# Current Status and Future Direction of Deep Learning Applications for Safety Management in Construction

Department OF Civil Engineering

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# Current Status and Future Direction of Deep Learning Applications for Safety Management in Construction


**SUBMITTED BY**

| | |
|---|---|
| Mehboob (Team Leader) | 19CE31 |
| Sabir Ali | 19CE45 |
| Kabir Ahmed | 19CE27 |
| Abrak Khan | 19CE26 |
| Abdul Saboor | 19CE72 |

**Batch 2019-20**

**SUPERVISOR**

**ENGR. SYED ABDULLAH SHAH**

**Lecturer Civil Engineering Department**

**CERTIFICATE**

| **Name.** | **Roll No**. |
|---|---|
| 1.MEHBOOB(LEADER) | 19CE31 |
| 2. SABIR ALI | 19CE45 |
| 3.KABIR AHMED | 19CE27 |
| 4.ABDUL SABOOR | 19CE26 |
| 5.ABRAK KHAN | 19CE72 |

**This project is submitted in the partial fulfillment of the requirement for the award of Degree of "Bachelor of Engineering" in Civil Engineering.**

**Project Supervisor** **Head of department**

**Date: _____________**

# DEDICATION

*Dedicated to our exceptional parents and adored siblings whose tremendous support and cooperation led us to this wonderful accomplishment.*

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Firstly, we are very grateful to the Almighty ALLAH for giving us the courage and opportunity to undertake our Final Year Project on an emerging Technology.

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# ABSTRACT

Deep learning applications in construction industry reduced the risk of safety significantly in a decade. Though out the world manual supervision of construction workers unsafe behaviors proved to be costly and time consuming as compare to the automatic supervision models , the deep learning specially in detections of constructions workers safety helmet at the site. Global research and local initiatives show growing interest in using Deep Learning for construction safety in Pakistan. This project has the aim and objectives to do comprehensive literature review of deep learning applications in construction safety management to development of mobilenetv2 (CNN model) model for safety helmet detections and significant future directions to use it for automatic detections of safety helmets of workers. To achieve the targets, a comprehensive review of existing literature on deep learning resulted in data collection to model selection and the training to achieve the proposed end results with a training and validation accuracy 92.7% and 97%. The model proved to be effective in future implementation for safety helmet detection in construction site. For real time supervision the model indicated to be effective with a diverse dataset training and has got the potential to show required results. This suggests the importance of deep learning applications for smart works in construction safety management.

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# CHAPTER No. 1. INTRODUCTION

## 1.1. Introduction To the Construction Industry and Its Importance

Global economic developments and expansions are significantly influenced by the building sector. It includes a broad range of tasks connected to the conception, arrangement, construction, and upkeep of physical structures, such as buildings, infrastructure, and transportation systems. The following are some major ideas emphasizing the building sector's significance:

- **Economic Impact**: An important factor in a nation's economy is the building sector. It produces employment, boosts economic expansion, and opens doors for a number of associated businesses, including manufacturing, transportation, and services.
- **Job Creation:** Construction projects require a diverse workforce, including architects, engineers, construction workers, project managers, and various skilled tradespeople. This sector provides employment to millions of people globally, both directly and indirectly.
- **Infrastructure Development:** Infrastructure development and maintenance, including roads, bridges, airports, railroads, and utilities, depend on construction. These infrastructure components are essential to the growth and operation of societies.
- **Commercial and Industrial Facilities**: Building projects for the commercial and industrial sectors provide places for manufacturing, trade, and businesses.
- **Transportation:** Building transportation networks—such as public transportation routes, highways, airports, and roads—is necessary to facilitate the movement of people and goods, which is critical to economic activity.
- **Technological Advancements:** Technological innovations that enhance productivity, safety, and sustainability in building projects—like Building Information Modeling (BIM), 3D printing, and automation—continue to be advantageous to the construction sector.

## 1.2. Background And Significance

More people than ever before are concerned about construction site safety as a result of the growing need for infrastructure due to urbanization. By wearing personal protective equipment, many accidents can be avoided (PPE)[1].However, due to discomfort and a lack of awareness of safety, wearing a safety helmet is often disregarded. Therefore, it is essential for their safety and can raise the bar for safety management to check that employees are wearing their safety helmets correctly. Conventional helmet-wearing inspections on construction sites primarily involve manned patrols and monitoring images. The latter is labour-intensive and time-consuming, and because inspectors using a manual monitor must stare at the screen for extended periods of time, fatigue may lead to errors in judgment. Because of this, new technologies based on deep learning analysis techniques to identify whether workers are wearing safety helmets on construction sites are emerging quickly [2]. With excellent and amazing result along with of deep learning applications regarding safety management in construction. this research will definitely benefit the construction industry to monitor the unsafe behaviour of workers not wearing safety helmet more easily and more accurately and help to reduce the head injuries in a great amount.

