CCTV: Closed-Circuit Television

DL: Deep Learning

**CHAPTER ONE**

**INTRODUCTION**

**1.1 Introduction**

Workplace safety has become a significant concern for many industries due to the effect of unsafe environments on productivity, and the resulting loss of workers[(Hayat & Morgado-Dias, 2022)](https://www.zotero.org/google-docs/?SqcKju). Not wearing a helmet correctly is a major reason for injuries and deaths in the construction and industrial production industries. Traditional ways of supervising mostly depend on people watching over things(Liang et al., 2024). People are essential resources in the construction industry, so their safety should be a top priority. Accidents occasionally occur during the construction of large projects, making construction sites one of the most dangerous places to work(Liang & Seo, 2022).

In the complicated and ever-changing world of construction sites, traditional ways of making sure that helmets are worn, such manual inspections, have a lot of problems.

Inspections by hand are quite inefficient and can't cover everything quickly or thoroughly. The whole site, they often just check some parts of the site, leaving other parts untested as safety blind spots. Also, human inspectors are prone to making mistakes because of tiredness, carelessness, or inconsistent standards, which can lead to missed or wrong conclusions(Jiao et al., 2025).



Figure 1.1.1 Workers on construction sites without helmets

The picture shows a common safety violation on construction sites: workers put their helmets on things like building irons or scaffolding instead of wearing them. This behaviour shows that safety rules aren't being followed and shows how important it is to have real-time monitoring systems to make sure that helmets are worn correctly, not merely there, on-site.

To reduce the risk of head trauma to workers working in high-risk workplaces such

as construction sites, we designed a new automated lightweight end-to-end convolutional neural network to identify whether all people on a construction site are wearing helmets. Firstly, we used YOLOv8, a cutting-edge deep learning object detection model, which powers a real-time helmet detection system. The suggested approach uses surveillance camera photos or video to determine whether on-site employees are wearing helmets.

This system seeks to improve worker safety, lower human error in monitoring, and aid in the enforcement of safety standards within Somalia's construction industry by utilizing the speed and precision of YOLOv8. In this study, we investigate how artificial intelligence can be used to address one of the most neglected safety concerns in low-resource settings in a useful and socially significant manner.

**1.2 Background of The Project**

The building industry in Somalia is still growing quickly, but many sites still don't follow fundamental safety rules. One of the most important problems is that construction workers don't wear helmets enough. Even though falling debris, slipping, or hitting someone on the head by mistake can cause serious head injuries, helmets are rarely required(Abdi & Hareru, 2024). Because of this, accidents at work often result in serious injury or death, and there is no established system for holding people accountable or keeping them safe. In a lot of situations, there are no official records, no follow-up investigations, and no one is held accountable, which means that the workers and their families don't get justice or money.



Figure 1.2.1 No helmet workers

The picture shows construction workers working on a building site without having helmets at all. This lack of basic personal protective equipment (PPE) is a major safety issue and shows how important it is to enforce rules right away. It shows how important automatic helmet detection systems are for finding and stopping these kinds of dangerous behaviours right away.

Some private construction firms in Somalia, like Docol, have started to make their workers wear helmets, although this isn't always the case. People generally only see workers wearing helmets when their bosses or corporate officials are around. Many workers take off their helmets or leave them in the absence of active supervision, which shows that they don't think safety is important. Also, Docol and other companies like it don't do all of the city's construction work. There are still a lot of structures being built by independent engineers or informal organizations that don't always follow safety rules. These gaps in enforcement and coverage nevertheless put thousands of workers at danger on construction sites where they don't have to be.



Figure 1.2.2 Helmet workers &No helmet workers

The picture depicts a group of construction workers from the same company. Some are wearing helmets while others are not, even though they are all working hard. This contradiction shows that people only wear helmets when corporate bosses are around and don't wear them when they aren't. It shows how hard it is to keep safety standards up to date and stresses the necessity for automated, real-time monitoring tools to make sure that PPE rules are always followed.

This project suggests an AI-based helmet detection system that uses real-time video and deep learning, with YOLOv8 as the engine. The technology automatically checks to see if workers are wearing helmets correctly and sends out alarms when they don't, even if there aren't any supervisors around. This helps make sure that helmets are always being worn on both formal and informal building sites in Somalia.

**1.3 Statement of The Problem**

In Somalia's construction industry, not following helmet-wearing rules puts workers' safety at significant risk. Many construction workers work in dangerous places without sufficient head protection, which raises the risk of serious injury, permanent disability, or even death. Even while there are safety rules, they aren't always followed, especially on big or crowded construction sites where managers can't keep an eye on every worker all the time.

The absence of effective and automated helmet detection systems leads to frequent violations of safety rules, most of which go unnoticed or unreported. This shows how badly we need a technical solution that can help with real-time monitoring and make sure that everyone follows the rules to raise safety standards in the industry as a whole.

Figure 1.3.1 head injury at work

The figure above illustrates the potential severity of head injuries sustained on construction sites when safety helmets are not used. Such injuries can lead to life-altering consequences, emphasizing the critical need for consistent helmet enforcement as a preventive safety measure.

To address this, the project proposes a real-time helmet detection system powered by YOLOv8 and deep learning. By analyzing video streams and detecting non-compliance automatically, the system enhances site safety, reduces manual oversight burdens, and supports a culture of accountability—ultimately contributing to a safer, more sustainable construction industry in Somalia.

**1.4 Objectives of The Project**

1. To develop a real-time helmet detection system using the YOLOv8 deep learning algorithm.
2. To create and train a dataset reflecting helmet use conditions specific to Somali construction sites.
3. To evaluate the performance and accuracy of the system in real-world construction environments.

These objectives aim to address the critical issue of occupational safety in Somalia's construction industry by leveraging advanced computer vision techniques. The goal of the project is to create a reliable, scalable, and context-aware system that can automatically check if helmets are being worn correctly on-site by combining deep learning with data that is relevant to the area.

**1.5 Benefits of The Project**

The suggested approach lowers the danger of head injuries and fatalities by providing a workable, AI-powered way to enforce the usage of helmets on construction sites. Instantaneous detection and alerting for non-compliance is made possible by combining real-time monitoring with YOLOv8, particularly in situations when manual supervision is insufficient or irregular.

