Journal Of Research Technology & Engineering
www.jrte.org

Safety Detection System: A Technological Leap in Sri Lanka's Construction Safety

Pavithra Madushani Wendabona

Faculty of Technology, International College of Business & Technology
Pmadushani97@yahoo.com

Received:11 Dec 2023; Revised: 18 Dec 2023; Accepted: 27 Dec 2023; Available online: 10 Jan 2024

Abstract: Sri Lanka's construction industry faces a safety crisis with 2000 to 3000 annual accidents, primarily due to non-compliance with safety regulations, notably the use of personal protective equipment. This research introduces a groundbreaking mobile application that employs AI and Computer Vision to detect safety gear non-compliance among workers, issuing real-time alerts. The app represents a significant leap in construction safety standards, showcasing the potential of technology to transform the sector. With its real-time alerts, it sets a new safety benchmark, demonstrating the industry's commitment to a safer, more prosperous Sri Lanka.

Index Terms: Construction Safety; Personal Protective Equipment; Helmet detection; Artificial Intelligence; Computer Vision (CV)

1 Introduction

The construction industry in Sri Lanka, a driving force behind economic development, grapples with a significant challenge - ensuring the safety and well-being of its workforce. This challenge is exacerbated by an alarming annual rate of 2000 to 3000 accidents on construction sites, primarily due to non-compliance with safety regulations, notably the consistent use of personal protective equipment (PPE), such as safety helmets.

In response to this pressing issue, this research introduces an innovative solution that harnesses the power of Artificial Intelligence (AI) and Computer Vision (CV) technologies. The ultimate goal is to proactively address safety compliance and significantly reduce workplace accidents, creating a safer environment for construction workers.

The primary concern revolves around persistent non-compliance with safety regulations, particularly the use of safety helmets, which places workers at substantial risk. Many laborers remove their helmets due to discomfort or non-compliance, exposing themselves to potentially fatal accidents. Traditional safety monitoring methods are labor-intensive, time-consuming, and reliant on constant supervision by safety managers, rendering them impractical for overseeing the multifaceted activities on construction sites.

Furthermore, existing technological solutions, while effective, are often inaccessible to smaller construction companies due to high costs and substantial hardware requirements. This research presents the "Guardian Helmet Safety Detection System," a pioneering mobile application tailored specifically for Sri Lanka's construction industry. This system leverages AI and CV technologies, operating seamlessly on Android smartphones, making it accessible, user-friendly, and cost-effective. Its core functionality is the accurate detection of workers not wearing essential safety gear, particularly safety helmets, and the prompt issuance of real-time alerts.

This innovative approach signifies a paradigm shift towards a safer, more efficient, and technologically-driven construction sector. By providing real-time alerts via SMS and audible alarms, this solution promises to be a game-changer, setting a new safety benchmark and symbolizing the industry's commitment to safeguarding lives and fostering economic progress in Sri Lanka.

2 LITERATURE REVIEW

The Fourth Industrial Revolution, commonly known as Industry 4.0, is characterized by the integration of advanced technologies such as Artificial Intelligence (AI), the Internet of Things (IoT), Cloud Computing, and Edge Computing into various industries [1]. In the construction sector, AI, particularly Computer Vision (CV), is gaining prominence for its applications in predicting worker behavior, task tracking, and monitoring, using vision cameras for industrial automation.

The construction industry faces a higher incidence of accidents due to its complex and demanding environments, coupled with potential safety protocol violations [2]. Accidents include machinery entanglements, falls from heights, slips, trips, and collisions with obstacles. Despite research efforts, the industry remains vulnerable to injuries and fatalities [3].

Efforts to address safety concerns are divided into reactive and proactive approaches. The reactive approach involves analyzing past accident reports using real-time data from cameras and sensors. Proactive strategies, such as educating workers and adhering to safety regulations, also play a role. The Occupational Safety and Health Agency (OSHA) provides guidelines to mitigate risks, particularly falls from heights [4].

Traditionally, construction worker safety relied on manual practices and personal vigilance, with periodic safety inspections by supervisors. However, manual monitoring of individual worker activities across construction sites proved labor-intensive, time-consuming, and prone to human error.

The early 21st century saw a transformative era with the integration of sensors and communication technologies into wearable devices, notably smart helmets [5]. Equipped with environmental sensors, these helmets monitored factors like temperature, humidity, and gas levels in real-time, enhancing workers' awareness of their surroundings. Wearable IoT devices, as explored by Li et al. [6], tracked vital signs and movements, enabling real-time monitoring of workers' health and preventing accidents due to fatigue.