## 1.3. Problem Statement: Safety Challenges in Construction Industry

Construction is a high-risk industry where accidents happen frequently to the workers. Severe head injuries frequently result in death. The state administration of work safety released accident statistics from 2015 to 2018, and 53 of the 78 construction accidents that were reported occurred as a result of workers failing to properly wear safety helmets, or 67.95% of the total number of accidents [3]. In addition to incidents involving safety helmets, some other important categories of mishaps and injuries at construction sites are as follows:

- **Work site Hazards:** Construction sites present numerous potential hazards, such as moving vehicles, electrical equipment, heights, and heavy machinery, all of which raise the possibility of mishaps and injuries.
- **Fall Hazards:** Falling from elevated surfaces, like ladders, scaffolding, and roofs, is a major source of construction-related fatalities. Adequate fall protection protocols are imperative.

- **Struck-by Accidents:** There is a chance that on-site automobiles, construction machinery, or falling objects will strike workers. By putting in place safety barriers and wearing the proper personal protective equipment (PPE), these risks can be reduced.
- **Electrical Hazards:** Faulty equipment, contact with live wires, and insufficient electrical safety precautions can all lead to electrical accidents. Training and routine inspections are crucial.
- **Trench and Excavation Hazards:** There are serious risks for construction workers from cave-ins and trench collapses. To avoid mishaps, trench box systems, sloping, and proper shoring must be implemented.
- **Hazardous Materials:** Working with hazardous materials like asbestos, lead, or chemicals is a common part of the construction industry. In order to avoid exposure and contamination, proper handling, storage, and disposal is essential.
- **Equipment Operation:** Accidents can occur when large machinery and equipment are used improperly. Sufficient maintenance, safety procedures, and training is essential.
- **Fatigue and Stress:** Physically taxing jobs and lengthy workdays can cause worker fatigue, which raises the risk of accidents. Employers need to encourage getting enough sleep and give breaks.
- **Communication:** To ensure that everyone is aware of potential hazards and to coordinate activities, effective communication between workers, contractors, and subcontractors is essential.
- **Weather Conditions:** Since construction is frequently done outside, inclement weather can compromise safety. It's essential to plan ahead and take safety measures, like dealing with slick surfaces or extremely hot or cold temperatures.
- **Mental Health:** The construction business can be mentally and physically taxing. For the safety and well-being of employees, it is imperative to address stress, substance abuse, and mental health disorders.

Monitoring the state in which construction workers are donning their safety protective equipment is crucial to safety management at the site. Wearing a safety helmet can lessen the impact of falling objects and the harm caused by employees falling from heights. Due to a lack of safety awareness, construction workers frequently disregard safety helmets. Workers who incorrectly wear safety helmets at construction sites have a significantly higher risk of injury. Manual labor is frequently required for traditional safety helmet worker supervision on construction sites [4]. Issues include a broad range of operations and challenging site worker management. These elements make manual supervision challenging and ineffective, and they make it challenging to precisely track and manage every worker at construction sites in real time [5]. Therefore, using traditional manual supervision alone to meet the modern requirements of construction safety management is challenging. Under these circumstances, research on the automatic identification and detection of safety helmet wearing conditions is still very important. In this work, we develop a deep learning-based model for the construction site safety helmet detection, building on earlier research on deep learning-based object detection.

## 1.4. Aim and Objectives

The of the project is to carry out a thorough analysis of deep learning applications' present state and potential future directions in order to improve safety management in the construction sector.

**Objectives of the study:**

1. To explore the applications of deep learning applications for safety management in construction.
2. To develop a deep learning model for predicting accidents related to safety helmets at the construction sites.
3. To propose future directions for research and development of deep learning for safety management in construction.

## 1.5. Scope of the Research

Scope of the project includes:

- Conduct a systematic literature review of deep learning applications for safety management in construction, with a focus on safety helmets.
- Develop a deep learning model for safety helmet detection and classification.
- Evaluate the performance of the developed model on a real-world construction dataset.

- Conduct a user study to assess the usability and feasibility of the developed model in real-world construction settings.
- Develop recommendations for the future development and deployment of deep learning models for safety management in construction.

# CHAPTER No. 2. LITERATURE REVIEW

## 2.1. Overview of Construction Safety Management

The process of identifying, evaluating, and controlling hazards on construction sites is known as construction safety management. It is an organized method of lowering the possibility of mishaps and injuries. Generally speaking, construction safety management includes the following actions:

- **Hazard identification**: This entails locating every possible risk on the construction site, including falling objects, electrical hazards, and unguarded machinery.
- **Risk assessment**: This entails determining each hazard's likelihood and severity.
- **Hazard control**: This entails putting safety precautions in place to manage the risks, like locking down or tagging out electrical equipment, employing helmet detect, fall protection gear, and machinery guards.
- **Employee training**: This entails educating staff members about safety protocols and how to recognize and report risks[6]

### 2.1.1. Deep Learning for Safety Helmet Detection

Construction sites are known for serious incidents involving head injuries. These incidents are caused by workers disregarding safety precautions, such as wearing safety helmets. Traditionally, manual labor has been required to supervise workers wearing safety helmets on construction sites [6]. It is challenging to satisfy the current requirements of construction safety management because of the shortcomings of conventional manual supervision. Studying the automatic detection and recognition of safety helmet wearing conditions is crucial as a result. Convolutional neural network-based approaches have become the new standard for object detection algorithms due to the rapid advancement of deep learning technology. These approaches offer notable improvements in speed and accuracy.