This continuous, computerized monitoring reduces human mistake and enhances safety enforcement in general. Additionally, it gives organizations the ability to create data-driven safety procedures that are supported by objective facts rather than shaky human perceptions.

Figure 1.5.1 Project’s main benefits

This figure highlights the core benefits of the proposed helmet detection system. Through improved safety, it actively reduces the risk of head injuries; ensured compliance strengthens adherence to safety rules; automatic monitoring eliminates the need for constant human oversight; and cost savings result from fewer accidents, legal penalties, and project delays.

**1.6 Research Questions**

1. How can deep learning techniques, specifically YOLOv8, be used to detect whether a construction worker is wearing a safety helmet in real time?
2. What type of image dataset and preprocessing methods are most effective for training a helmet detection model in the context of Somali construction environments?
3. How can the system be integrated with surveillance cameras to provide continuous monitoring and immediate alerts for helmet violations?
4. What level of accuracy and performance can the system achieve in detecting helmets under various real-world conditions such as lighting, motion, and occlusion?

**1.7 The Scope of The System**

This one-year study will be created and evaluated in Mogadishu, Somalia, by SIMAD University. The device will automatically identify employees not wearing helmets in live camera feeds using YOLOv8, a deep learning-based object detection algorithm, and promptly notify site supervisors.

By automating helmet identification and alerting in dangerous areas, the research seeks to lower the likelihood of injuries. In addition to analyzing how AI-driven safety solutions may strengthen enforcement, increase reporting accuracy, and facilitate well-informed decision-making within Somalia's construction industry, it will assess how well deep learning performs real-time monitoring in difficult outdoor circumstances.

**1.8 Chapter Summary**

This chapter introduced the motivation for developing an AI-based helmet detection system to improve construction site safety in Somalia. It outlined the risks posed by inadequate manual monitoring and highlighted the need for real-time, automated detection using deep learning. The chapter summarized key objectives, such as deploying YOLOv8 for accurate helmet identification and reducing accident risks. It also defined the project’s scope, location, and duration, with SIMAD University leading the initiative.

**1.9 Project Organization**

Project organization is a well-planned project structure helps the reader to go across the research process from problem identification to solution application and evaluation. Every chapter logically develops the previous one before it guarantees coherence and clarity.

**Chapter 1: Introduction** Sets the stage by outlining the project's background, objectives, scope, and significance, framing the research within the context of helmet detection for construction workers.

**Chapter 2: Literature Review** Examines a literature review and relevant works associated with the problem addressed in the study.

**Chapter 3: Methodology** Describes the research design, including data collection, algorithm selection, and the system development process, detailing the technical approach taken.

**Chapter 4: Results and Discussion** Explains the classification system's creation process, implementation specifics, and results analysis, all of which serve to highlight the system's usefulness.

**Chapter 5: Conclusion and Recommendations** summarizes the results, considers the project's impact, and makes recommendations for future research and system improvements in order to close the study.

**CHAPTER TWO**

**LITERATURE REVIEW**

### 2.1 Introduction

This chapter reviews existing literature on helmet detection, deep learning, and occupational safety systems relevant to the Somali context. It will also organize the papers that were reviewed based on how much they contribute to our understanding of PPE detection in the manufacturing sector. Research on the application of deep learning models, particularly object detection architectures like YOLO (You Only Look Once), SSD (Single Shot Multibox Detector), and Faster R-CNN, for detecting safety helmet violations through image and video analysis is its main focus(Ahmed et al., 2023). Computer vision techniques for safety enforcement, human-object interaction recognition, and real-time video monitoring are also covered in the review(Ahmed et al., 2023).

The limited use of real-time, AI-based detection systems designed for helmet enforcement on low-resource, high-risk construction sites, like those in Somalia, is one of the research gaps highlighted by the paper. Many current methods are inflexible in outdoor settings, have delayed detection, or necessitate costly infrastructure(Kim et al., 2018). By putting in place a YOLOv8-based helmet detection system that can precisely identify non-compliance in real-time, this initiative seeks to close these gaps. The technology aids in the creation of more intelligent, quick, and scalable safety solutions for the construction sector by emphasizing dependable deployment in actual construction environments.

### 2.2 Related work

There has been a lot of research in the last several years on how deep learning can be used to make construction sites safer. In particular, helmet detection systems have gotten better as object detection models have become more accurate and effective. This section is organised around significant topics that show how the discipline has changed over time, focusing on important technical trends, trade-offs, and new ideas. Instead of presenting papers one by one.

2.2.1 Evolution of Object Detection Models for PPE Monitoring

The growth of helmet detection systems has largely paralleled the growth of object detection algorithms based on deep learning. Many people used early frameworks like YOLOv3 because they were fast and accurate. (Zhao et al. 2019) suggested a system that uses YOLOv3 to find safety officers and keep an eye on vests, helmets, and pedestrians. Their solution combined the Kalman filter and the Hungarian algorithm to track people, and it was able to find 89% of pedestrians, 84% of helmets, and 94% of vests.

In the same way, (Delhi et al. 2020) used a mix of CNN and YOLOv3 to keep an eye on PPE compliance in real time. Their technology put construction workers into four safety groups and sent them automatic alerts when they broke the rules. These early efforts showed that object detection might be used for construction safety, but they were still limited in how well they could adapt and find things.

2.2.2 Speed vs. Accuracy Trade-Off in Real-Time Detection

One problem that keeps coming up in helmet detection studies is finding a balance between accuracy and speed. (Wang et al. 2023) tested several versions of YOLO (YOLOv3, YOLOv4, and YOLOv5) on a dataset from a construction site. YOLOv5x had the highest mean average precision (mAP) at 86.55%, while YOLOv5s was faster at 52 FPS. This shows that there is a trade-off that must be made in real-time applications.

(Jiao et al. 2025) suggested a lightweight convolutional neural network with MobileNet as the backbone to improve performance efficiency. The model used depth-wise separable convolutions to make multi-scale feature maps, which made it possible to find things quickly while still being accurate enough. These studies show how important it is to make models as fast and accurate as possible, especially when they will be used in the real world where resources are limited.