Advancements in video surveillance and computer vision technologies also revolutionized safety monitoring practices [7]. Closed-circuit television (CCTV) cameras with computer vision algorithms detected unsafe behaviors and conditions, introducing proactive safety measures. This included identifying workers without required Personal Protective Equipment (PPE), unauthorized access, and potential hazards. Automated alerts facilitated swift supervisor intervention [8].

Helmet detection technologies, driven by deep learning and Convolutional Neural Networks (CNNs), further enhanced safety measures [9]. These systems monitored construction sites in real time, triggering alerts when workers were detected without helmets. Some systems integrated access control, ensuring only equipped workers could access hazardous areas. These technologies played a pivotal role in preventing accidents, improving overall worker safety, and ushering in a new era of construction site security and compliance [10].

3 RESEARCH DESIGN

The research focuses on construction companies in Sri Lanka as the population. Due to constraints in time and budget, a purposive sampling method is employed, selecting a convenient sample of construction companies based on ease of access.

The sample selection relies on the National Registration and grading scheme for constructors conducted by the Construction Industry Development Authority. Criteria for selection include companies specified in building construction with a financial limit above 500 million.

Preliminary data for this research were obtained through an extensive literature review and a questionnaire survey specifically aimed at local contractors engaged in building construction. Additionally, secondary data about both fatal and non-fatal accidents in the Sri Lankan construction industry were collected from the Labor Department of Sri Lanka. These data were analyzed to identify trends in health and safety conditions within the country's construction sector. Moreover, secondary data regarding construction investment and the contribution of construction to the national GDP were sourced from the Department of Census and Statistics in Sri Lanka. This information was used to assess the trends in construction investment and its impact on the national economy.

The study also involved an examination of the causes and effects of subpar health and safety practices within the construction industry. This was achieved through an in-depth review of relevant international literature. To ensure the questionnaire's validity in capturing factors pertinent to the Sri Lankan context, a pilot study was conducted. Experienced building construction practitioners (specialists) in Sri Lanka provided valuable input during this pilot study.

A comprehensive questionnaire was developed, divided into four parts. The first part gathered background information from the respondents. The second part focused on the effects of inadequate health and safety practices, allowing respondents to indicate their views on the recognized consequences of poor health and safety in the building construction industry. These consequences were categorized into five major groups, covering incidents such as falls, electricity hazards, fire hazards, machinery-related accidents, and incidents involving tools and objects. The third part of the questionnaire concentrated on how those accidents can be minimized through Artificial Intelligence and mobile technology. Finally, the fourth part solicited the respondents' ideas for mitigating risks in the building construction industry in Sri Lanka through simple mobile applications.

4 METHODOLOGY

The Helmet detection application, a cutting-edge mobile solution tailored for the construction industry in Sri Lanka, is designed to bolster safety compliance and foster a culture of safety on construction sites. At its core, the application employs advanced technology, notably an artificial intelligence (AI) model for safety helmet detection, to automate and enhance safety monitoring.

The primary objective of the Helmet Detection application is to ensure the adherence of construction site workers to safety regulations, particularly those related to the use of safety helmets. The AI-based safety helmet detection system plays a pivotal role in this, automatically identifying individuals wearing safety helmets and those who are not. This innovative technology facilitates immediate compliance enforcement, contributing significantly to a safer working environment.

In addition to safety helmet compliance monitoring, the application functions as a real-time communication platform. It establishes seamless communication channels between construction site workers and supervisors, enabling prompt interaction for safety guidance, incident reporting, and safety-related inquiries. This real-time communication feature plays a crucial role in creating a responsive and safety-conscious work environment.

Recognizing the importance of weather conditions in construction safety, the Helmet Detection application integrates real-time weather data. This functionality empowers workers and supervisors with essential information, enabling them to make informed decisions related to safety and work planning. The inclusion of weather information enhances overall situational awareness on construction sites.

Efficient working time monitoring is facilitated through the application's user-friendly time-tracking tool. This tool allows workers to accurately monitor their working hours, simplifying the process of recording and calculating cumulative hours worked. This contributes to efficient time management and ensures that workers are adhering to stipulated work hours.

To address safety violations swiftly, the Helmet detection application incorporates SMS notifications and audible alarms. When non-compliance is detected, the system sends SMS notifications to safety managers, prompting immediate action. Simultaneously, audible alarms are triggered to alert workers, reinforcing safety protocols and creating an immediate response mechanism for addressing safety issues.

The application maintains a comprehensive safety compliance database in real time. This database records data on individual workers' safety-related activities, including timestamps, location data, and descriptions of safety violations. This repository of information serves as a valuable resource for analysis and compliance tracking, allowing for continuous improvement in safety protocols.