The techniques build convolutional neural networks with varying depths to detect safety helmets, and they incorporate additional techniques like multiscale training, adding more anchors, and introducing online hard example mining to enhance detection accuracy.

### 2.1.2. Advantages Of Deep Learning-Based Safety Helmet Detection Method

Methods for detecting safety helmets based on deep learning have a number of advantages over conventional techniques:

- **Accuracy**: Even in difficult circumstances, deep learning models are capable of detecting safety helmets with a high degree of accuracy.
- **Robustness**: Compared to traditional methods, deep learning models exhibit greater resilience to variations in lighting and other environmental factors.
- **Scalability**: It is possible to scale up deep learning models to detect safety helmets in real time, even on sizable construction sites.

### 2.1.3. Challenges Of Using Deep Learning for Safety Helmet Detection

The application of deep learning to safety helmet detection is fraught with difficulties.

- **Need for large amounts of training data:** To be effective, deep learning models need a lot of training data. This data can be difficult and expensive to collect.
- **Need to develop robust models**: Because lighting, backgrounds, and other factors can vary greatly in real-world settings, deep learning models must be resilient enough to function there.

## 2.2. Key Safety Challenges in Construction Industry

**Unsafe Behaviours**

Unsafe behavior is one of the main obstacles to helmet safety in the construction sector. This may involve employees donning their helmets improperly or not at all. Employees may act in an unsafe manner for a variety of reasons, such as:

- **Lack Of Training**: It's possible that workers are not adequately instructed on the significance of donning safety helmets or the correct way to do so.

- **Negligence:** Sometimes workers just forget to put on their helmets because they're in a rush or don't think they're necessary. Pressure to finish the job quickly: Employees may experience pressure from managers or co-workers to finish the job quickly, even if it means forgoing safety precautions like donning a helmet.
- **Poor helmet quality:** Poor quality helmets pose another challenge to helmet safety. Certain safety helmets might not be constructed correctly or be made of subpar materials. They may therefore be less successful in preventing head injuries among employees.
- **Improper helmet Fit:** For safety helmets to work effectively, the fit must be correct. Oversized or undersized helmets have the potential to come off during an accident, leaving the worker unprotected.
- **Damage To helmet: Over** time, damage to safety helmets may occur, potentially decreasing their effectiveness. It's critical to routinely check helmets for damage and replace them as needed.

## 2.3. Current State-of-The-Art Deep Learning Models and Techniques for Safety Management

As of right now, the most advanced deep learning models and safety management techniques can accurately identify, categorize, and forecast dangerous behaviors and situations in real time. By giving businesses the means to proactively prevent mishaps and injuries, this could completely transform safety management. The following are a few of the most intriguing deep learning models and methods for safety management:

- **Object detection models:** One of the most promising deep learning models for safety helmet detection is object detection. Safety helmets can be identified in photos and videos by these models, even in difficult situations like dim lighting and occlusion. Say Faster R-CNN: A real-time object detection algorithm that is more accurate but operates more slowly that can identify safety helmets. and YOLOv5s: A quick, light-weight object detection algorithm that has demonstrated excellent accuracy in identifying safety helmets.

- **Predictive analytics models:** Based on past behavior and other factors, predictive analytics models can be utilized to forecast the likelihood of a worker not donning a safety helmet. Workers who are most likely to forget to wear a safety helmet can be the focus of safety interventions using this information. For example, a deep learning-based predictive safety analytics framework can identify specific workers, identify when a worker is likely to wear a safety helmet, and predict the likelihood that a worker will not wear a safety helmet.
- **Activity Recognition Mode:** One kind of deep learning model that can be used to identify and categorize human activities from pictures and videos is the activity recognition model. Large datasets of video clips labelled with various activities, like walking, running, sitting, and standing, can be used to train these models. These models can be used in real-time systems to identify and categorize human activities as they happen once they have been tr**aine**d[7].
- **Anomaly Detection Model:** One kind of deep learning model that can be used to find unusual patterns in data is an anomaly detection model. Large datasets of typical data are used to train these models, which enable them to recognize patterns that differ from the norm. These models can be used in real-time systems to identify anomalies in data as they happen once they have been trained[8].