2.2.3 Enhancing Detection Accuracy through Model and Dataset Improvements

Recent research has pushed the limits of accuracy by using new model architectures and dataset techniques. (Lo, Lin, &Hung 2023) looked at YOLOv3, YOLOv4, and YOLOv7 to see which one was best for finding PPE. Their YOLOv7 model got an excellent mAP of 97.29% at 25.02 FPS by using a lot of data augmentation techniques, such flipping, cropping, and adding noise.

Other researchers also made a better version of the YOLOv5 model just for finding helmets. They said that the precision and recall rates were 93.16% and 88.96%, respectively. These changes point to a trend towards better accuracy and contextual robustness, which opens the door to looking at the newer YOLOv8 architecture, which promises even more benefits in accuracy, speed, and model efficiency(Liang et al. 2024).

Wang et al. worked on worker safety by building real-time helmet identification models based on the YOLOv3, YOLOv4, and YOLOv5 architectures. The CHV dataset has 1,330 labeled photos in six categories (helmet colors, person, and vest). YOLOv5x had the highest mean average precision (mAP) of 86.55%, but YOLOv5s had the fastest performance at 52 FPS, showing the trade-off between speed and accuracy(Ahmed et al., 2023).

**Table 2.2.1** Summary of literature review

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Researcher |  | Model Used | Dataset | Focus Area | Performance | Strengths | Limitations |
|  |  |  |  |  |  |  |  |
| Liang et al. |  | Improved YOLOv5 | Custom | Helmet detection | Precision: 93.16%, Recall: 88.96% | Optimized loss function, robust detection | Lacks deployment in live site scenarios |
| Zhao et al. |  | YOLOv3 + Kalman | Custom | Safety officer & pedestrian tracking | Helmet: 84%, Pedestrian: 89% | Multi-object tracking | Focuses on structured sites; less real-world variability |
| Delhi et al. |  | CNN + YOLOv3 | Mixed (online + captured) | Hard hat & vest compliance | Not reported | Automatic alerts, safety classification | No local datasets or accuracy metrics shared |
| Wang et al. |  | YOLOv3–v5 | CHV (1,330 images) | Helmet, person, vest | mAP: 86.55%, Speed: 52 FPS | Speed vs. accuracy balance | Dataset not representative of developing regions |
| Lo, Lin, Hung |  | YOLOv4, YOLOv7 | 11,000 images | PPE detection | mAP: 97.29%, 25.02 FPS | High accuracy, extensive augmentation | Dataset lacks African/low-resource environment |
| Jiao et al. |  | Lightweight CNN | Not specified | Real-time helmet detection | Not reported | Fast, compact model | Real-world validation missing |

**2.3** **Synthesis and Identification of Research Gaps**

While the reviewed literature demonstrates the promising capabilities of deep learning in helmet detection, it also reveals three major limitations that must be addressed for effective deployment in Somalia’s construction sector:

* Lack of Locally Relevant Datasets: Most of the models have been trained and evaluated using data from developed countries. In these datasets, the surroundings are usually regulated, with the same lighting, clothing, and site architecture. This is very different from Somali construction sites, which are usually dustier, less consistent, and more chaotic.
* Underutilization of Advanced Architectures Like YOLOv8:Models like YOLOv5 and YOLOv7 have worked well, but not much research has used the newest YOLOv8 architecture. This architecture combines greater detection accuracy with better computing efficiency, which are both important for use in low-resource settings.
* Lack of Real-Time, On-Site Helmet Monitoring: A lot of the solutions available now are meant for analyzing events after they happen or for judging still images. There aren't many systems that work live and send out notifications right away when something goes wrong in active, changing building sites like those in Somalia.

**2.4** **Direction of the Project**

### To address the above challenges, this project proposes a real-time helmet detection system based on the YOLOv8 architecture, designed specifically for deployment in Somali construction environments.

* Development of a YOLOv8-Based Detection Model: The main goal of the project is to develop a deep learning model that can find helmets in real time with a lot of accuracy and speed. We chose YOLOv8 because it strikes a good mix between size, speed, and precision.
* Integration with Live CCTV Infrastructure: The system will be designed to connect with existing surveillance setups, enabling constant monitoring and immediate alert generation when workers are detected without helmets.
* Creation of a Local Dataset: A dataset composed of some images and short video clips captured from actual construction sites in Mogadishu will be used to train and evaluate the model. This ensures that the system is optimized for real-world conditions unique to Somali contexts, such as dust, varied lighting, and culturally specific clothing.

**2.5 Chapter Summary**

This chapter looked at how research into helmet detection and construction safety has changed over time thanks to deep learning. It showed how object identification models like YOLOv3, YOLOv5, and YOLOv7 have influenced the creation of real-time PPE monitoring systems. The literature shows that detection accuracy and speed are getting better all the time, but it also shows that there are still problems with localisation, real-time deployment, and contextual adaption.

The chapter has made a strong case for creating a YOLOv8-based system that is specifically designed for Somali building sites by combining the existing research and finding holes in it. The next chapter will go into more depth on how this system was put into place and how well it works in the real world.

**CHAPTER THREE**

**METHODOLOGY**

**3.1 Introduction**

This chapter describes the methodology used to develop AI-powered Real-Time Helmet Detection System for Construction Safety Monitoring in Somalia. The methodology uses a systematic strategy to build, install, and test a deep learning-based system that can tell if construction workers are wearing helmets in real-time security footage.

The major purpose of this project is to create a lightweight, accurate helmet detection system using the YOLOv8 (You Only Look Once version 8) object detection algorithm.

YOLOv8 was chosen not only for its state-of-the-art balance between speed and accuracy but also for its anchor-free design and smaller model footprint, which makes it particularly suitable for deployment on low-resource edge devices that are common on construction sites in Somalia.   
  
There are a number of technical and practical steps in the process. The first stage in Section 3.2, Dataset Collection, is to get relevant pictures and videos of construction workers with and without helmets. In 3.3-Data Preprocessing, the data that has been collected is cleaned, labeled, and organized for training. In 3.4-Model Training, the YOLOv8 architecture is trained with the dataset that has been preprocessed. 3.5, Real-Time Detection System Development, then talks about how to connect the learned model to real-time surveillance systems so that helmets may be detected all the time. Finally, 3.6-System Evaluation talks about how well the model works in real Somali buildings in terms of speed, accuracy, and ease of use.