Supervisors are provided with a dedicated dashboard within the Helmet detection application, displaying real-time safety helmet compliance alerts. This feature empowers supervisors to monitor safety compliance efficiently, make data-driven decisions, and intervene promptly when necessary. The supervisor dashboard enhances overall oversight and management of safety protocols on construction sites.

In summary, the Helmet detection application operates as a multifaceted system, seamlessly integrating advanced technologies and practical features to enhance safety compliance, communication, and overall safety management within the construction industry in Sri Lanka. The combination of real-time data, communication tools, and compliance enforcement mechanisms contributes to a proactive and safety-focused work environment (Fig. 1).

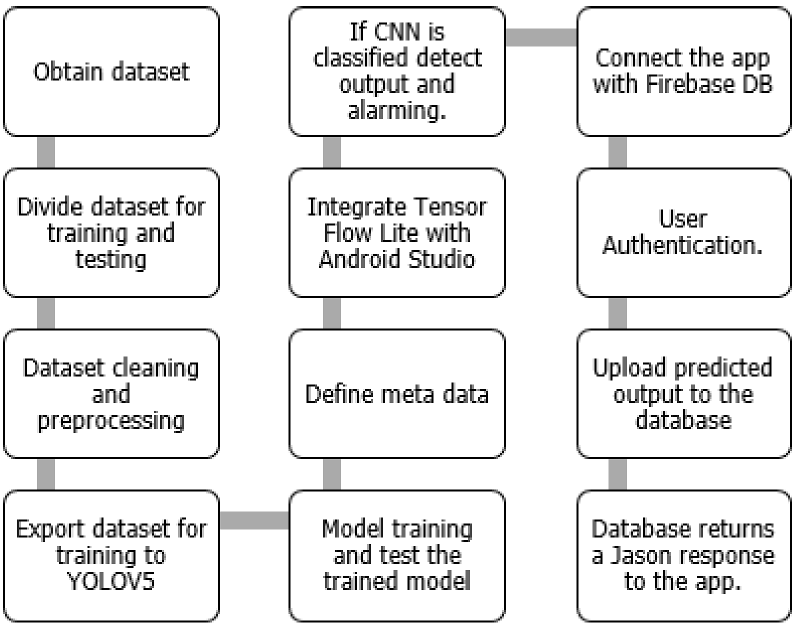

Fig.1. Workflow of the system

5 HELMET DETECTION BASED ON DEEP LEARNING

A. Build a helmet dataset

In the process of curating a dataset for training a YOLO (You Only Look Once) object detection model, a web crawler was employed to collect a diverse set of 600 images from Google. These images are targeted to be representative of the objects or entities that the model will be trained to detect. And divided images into 03 groups for training, testing, and verification.

Training Set:

- The training set, constituting a significant portion of the dataset, serves as the primary resource for teaching the model to recognize and localize objects within images accurately. The model learns from the diverse characteristics present in these images, gaining an understanding of the spatial relationships and visual features associated with each object class.

Testing Set:

- The testing set functions as an independent evaluation tool for assessing the model's generalization and predictive capabilities. Images in this set are distinct from those in the training set, providing a measure of the model's performance on unseen data. Evaluating the model on this separate set helps gauge its effectiveness in real-world scenarios.

Verification Set:

- The verification set, also known as the validation set, serves as an intermediary checkpoint during the training process. It helps prevent overfitting by providing a set of images that the model has not seen during training. This set aids in fine-tuning the model's parameters and ensures that it generalizes well to unseen data.