All things considered deep learning could completely transform safety management. DL models can be used to better understand and prevent risks, create individualized safety education plans, and increase the efficiency of safety inspections. The application of DL to safety management is still fraught with difficulties, though, including the requirement for vast volumes of data and specialized knowledge.

Here are some examples of how state-of-the-art deep learning models and techniques are being used for safety management in different industries:

- **Construction**: DL models are being utilized to identify hazardous behaviors and circumstances on building sites, forecast the probability of mishaps, and create innovative safety protocols and instruments.

- **Manufacturing**: DL models are employed to recognize potential safety risks in manufacturing facilities, forecast the probability of mishaps, and create customized safety education initiatives for employees.
- **Healthcare**: Hospitals and other healthcare settings are using DL models to identify safety hazards, forecast the possibility of patient safety incidents, and create new safety management tools and protocols.

## 2.4. Applications of Deep Learning in construction safety

Deep learning has seen remarkable development in the field of construction industry related to safety tasks. Following is the table of common applications of deep learning in construction safety.

| S. no | Applications | Reference | | | | | | | | | | | | | | | Frequency |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | [9] | [10] | [16] | [11] | [12] | [13] | [14] | [15] | [16] | [17] | [18] | [19] | [20] | [7] | [21] | |
| 1 | Safety helmet | ✔ | | | | | | ✔ | | ✔ | ✔ | | | | | | 04 |
| 2 | Fall from height | | ✔ | ✔ | | | | | | | | | | | | | 02 |
| 3 | Man equipment accidents | | | | | | | | | | | | ✔ | | ✔ | | 02 |
| 4 | Other accident | | | | ✔ | ✔ | | | | | | | | ✔ | | ✔ | 04 |
| 5 | Crack detection | | | | | | ✔ | | ✔ | | | ✔ | | | | | 03 |

## 2.5. Gap Analysis: Identifying Areas Where Deep Learning Can Make a Difference

### Deep Learning Models for safety Helmet Detection

Applications deep learning models in safety helmet detection have several advantages which includes:

**Accuracy**: When it comes to helmet detection, deep learning models can outperform conventional techniques, particularly in intricate scenes with significant occlusion, fluctuating light levels, and small targets. This is so that deep learning models—which can recognize helmets even in challenging lighting conditions or with partial obscurity—can better comprehend the context of an image by learning intricate relationships between data.

**Speed:** Deep learning models are significantly faster than conventional techniques for helmet detection because they can process images in parallel. This holds significance for helmet detection applications that necessitate real-time detection, like those found in factories and construction sites.

**Robustness**: Helmet detection can be trained in deep learning models under a range of lighting and occlusion scenarios. This is so that even in dimly lit or partially obscured environments, deep learning models can recognize helmets thanks to their ability to learn the fundamental characteristics of the helmet.

**Scalability**: Deep learning models can be trained using datasets from various factories and construction sites. This enables the development of helmet detection systems that can be applied to a variety of settings. This holds significance for applications requiring helmet detection to be implemented in diverse environments.

**Adaptability**: Deep learning models are flexible enough to adjust to new circumstances. To enhance its performance in a particular setting, a deep learning model for helmet detection, for instance, can be retrained using fresh data. For helmet detection applications, where the environment may change over time, this is crucial.

**Gap analysis:**

Despite the advantages of deep learning for helmet detection, there are still some gaps that need to be addressed. Following are some of the gaps which are still needed to be researched for more opportunities.

- Current models are not able to detect safety helmets in all conditions: The inability of the current models to identify safety helmets in difficult situations, like dim lighting or occlusion, indicates a need for improvement. Un et al. discovered that under difficult circumstances, like dim lighting and occlusion, existing deep learning models struggle to identify safety helmets. Using a dataset of more than 10,000 photos of workers on construction sites, the authors tested their proposed model and discovered that, under typical circumstances, the model identified workers wearing safety helmets with 98.1% accuracy. However, under dim lighting and in occlusion, the accuracy of the model decreased to 95.2% and 93.1%, respectively[22].
- Current models are not able to detect all types of safety helmets. In their review of several deep learning models for hard hat detection, Yang et al discovered that the models in use today struggle to identify all kinds of hard hats. For instance, hard hats worn at an angle or with partial obscuration may go undetected by current models[23].
- To create safety helmet detection systems that are more precise and effective, these gaps must be filled. To close these gaps, researchers are creating new deep learning models and algorithms. For instance, scientists are working on models that can identify a greater range of safety helmets and are more resilient to harsh environments. These models will also be more economical to compute.

# CHAPTER No. 3.
# METHODOLOGY

## 3.1. Introduction

The introduction to the research methodology chapter sets the stage for investigating the current status and future directions of deep learning for safety management in construction. This chapter outlines the systematic approach employed to explore the existing landscape of deep learning applications in the construction industry. Through a comprehensive literature review, relevant research papers, and academic resources are surveyed to understand the advancements and limitations of current safety management techniques. The methodology also encompasses the identification and evaluation of key deep learning models utilized in safety helmet detection. By employing a rigorous and systematic research methodology, this study aims to contribute insights that pave the way for future developments and recommendations in enhancing safety protocols within the construction domain.