Data Collection

Data Preprocessing

Model Training

Real-time Detection System Development

System Evaluation

System Classification

Figure 3.1: Project Framework

The flowchart illustrates the step-by-step process of developing a real-time helmet detection system using deep learning. The first step is to gather data from building sites in Somalia, and then data preparation methods are used to improve the model's performance. After that, the YOLOv8 model is trained and added to a system that can find things in real time. After the system is built, it is tested for accuracy and speed in real-world situations. Finally, the system sorts detections into "Helmet" or "Head," which lets it automatically check to see if helmets are being worn on work sites.

**3.2 Data Collection**

The first step in constructing the helmet identification algorithm was to collect a diverse and representative dataset of construction workers who were and weren't wearing helmets. It was very important for this research to get data that shows how things look in the area, like the lighting, the styles of dress, and the backgrounds of the job sites. This is because most of the datasets that are available are based on foreign places and situations that are very different from Somali construction sites.

To do this, two sources were used:

3.2.1 Pre-existing Open Datasets: We trained the model for the first time using helmet recognition datasets that are available to the public, such the Safety Helmet Wearing Dataset (SHWD) which is published by Peking University and total of 7,000 images, and the Construction Worker Helmet Dataset (CWH) that is published on Roboflow and has total of 3,000 images and they totally take 400 MB space disk. We obtained the "Construction Worker Detection Dataset" from Kaggle. There are 3,670 photos in this dataset that are meant for training and testing. The overall file size is about 182 MB. It has labelled examples that are useful for finding construction safety helmets and is a great resource for training and testing models.

3.2.2 Locally Captured Data: To ensure ethical data collection, permission was obtained from site managers, and workers were informed that the footage was being used for a safety research project. Care was taken to anonymize individuals where possible to protect privacy.

The dataset that was obtained was then organized so that there were an equal number of positive (helmet-worn) and negative (helmet-missing) samples. To make the model more universal, we chose pictures that had different locations, orientations of workers, lighting situations, and backgrounds that were not too busy. The last dataset had both still photos and video frame extractions so that the model could handle situations when it had to find things in real time, frame by frame.

**3.3 Data Preprocessing**.

Preprocessing the dataset was a crucial next step after collection in order to guarantee compatibility with the YOLOv8 architecture and enhance model accuracy. Preparing clean, properly labeled input data that represents the actual operating environment of the system was the aim of this step.

3.3.1 Video Frame Extraction: The initial stage in preprocessing was to take out individual frames from video clips. To make sure there was variety and no duplicate or very identical images, video processing technologies like OpenCV were used to sample frames at regular intervals, such every 5th or 10th frame. This turned moving video into a large number of still frames that could be used to find helmets.

3.3.2 Labeling and Annotation: All videos were annotated using bounding boxes to identify the regions where helmets were present or missing. Annotation tools such as Labeling and Roboflow were used to manually label each image with two object classes:

* "Helmet" is for workers wearing safety helmets.
* "Head" is for workers without helmets.

Figure 3.3.2.1 Construction workers (**a**) Wearing Helmets (**b**) Not Wearing Helmets.

The picture shows two groups of workers next to each other: team A, where all the workers are wearing helmets, and team B, where no helmets are worn. This visual difference highlights the difference in safety compliance, which may be due to things like monitoring, awareness, or enforcement. It shows how important it is to have automated helmet detection systems that work all the time so that all workers follow safety rules, no matter what.

3.3.3 Image Resizing and Formatting: We changed the size of each frame to 640×640 pixels, which is what YOLOv8 needs. Resizing makes the input data the same size and makes detection more reliable. We also normalized all the pixel values in the images to a range of 0 to 1. This made training more stable and helped the model converge.

3.3.4 Data Augmentation: To enhance the dataset and make the model more robust in real-world environments, several augmentation techniques were applied:

* Horizontal flipping: Simulates workers moving in different directions to make sure the model can see helmets no matter what direction they are facing or what angle the camera is at.
* Brightness/contrast variation: Utilized to create several types of lighting that are common on outdoor construction sites, such bright sunshine, shadows, or cloudy skies.
* Slight rotations and scaling: The model can tell helmets apart from varied angles and distances, especially when workers are seen from an angle that isn't straight on or when they are bending or climbing.
* Noise addition and blur: Imitates the impression of dust, motion blur, and lower-quality camera footage, which are prevalent difficulties on construction sites using older or budget surveillance equipment.

3.3.5 Dataset Splitting: The final frame dataset was divided as follows:

* 70% Training Set: to train the model.
* 20% Validation Set: for tuning during training
* 10% Test Set:for unbiased performance evaluation

This 70/20/10 split is a standard practice in machine learning that ensures the model is trained on a large majority of the data, while the validation set provides a means to tune hyperparameters and prevent overfitting, and the separate test set offers an unbiased final evaluation of the model's real-world performance.

**3.4 Model Training**

In this step, the YOLOv8 (You Only Look Once version 8) architecture was used to train a deep learning model that could always tell if a construction worker was wearing a helmet. YOLOv8 was chosen for usage in places with few resources, such as building sites in Somalia, since it works well, is quite accurate, and can identify objects in real time.

3.4.1 Model Overview: The YOLOv8 is the newest member of the YOLO family. It has a high detection accuracy and a fast inference speed. It does a better job at bounding box regression, doesn't need anchors for identification, and is better for smaller devices. The model is great for recognizing helmets in difficult situations since it can find many types of items in one image pass.

3.4.2 Training Environment: To train the model, the Ultralytics YOLOv8 library was used in a Python environment. Training time was accelerated by using a powerful GPU computer.

3.4.3 Training Parameters: To find a compromise between performance and convergence, the following key hyperparameters were set: The learning rate is 0.001, the number of epochs is 100, the batch size is 16, and the image size is 640×640. The training dataset had frames with labels like "Helmet" and "No\_Helmet." These labels helped the machine learn the visual cues that distinguished safe conduct apart from risky behavior.