## 3.2. Research Design

The research design for the project adopts a mixed-methods approach, commencing with a comprehensive literature review to understand the current state of deep learning applications in construction safety. Quantitative analysis assesses the performance of existing safety helmet detection models, considering factors such as accuracy and adaptability. Additionally, qualitative insights are gathered through expert interviews within the construction safety domain to understand practical challenges. This balanced approach aims to provide a comprehensive perspective on the current status of deep learning in construction safety and inform future directions for enhanced safety protocols.

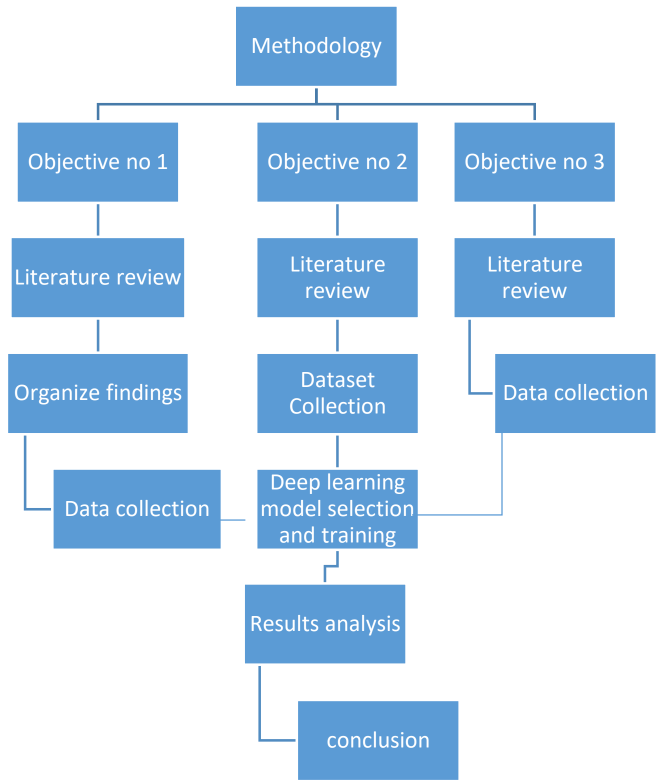


Figure 1 Research Design

## 3.3. Data Collection

The purpose of the data gathering process was to conduct a thorough examination of the literature in order to comprehend the state of deep learning today and its potential future consequences. To create the model, we need a dataset consisting of at least 1000 photographs of two groups of people: those wearing helmets and those who did not. We used available sources, such as Kaggle (an open-source website dataset of various model training), to fulfill this requirement.

## 3.4. Deep Learning Model Selection

A deep learning system is made up of several neural networks, each of which is an expert in a different topic. While some have the ability to extract features from images and forecast outcomes for real-time work, others are utilized to extract data from text and predict results. For safety helmet recognition, we choose the deep learning model **MobileNetV2**.

## 3.5. Object Detection Model

For mobile and embedded vision applications, MobileNetV2 is a convolutional neural network architecture that is both lightweight and effective. It is regarded for striking a balance between efficiency and accuracy and is an expansion of the original MobileNet architecture.

The picture classification model in the code is based on the MobileNetV2 feature extractor. The model comprises more layers, like Flatten, Dense, Dropout, and a final Dense layer for classification, after the feature extraction.

### 3.5.1. Architecture of MOBILENETV2 Model

Following is the complete architecture of the model with table and explanation:

| Layer Type | Output Shape | Parameter# |
|---|---|---|
| Keras-layer(KerasLayer) | (None, 1280) | 2257984 |
| Flatten (Flatten) | (None, 1280) | 0 |
| Dense (Dense) | (None, 512) | 655872 |
| Drop (Dropout) | (None, 512) | 0 |
| Dense-1 (Dense) | (None, num-classes) | 5133 |

Total params: 2,918,989

Trainable params:2,918,989

Non-trainable params:0

**Feature Extractor:**

The model utilises a pre-trained MobileNetV2 module obtained from TensorFlow Hub, with the module handle referred to as MODULE_HANDLE. The primary function of this layer is to extract significant features from the input images. This approach utilizes transfer learning, where a pre-trained model is employed as a feature extractor, and supplementary layers are appended for the purpose of categorization.

```
module selection = ("mobilenet_v2", 224, 1280)
handle_base, pixels, FV_SIZE = module_selection
```

```
MODULE_HANDLE ="https://tfhub.dev/google/tf2-preview/{}/feature_vector/2".format(handle_base)
IMAGE_SIZE = (pixels, pixels)
BATCH_SIZE = 32
```

**Flatten Layer:**

The purpose of this layer is to transform the output of the feature extractor, which is in a multi-dimensional format, into a one-dimensional format. Prior to transmitting the characteristics to the completely connected layers, this stage is crucial.