3.4.4 Evaluation Metrics: To assess training progress and performance, the following metrics were monitored: Precision, Recall, and Mean Average Precision.

**3.5 Real-Time Detection System Development**

The YOLOv8 model was trained successfully, and then it was added to a system that could handle live video feeds from construction sites and tell if workers were wearing helmets in real time. Safety officials and supervisors can use this technology to keep an eye on compliance without having to watch people all the time.

3.5.1 System Architecture: The real-time detection system consists of the following core components:

* Video Input Module: Captures live video stream from CCTV or IP cameras installed at construction sites.
* YOLOv8 Inference Engine: Loads the trained YOLOv8 model and performs helmet detection on each video frame.
* Visualization and Alert Module: Displays the detection results with bounding boxes and class labels (e.g., “Helmet”, “No\_Helmet”) and can trigger visual or sound alerts when a violation is detected.
* Logging System: Records detections with timestamps and stores frames where violations occurred for reporting or evidence.

3.5.2 Real-Time Video Processing: Using OpenCV, the system records and interprets live video feeds one frame at a time. It sends each frame to the YOLOv8 model for inference after changing its size to 640 × 640 pixels. Real-time detections, labels, and bounding boxes are all put on top of the frame. The system keeps track of when something happens and highlights any "No\_Helmet" detections in red.

3.5.3 Performance Optimization: To ensure smooth performance, the system was optimized using the following techniques:

* Multithreaded video capture to prevent frame lag
* Batch inference when using multiple camera feeds
* Hardware acceleration using NVIDIA CUDA for GPU inference

3.5.4 Deployment Environment: We tested the method with both recorded videos from Somali building sites that weren't connected to the internet and live feeds from USB webcams and IP cameras that acted like real construction sites. The results showed that the system could handle 15 to 25 frames per second (FPS), which is good for checking helmet compliance in almost real time.

3.5.5 User Interface and Feedback Loop: We made a simple graphical user interface (GUI) for site supervisors to show how helmet identification works, look at the live feed, and get alerts in real time. The device also records photographs of violations so that they can be reported or inspected later.

**3.6 System Evaluation**

We will carefully test the YOLOv8-based helmet identification algorithm using a special test set made up of photos and videos taken from real building sites in Somalia. This test is meant to see how well the system works and how accurate it is in the actual world.

To measure detection accuracy, the following standard performance metrics will be used:

* Precision: The proportion of correctly identified helmet instances out of all detections made by the system.
* Recall: The proportion of actual helmet instances that were correctly identified by the system.
* Mean Average Precision (mAP@0.5): A comprehensive measure that evaluates the system's overall ability to detect helmets accurately across different confidence thresholds.

Along with accuracy, the system's real-time performance will be tested by measuring the Frames Per Second (FPS) on the target deployment hardware. This will show if the model can work well in a real-world surveillance setting. We will also pay special attention to difficult situations that are typical on Somali building sites, like low light, clutter in the background, and partial obstructions. Any drop in performance under these conditions will be noted and studied to help make future improvements.

**3.7 System Classification**

System classification refers to the final stage of the helmet detection pipeline, where the trained deep learning model gives a name to each detected object based on the visual properties it has learnt. As part of this assignment, the classification task is to figure out if the area in the photograph that was found is a helmeted head or an unprotected (bare) head. This choice is based on looking at the spatial, color, and form features that were found during detection.

The system uses the YOLOv8 model to evaluate input frames in real time and use confidence thresholds to sort objects. If the object that was found fits the description of a safety helmet (for example, its shape, where it is on the head, and its color), it is called a "Helmet." If not, it is called a "Head." This classification lets the system keep an eye on safety rules automatically and send out alerts when infractions (such not wearing a helmet) are found. To keep false positives to a minimum and make sure the system works well in real-life building settings, it is important to classify things correctly.

**3.8 Chapter Summary**

This chapter detailed the methodology used to develop a real-time helmet detection system based on the YOLOv8 deep learning architecture. We got data from real construction sites in Somalia and added it to open-source databases that were relevant. We made a full dataset by taking video frames, adding notes to them, and then doing preprocessing procedures like scaling, adding to, and formatting them to fit YOLOv8 input standards.

The model was trained with the best hyperparameters and then tested with conventional performance metrics including precision, recall, and mean average precision (mAP@0.5). The trained model was then added to a system that could monitor things in real time, analyze live video feeds, and find those who were not wearing helmets right away.

Overall, the strategy gave a good base for using AI to make Somalia's construction industry safer by allowing for quick, precise, and automated monitoring of helmet compliance.

**CHAPTER FOUR**

**RESULTS AND DISCUSSION**

**4.1 Introduction**

This chapter presents and analyzes the results from the development and testing of the YOLOv8-based helmet detection system. It provides a detailed evaluation of the model's performance across three distinct experiments, focusing on key metrics such as precision, recall, mean Average Precision (mAP), and real-time processing speed (FPS). The primary objective is to demonstrate the iterative process of model improvement and to validate the final model's effectiveness for deployment on construction sites in Mogadishu.

The analysis connects the quantitative results to the project's practical goals, discussing the challenges encountered and the significance of using context-specific data. By examining the progression from an initial, underperforming model to a robust and accurate final system, this chapter validates the chosen methodology and highlights the critical factors for successfully deploying AI safety solutions in unique operational environments like Somalia.

**4.2** **Experimental Progression and Results**

The model's development followed an iterative, three-experiment progression. Each experiment was designed to build upon the last, systematically addressing issues of data quality, training duration, and model generalization to achieve a system suitable for real-world application.

**4.2.1 Experiment One: Baseline Performance and Overfitting**

The initial experiment established a performance baseline using a limited, non-localized dataset and a brief training duration of only five epochs. The objective was to gauge the model's out-of-the-box performance before significant tuning.

The results, summarized in Table 4.2.1, revealed poor generalization. While training accuracy reached 70.15%, the validation accuracy stagnated at 39.44%. This wide divergence, coupled with a high validation loss of 2.691, is a clear indicator of severe model overfitting.