**Dense Layer (Fully Connected Layer):**

Following the flatten layer, a dense layer with 512 units and ReLU activation is included, connecting all units together. This layer incorporates non-linear elements into the model.

**Dropout Layer:**

Dropout is implemented with a dropout rate of 0.2. Dropout is a regularization method that introduces randomness by setting a portion of input units to zero throughout the training process. To mitigate overfitting, it diminishes the model's dependence on particular inputs.

**Final Dense Layer:**

The ultimate dense layer produces the probability of categorization for each category in the dataset. The quantity of units in this layer is determined by the value of train_generator.num_classes, which signifies the total number of classes contained in your dataset. The employed activation function is softmax, which does the normalization of the output probabilities.

**Model Compilation:**

The model is constructed with the Adam optimizer, employing a defined learning rate (LEARNING_RATE). The loss function employed is categorical crossentropy, and accuracy is selected as the assessment parameter throughout the training process.

**Data Augmentation:**

```
train_datagen = tf.keras.preprocessing.image.ImageDataGenerator(
      rescale = 1./255,
      rotation_range=40,
      horizontal_flip=True,
      width_shift_range=0.2,
      height_shift_range=0.2,
      shear_range=0.2,
      zoom_range=0.2,
      fill_mode='nearest',
      validation_split=0.15)
```

**Training:**

The model is trained by utilizing the fit approach, which involves passing the training and validation data generators. The number of epochs is defined as 12 (EPOCHS), and the training progress is recorded in the history object.

```
train_generator = train_datagen.flow_from_directory(
    train_dir,
    subset="training",
    shuffle=True,
    seed=42,
    color_mode="rgb",
    class_mode="categorical",
    target_size=IMAGE_SIZE,
    batch_size=BATCH_SIZE)
```

**Training Visualization:** Finally, training and validation accuracy and loss are visualized using matplotlib.

# CHAPTER No. 4. SUSTAINABLE DEVELOPMENT GOALS

## 4.1. What Are Sustainable Development Goals?

The Sustainable Development Goals (SDGs) are a set of 17 global targets that were unanimously adopted by all United Nations member states in 2015, as part of the 2030 Agenda for Sustainable Development. The SDGs cover a wide range of interconnected issues, including poverty, malnutrition, healthcare, education, gender equality, access to clean water, sanitation, affordable and renewable energy, economic development, industrial advancement, reduced inequalities, sustainable urban areas and communities, and more. Below is a comprehensive compilation of the 17 Sustainable Development Goals.:

- • **Goal 1: No Poverty**: The objective is to eliminate poverty globally, creating a world where extreme economic hardship does not exist.
- • **Goal 2: Zero Hunger:** The aim is to achieve a world without hunger, guaranteeing that everyone has access to an adequate and nourishing food supply**.**
- **Goal 3:** aims to enhance the health and well-being of individuals by prioritizing illness prevention, ensuring access to healthcare, and providing comprehensive health services.
- **Goal 4:** is to guarantee universal access to inclusive and high-quality education, promoting continuous learning opportunities and the acquisition of skills.
- **• Goal 5: Gender Equality:** Advocating for gender equality, empowering women, and guaranteeing equal opportunities for both genders in every sphere of life
- **Goal 6**: Clean Water and Sanitation: Ensuring that everyone has access to clean water and sanitation, and encouraging sustainable techniques for managing water.
- **Goal 7:** aims to enhance the availability of cost-effective and environmentally friendly energy sources in order to support sustainable development. Goal
- **8: Decent Work and Economic Growth:** Promoting continuous, comprehensive economic expansion, complete workforce participation, and satisfactory employment opportunities for all individuals.

- **Goal 9: Industry, Innovation and Infrastructure**: Promoting economic advancement through fostering innovation, constructing robust infrastructure, and encouraging sustainable industrialization.
- **Goal 10: Required Inequalities: Striving to diminish disparities both within and across nations in order to guarantee equitable opportunities and results for every individual.**
- **Goal 11: Sustainable Cities and Communities:** Creating sustainable, inclusive, and resilient cities and communities that prioritize environmental conservation and human well-being.
- **Goal 12: Responsible Consumption and Production:** Encouraging sustainable consumption and production patterns to minimize environmental impact and promote responsible resource use.
- **Goal 13: Climate Action:** Taking urgent action to combat climate change and its impacts, fostering global collaboration for a sustainable and resilient future.
- **Goal 14: Life Below Water:** Con-serving and sustainably using marine resources to protect life below water, addressing threats to ocean ecosystems
- **Goal 15: Life on Land:** Protecting, restoring, and promoting sustainable use of terrestrial ecosystems, ensuring biodiversity and combating desertification.
- **Goal 16: Place, Justice and Strong Institution:** Promoting peaceful and inclusive societies, ensuring access to justice, and building strong institutions for effective governance and rule of law.