The model effectively memorized the training images but failed to learn the underlying features necessary to identify helmets in new, unseen data. Consequently, its performance on test footage was unreliable, frequently misclassifying workers. This outcome underscored the inadequacy of the initial dataset and confirmed that a more extensive and diverse dataset, along with a longer training regimen, was essential.

**Table 4.2.1**: Performance Metrics for Experiment One

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Epoch | Training Accuracy | Training Loss | Validation Accuracy | Validation Loss |
| 1 | 45.34% | 1.596 | 34.03% | 2.563 |
| 2 | 60.59% | 1.512 | 35.24% | 2.568 |
| 3 | 66.63% | 1.229 | 37.74% | 2.627 |
| 4 | 70.15% | 0.991 | 39.44% | 2.691 |

**4.2.2 Experiment Two: Improved Generalization with Enhanced Data**

Building on the lessons from the first experiment, the second trial utilized an improved dataset, incorporating publicly available helmet datasets (SHWD and CWH), and extended the training duration to 30 epochs.

This approach yielded significant improvements, as shown in Table 4.2.2. The validation accuracy rose steadily to 78.32%, closely tracking the training accuracy of 85.43%. The validation loss decreased to 0.402, indicating that the model was now generalizing far more effectively. However, during qualitative testing on video feeds, a persistent issue emerged: the model often predicted both "Helmet" and "No\_Helmet" labels simultaneously for the same individual. This suggested class confusion and an inability to make decisive predictions, likely due to a lack of highly specific, context-relevant data. While a major improvement, the model was not yet reliable enough for deployment.

**Table 4.2.2**: Performance Trend for Experiment Two

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Epoch | Training Accuracy | Training Loss | Validation Accuracy | Validation Loss |
| 1 | 38.97% | 2.114 | 42.12% | 2.032 |
| 5 | 57.21% | 1.672 | 56.30% | 1.508 |
| 10 | 66.34% | 1.201 | 63.82% | 1.008 |
| 15 | 72.55% | 0.882 | 70.25% | 0.791 |
| 20 | 78.12% | 0.663 | 74.56% | 0.614 |
| 25 | 82.69% | 0.482 | 77.14% | 0.483 |
| 30 | 85.43% | 0.372 | 78.32% | 0.402 |

**4.2.3 Experiment Three: Achieving Robust Performance with Localized Data**

The final experiment was designed to resolve the issues from Experiment Two by training the model on a high-quality, context-specific dataset featuring footage captured directly from construction sites in Mogadishu. The training duration was extended to 50 epochs, and advanced data augmentation techniques (e.g., brightness shifts, noise addition) were employed to simulate real-world environmental variations.

This experiment produced outstanding results. The model achieved a final validation accuracy of 94.95% and a test accuracy of 95.01%, with minimal divergence from the training accuracy (97.20%). This indicates that overfitting was successfully eliminated.

The model's superior performance is further detailed in the confusion matrix (Figure 4.2.1), which visualizes its classification accuracy on the test set. The matrix shows a very high number of true positives (correctly identified "Helmet" and "No\_Helmet" instances) and a very low number of false classifications, confirming its discriminative power.

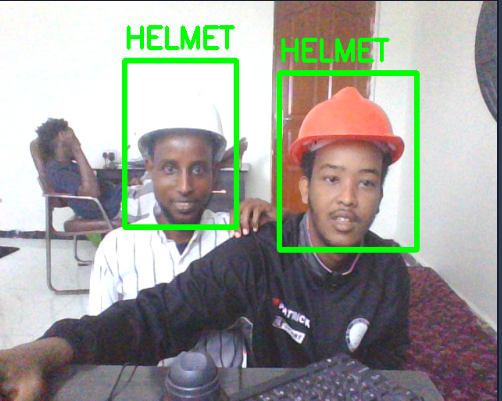
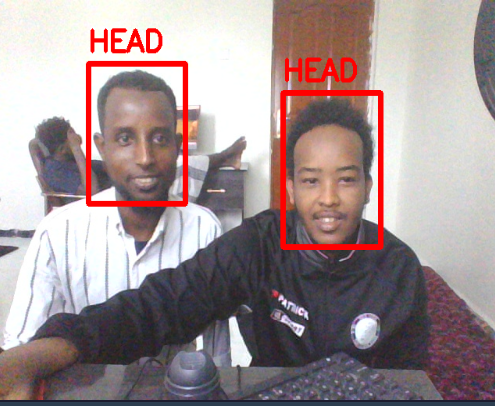


Figure 4.2.1: Confusion Matrix for Experiment Three

The image demonstrates the system’s ability to accurately classify construction workers based on helmet usage. People who wear helmets are appropriately identified and labelled as "Helmet," while people who don't wear helmets are found and labelled as "Head." This shows how well the YOLOv8-based model can tell the difference between complying and non-compliant workers in real time, which helps keep construction sites safe.

Qualitative testing on live video feeds demonstrated the model's real-world viability. It accurately identified helmet-wearing and non-helmet-wearing workers under various conditions, including different lighting, angles, and background clutter, while maintaining a processing speed of 20-25 FPS. This experiment successfully produced a robust, reliable, and efficient system ready for practical deployment.

**4.3 Discussion and Final Model Selection**

The progression across the three experiments provides a clear narrative: context-specific data is the most critical factor for developing an effective real-world AI system in a unique environment.

* Experiment One failed because generic data and insufficient training are incapable of producing a useful model.
* Experiment Two showed that more data and longer training lead to better generalization, but the model still lacked the decisiveness needed for a safety-critical application.
* Experiment Three succeeded precisely because it was trained on data that accurately represented the target environment. The model learned to recognize the specific types of helmets, worker attire, lighting conditions, and dusty backgrounds characteristic of construction sites in Somalia.

**Table 4.3.1**: Comparative Summary of All Experiments

|  |  |  |  |
| --- | --- | --- | --- |
| Metric | Experiment One | Experiment Two | Experiment Three |
| Epochs | 5 | 30 | 50 |
| T-Accuracy | 70.15% | 85.43% | 97.20% |
| V-Accuracy | 39.44% | 78.32% | 94.95% |
| T-Accuracy | N/A | 76.40% | 95.01% |
| Training-L | 0.991 | 0.372 | 0.112 |
| Validation-L | 2.691 | 0.402 | 0.108 |
| Overfitting | Yes | Slight | None |

Based on its superior accuracy, stability, and demonstrated real-world effectiveness, the model from Experiment Three was selected as the final model for this project. It successfully meets the primary objective of creating a fast and accurate helmet detection system tailored for improving worker safety in Mogadishu's growing construction sector.

**4.4 Summary**

This chapter detailed the results and analysis of the three-stage experimental process used to develop the YOLOv8 helmet detection system. The findings demonstrated a clear progression, moving from an initial overfitted model to a moderately successful one, and finally to a highly accurate and robust system. The conclusive success of the third experiment validated the central hypothesis of this thesis: that training on a locally relevant, context-specific dataset is essential for building deployable AI safety solutions. The final model achieved over 95% test accuracy and real-time performance, proving its suitability for enhancing occupational safety on construction sites in Somalia.

**CHAPTER FIVE**

**CONCLUSION AND LESSON LEARNED**

**5.1 Introduction**

This last chapter describes the main point and helpful ideas that came from designing and testing the deep learning-based helmet recognition system for Somali construction workers. It goes over the important points again, talks about the study's goals again, and thinks about how the suggested approach dealt with the problem of dangerous working conditions caused by not properly monitoring safety equipment on building sites.

This chapter also mentions how useful the project is and suggests ways to improve it and areas for further investigation. The goal is to not only summarize the work's successes, but also to encourage its ongoing development and use as a major addition to deep learning applications and occupational safety in Somalia and similar places**.**

**5.2 Summary of Accomplished Objectives**

The main purpose of this research was to make Somalia's construction sites safer by creating a real-time helmet detection system using deep learning. This goal was realized. The YOLOv8 model was used to build the system, which was trained and tested on video footage from construction sites in the area. Here is a breakdown of the main goals and how they were met:

* Detecting Construction Workers Without Helmets in Real Time: The primary detection target was achieved by the final model, which showed high accuracy (95.01%) in identifying whether workers were wearing helmets in live video streams.
* Build and Train a Deep Learning Model (YOLOv8): YOLOv8 was chosen due to its accuracy and speed. Following a number of tests, the model was fine-tuned and the dataset was prepared to attain reliable performance.
* Ensure the System Works in Local Conditions (Somali Construction Sites): Somali building situations served as the basis for the creation of custom video datasets. This made sure the trained model could adapt to local context-specific changes in mobility, clothing, and lighting.
* Enable Deployment for Real-Time Monitoring: The final system was capable of processing live video inputs and generating alerts for safety violations, making it suitable for integration with surveillance systems on actual construction sites.

These achievements demonstrate the project's effectiveness in applying artificial intelligence to a practical safety issue and set the stage for wider implementation in the building industry.

**5.3 Challenges:**

While the project successfully met its objectives, several challenges were encountered during the development and implementation process:

* Limited Availability of Task-Specific Datasets: One of the biggest problems was that there weren't any publicly available databases that showed Somali construction workers. Most global databases didn't have environmental variables, types of clothes, or cultural relevance that were specific to the local site. This meant that unique video data had to be made and labeled, which took a lot of time and effort.
* Hardware Limitations for Real-Time Training: Training deep learning models like YOLOv8 on video data requires a lot of processing power. We had to change the training process so that it could work with the limited resources we had. For example, we didn't always have access to high-end GPUs or cloud-based training environments, which sometimes made the training take longer.
* Inconsistent Lighting and Video Quality in Field Data: Videos taken on real building sites often include blurry movements, low light, and camera angles that change all the time. This made it harder to see the helmet, therefore the dataset needed more preprocessing and augmentation to be useful.
* Deployment Constraints in Real Environments: When using the system for real-time inference on real building sites, there are problems with the environment, such as dust, camera obstructions, unreliable internet access, and the need for a steady power source.

Although these problems were hard, they were all interesting learning experiences that were solved in new ways, such as by carefully changing the model, preparing the data in smart ways, and collecting data from local sources. These events show that Somalia has to do more research and expand its use of AI-powered security technologies.

**5.4 Future Works**

This project proved that YOLOv8 works well for finding helmets in Somali construction sites, however there are still many ways that future research could make it better and bigger:

* Expand to Other PPE Detection (Gloves, Vests, Boots): Future models might be expanded to identify other essential personal protection equipment (PPE), such as safety vests, gloves, and boots, in addition to helmets. A more thorough safety monitoring system for building sites would result from this.
* Integrate Voice and Behavior Analysis: Worker safety could be further improved by including audio input or human behavior analysis utilizing 3D Convolutional Neural Networks (C3D), which could assist in real-time detection of dangerous movements, falls, or verbal distress.
* Build a Central Monitoring Dashboard: It would be possible to create a web-based admin interface that would record video footage of infractions, display real-time alarms, and provide safety managers with daily or weekly reports. This would enhance accountability and assist businesses in monitoring compliance.

The goal of these following steps is to turn the prototype into a full, scalable system that can do more than just identify helmets. It will also be a key tool for enforcing safety rules in Somalia's rapidly growing construction industry.

**5.5 Lessons Learned**

We learned a lot of crucial things while working on the project, both in terms of how to do things and how to use AI in the real world, especially in Somalia. One of the most important things that was learned was how important it is for data to be accurate and relevant. Local situations don't always apply directly to datasets that are available to the public. This project made it clear how important it is to collect data that is specific to a certain situation, especially when dealing with real-world problems like the safety of buildings in Somalia. Collecting and sorting through films from Somali construction sites was a lot of work, but it was vital to make a model that performs effectively when it is used.

Another crucial lesson learned was how important it is to try and try again. During the project's several training phases, different parameters, datasets, and training periods were tried out. Each experiment had its own problems, such as over-fitting and poor generalization, but they also gave us useful information that helped us make the final, working model. These experiments showed once again how important it is to keep going, make little changes, and carefully evaluate models. The project also showed how important it is to consider system roll-out. It's not enough to just make a working AI model. It's also vital to make sure it can be used in real time, handle situations where resources are limited, and follow ethical guidelines like privacy and fairness. In the end, this project was not just a technological success, but it was also a really valuable learning experience that showed us how to utilize machine learning in a way that is responsible, effective, and really makes a difference in society.