These goals are interconnected, recognizing that actions performed in one area will affect outcomes in other areas. The specified timescale for achieving the Sustainable Development Goals (SDGs) is 2030. It is strongly encouraged for all institutions, such as governments, corporations, civil society, and individuals, to actively contribute to achieving these goals by participating in cooperative efforts and adopting sustainable practices.

My research project, "Current Status and Future Direction of Deep Learning Applications for Safety Management in Construction," aims to explore the use of deep learning methods to safety management in the construction industry. Furthermore, you have developed an advanced deep learning model that is intended to predict events related to safety helmet use on construction sites. Let's choose two or three Sustainable Development Goals (SDGs) that closely align with your project so that we can draw a connection between the two.

1. **Goal 3: Achieving Optimal Health and Well-being:**
   Our program, which focuses on the health and wellbeing of construction workers, directly supports Goal 3. Construction sites frequently experience accidents using safety helmets, which is a serious problem that your deep learning system is intended to predict and lessen. By employing technology innovations to enhance safety protocols, you are proactively working to ensure the health and welfare of construction industry workers**.**
2. **Goal 8 focuses on promoting decent work opportunities and fostering economic growth.**
   Goal 8 is to achieve long-lasting, comprehensive, and environmentally-friendly economic expansion, as well as assuring adequate and meaningful employment opportunities for everyone. Your project is in accordance with this purpose as it focuses on boosting safety in the workplace, notably within the construction sector. Utilizing your deep learning model to implement efficient safety management boosts the provision of satisfactory and secure working conditions. Consequently, this contributes in promoting the overarching purpose of fostering economic progress while ensuring the welfare of employees
3. **Goal 9 focuses on the development of industry, innovation, and infrastructure.**
   Goal 9 emphasizes the significance of building a strong infrastructure, encouraging fair and sustainable industrialization, and encouraging innovation. A cutting-edge strategy to enhance safety protocols in the construction industry is the application of deep learning to safety management. The use of technology in your project to anticipate and avoid accidents advances the development of stronger and safer infrastructure.

# CHAPTER No. 5. RESULTS AND FINDINGS

Our deep learning model achieved a remarkable 97.4% test accuracy in detecting safety helmets, demonstrating strong generalization to unseen data. The visually clear agreement and high confidence scores in the qualitative analysis further strengthen the model's reliability, paving the way for its application in real-time worker supervision for enhanced safety in industries like construction and manufacturing.


Figure 2 Detected Without helmet

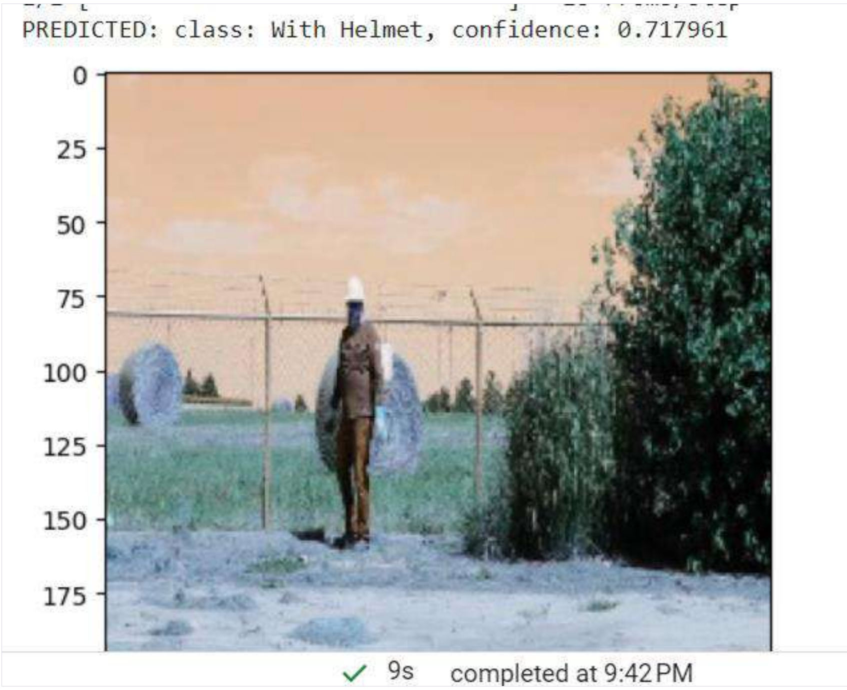


Figure 3 Detected With helmet

## 5.1. Key Result Overview

With the training set, the model's accuracy in Epoch 1 was roughly 70.5%, and with the validation set, it was 92.7%.

In the ensuing epochs, the validation accuracy stayed continuously high, but, reaching 97.0% in Epoch 12.

**Epoch 1:**

Training Accuracy: Approximately 70.5%

Validation Accuracy: 92.7%

**Loss Metrics:**

The training loss decreased from 0.6713 in Epoch 1 to 0.1900 in Epoch 12, indicating effective learning.