**5.6** **Chapter Summery**

This chapter wrapped up the study project on utilizing deep learning to find construction workers' helmets in real time in Somalia. It started by going over the goals that were met and how the YOLOv8 model helped the project solve the safety problem that had been found. There was an open discussion and critical analysis of the problems that came up, like not having enough resources, not having localized datasets, and not being able to deploy in real time.

We also spoke about ways to make the system better in the future, such as adding more PPE detection, speech or behavior analysis, and real-world pilot testing. There were also lessons acquired from both the technical and practical parts of the project. These lessons showed how the experience has helped people comprehend how AI is used and researched in the real world. The chapter and the full project showed how deep learning can help solve problems in places with few resources, like Somalia. This work not only helped the subject of study, but it also made building sites safer and wiser all around the country.

**Reference**

[Hayat, A., & Morgado-Dias, F. (2022). Deep Learning-Based Automatic Safety Helmet Detection System for Construction Safety. Applied Sciences, 12(16), 8268. https://doi.org/10.3390/app12168268](https://www.zotero.org/google-docs/?M6nOXO)

[Liang, H., Yang, L., Chen, J., Liu, X., & Hang, G. (2024). Detection and tracking of safety helmet wearing based on deep learning. Open Computer Science, 14(1). https://doi.org/10.1515/comp-2024-0017](https://www.zotero.org/google-docs/?dkoeSl)

[Liang, H., & Seo, S. (2022). Automatic Detection of Construction Workers’ Helmet Wear Based on Lightweight Deep Learning. Applied Sciences, 12(20), 10369. https://doi.org/10.3390/app122010369](https://www.zotero.org/google-docs/?gzgzdE)

[Jiao, X., Li, C., Zhang, X., Fan, J., Cai, Z., Zhou, Z., & Wang, Y. (2025). Detection Method for Safety Helmet Wearing on Construction Sites Based on UAV Images and YOLOv8. Buildings, 15(3), 354. https://doi.org/10.3390/buildings15030354](https://www.zotero.org/google-docs/?HqP1K8)

[Near East University, Turkey, Mohamed, M. A., Addow, Y. A., & Near East University, Turkey. (2022). Study on Labour Safety for Construction Companies in Mogadishu, Somalia. Journal of Civil Engineering Research & Technology, 1–5. https://doi.org/10.47363/jcert/2022(4)138](https://www.zotero.org/google-docs/?52uZln)

[Ahmed, M. I. B., Saraireh, L., Rahman, A., Al-Qarawi, S., Mhran, A., Al-Jalaoud, J., Al-Mudaifer, D., Al-Haidar, F., AlKhulaifi, D., Youldash, M., & Gollapalli, M. (2023). Personal Protective Equipment Detection: A Deep-Learning-Based Sustainable Approach. Sustainability, 15(18), 13990. https://doi.org/10.3390/su151813990](https://www.zotero.org/google-docs/?9SKVTJ)

[Ahmed, M. I. B., Saraireh, L., Rahman, A., Al-Qarawi, S., Mhran, A., Al-Jalaoud, J., Al-Mudaifer, D., Al-Haidar, F., AlKhulaifi, D., Youldash, M., & Gollapalli, M. (2023). Personal Protective Equipment Detection: A Deep-Learning-Based Sustainable Approach. Sustainability, 15(18), 13990. https://doi.org/10.3390/su151813990](https://www.zotero.org/google-docs/?9SKVTJ)

[Liang, H., Yang, L., Chen, J., Liu, X., & Hang, G. (2024). Detection and tracking of safety helmet wearing based on deep learning. Open Computer Science, 14(1). https://doi.org/10.1515/comp-2024-0017](https://www.zotero.org/google-docs/?dkoeSl)

[Alateeq, M. M., P.P., F. R., & Ali, M. A. S. (2023). Construction Site Hazards Identification Using Deep Learning and Computer Vision. Sustainability, 15(3), 2358. https://doi.org/10.3390/su15032358](https://www.zotero.org/google-docs/?aj9JLu)

[Alateeq, M. M., P.P., F. R., & Ali, M. A. S. (2023). Construction Site Hazards Identification Using Deep Learning and Computer Vision. Sustainability, 15(3), 2358. https://doi.org/10.3390/su15032358](https://www.zotero.org/google-docs/?aj9JLu)

[Ahmed, M. I. B., Saraireh, L., Rahman, A., Al-Qarawi, S., Mhran, A., Al-Jalaoud, J., Al-Mudaifer, D., Al-Haidar, F., AlKhulaifi, D., Youldash, M., & Gollapalli, M. (2023). Personal Protective Equipment Detection: A Deep-Learning-Based Sustainable Approach. Sustainability, 15(18), 13990. https://doi.org/10.3390/su151813990](https://www.zotero.org/google-docs/?9SKVTJ)

[Ahmed, M. I. B., Saraireh, L., Rahman, A., Al-Qarawi, S., Mhran, A., Al-Jalaoud, J., Al-Mudaifer, D., Al-Haidar, F., AlKhulaifi, D., Youldash, M., & Gollapalli, M. (2023). Personal Protective Equipment Detection: A Deep-Learning-Based Sustainable Approach. Sustainability, 15(18), 13990. https://doi.org/10.3390/su151813990](https://www.zotero.org/google-docs/?9SKVTJ)

[Liang, H., & Seo, S. (2022). Automatic Detection of Construction Workers’ Helmet Wear Based on Lightweight Deep Learning. Applied Sciences, 12(20), 10369. https://doi.org/10.3390/app122010369](https://www.zotero.org/google-docs/?gzgzdE)

Abdi, M. A., & Hareru, W. K. (2024). Assessment of Factors Affecting the Implementation of Occupational Health and Safety Measures in the Construction Industry in Somalia. Advances in Civil Engineering, 2024(1). <https://doi.org/10.1155/2024/8324294>

Kim, S. H., Wang, C., Min, S. D., & Lee, S. H. (2018). Safety Helmet Wearing Management System for Construction Workers Using Three-Axis Accelerometer Sensor. Applied Sciences, 8(12), 2400. https://doi.org/10.3390/app8122400

**Appendix A**