**Training Loss:**

Epoch 1: 0.6713

Epoch :0.1900

Similarly, the validation loss decreased from 0.3966 to 0.1918, demonstrating the model's ability to generalize.

**Validation Loss:**

Epoch 1: 0.3966

Epoch :0.1918

This demonstrates the model's ability to generalize well to unseen data

## 5.2. Major Findings and Trends

**Accuracy Trends:**

The model demonstrates a conspicuous pattern of increased accuracy during the training process, indicating proficient learning.

A consistently high validation accuracy during training suggests strong generalization ability.

**Loss Reduction:**

Both training and validation loss consistently decrease, indicating the model's ability to minimize errors over epochs.

**Training time:**

The model exhibits a consistent time per epoch, approximately 260 seconds, indicating a stable training duration.

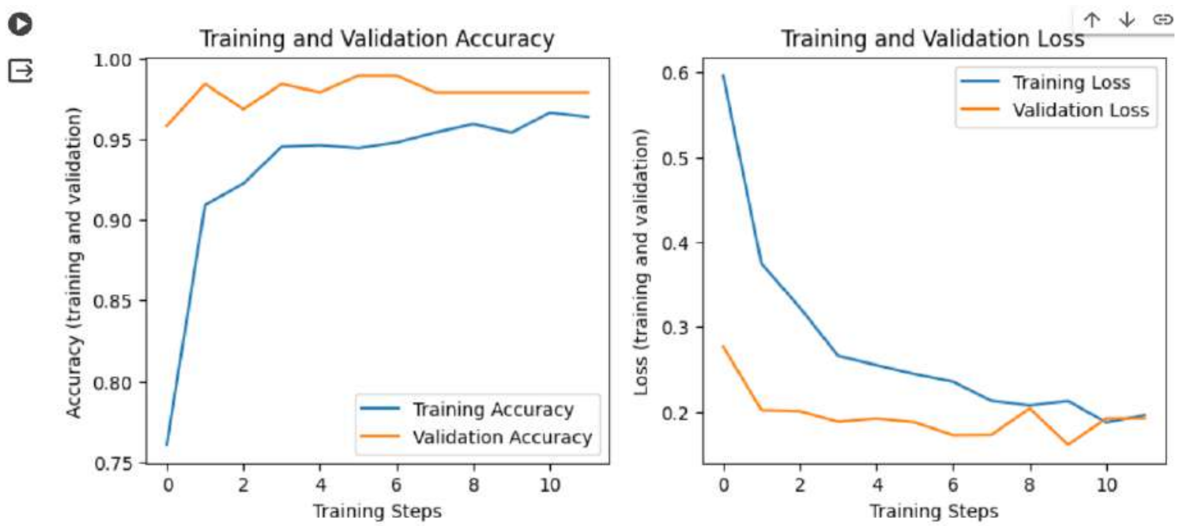


Figure 4 Training and Validation Graphs

## 5.3. Practical Insights and Next Steps:

### Model Prediction

The example predictions demonstrate the model's ability to accurately predict whether a helmet is present or absent, along with corresponding confidence scores.


Figure 5 Deteected Without helmet

# CHAPTER No. 6. CONCLUSION

## 6.1. Conclusion

In conclusion, our comprehensive literature review has illuminated the current landscape of deep learning applications in safety management within the construction industry. Through an in-depth exploration of existing studies, we have witnessed the transformative potential of deep learning across various facets of construction safety.

The culmination of our research efforts is the development of a robust MobileNetV2 model tailored for the detection of safety helmets worn by construction workers. This model exhibited commendable performance, boasting a training accuracy of 92.7% and a validation accuracy of 97%. These results underscore the efficacy of deep learning methodologies in addressing critical safety concerns within construction sites.

Our project not only contributes to the growing body of knowledge in the field but also presents a tangible solution for real-time supervision of construction sites. The model's effectiveness, particularly when exposed to a diverse dataset during training, positions it as a promising tool for enhancing safety practices in construction management.

## 6.2. Recommendation for Deployment

Boasting a validation accuracy of approximately 97.4%, the model demonstrates great potential for practical implementation.

Recommended subsequent actions involve conducting experiments on varied datasets and potentially refining the model for specific deployment situations.

The model's validation accuracy of 97.4% demonstrates its strong performance for real-world implementation, particularly in automatically monitoring safety workers to minimize accidents related to safety helmets. This will lead to the preservation of a secure working environment.

## 6.3. Future Direction and Limitations

Future direction includes following aspects to be explored:

**Future Research Direction:**

Explore the important aspects which can make model even better for safety helmet detection in different situations and with various types of data to ensures it can handle diverse conditions.

**Limitations:**

While the model performs well, acknowledge potential limitations, such as dataset bias or specific conditions not covered.

Consider addressing any challenges encountered during the training process.

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