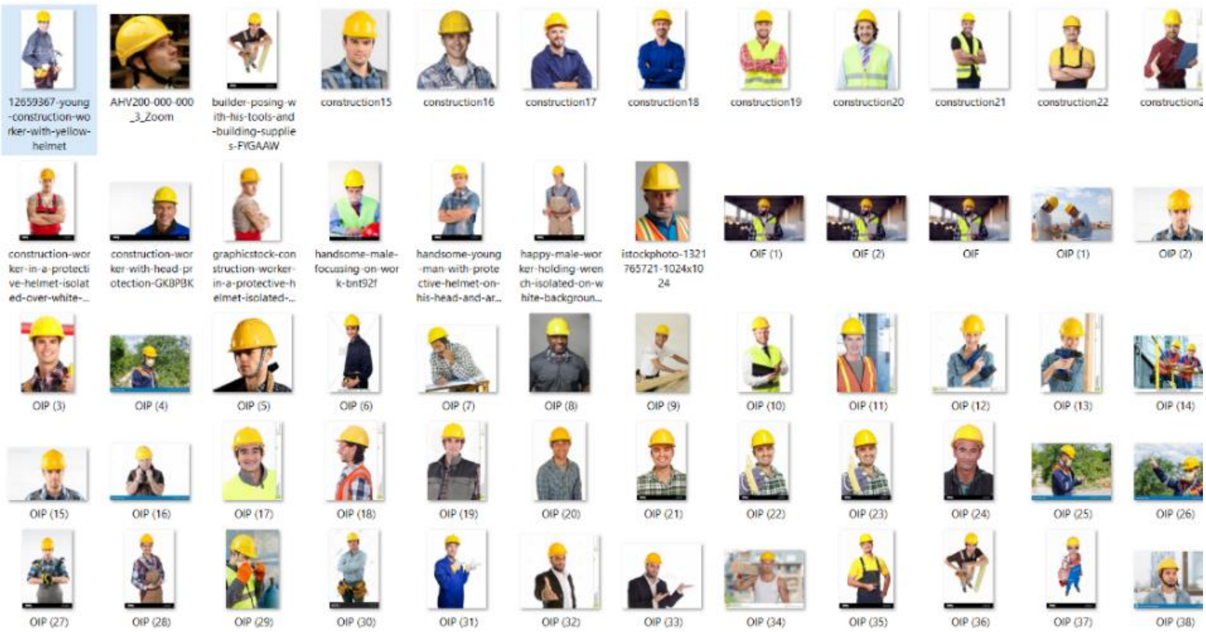

Fig.2. Dataset to train the model

Once the image collection is complete, the next step involves annotation. The annotation process is crucial for teaching the model to recognize and locate objects within the images accurately. This is achieved using a tool called LabelImg, which allows the user to draw bounding boxes around the objects of interest in each image. Additionally, each bounding box is assigned a corresponding label that indicates the class of the object contained within (Fig. 3).

Fig.3. Image Annotations

B. Image Preprocessing

In the preprocessing phase, meticulous attention is given to aligning bounding box annotations, meticulously created during the labeling process, with preprocessed images. Should resizing or other transformations be applied, the bounding boxes undergo careful adjustment to preserve accurate spatial relationships with the objects depicted in the images. This meticulous alignment ensures the model is provided with precise localization information during training, contributing to its ability to discern and accurately locate objects.

Subsequently, the refined dataset is systematically organized into batches, a pivotal step designed to optimize the efficiency of the model training process. The images are resized to a specified height and width (32x32 pixels), and a batch size of 20 is chosen for efficient processing. The implementation of batching not only serves to streamline memory usage but also facilitates the iterative optimization of model parameters. This deliberate organization enhances the model's ability to learn patterns effectively, striking a balance between computational efficiency and the thorough exploration of the dataset.

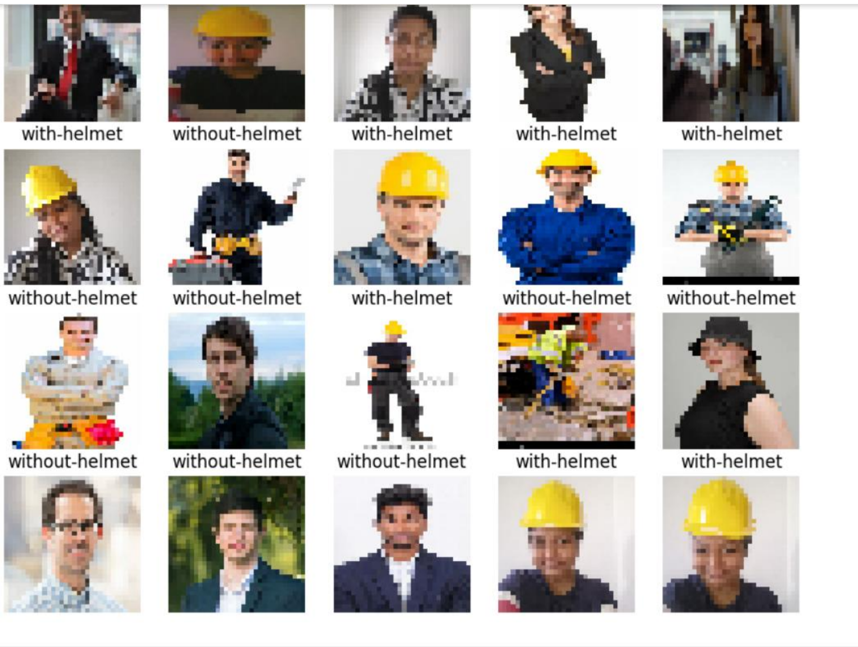

Fig. 4. Loading the Dataset

C. Model Training

In the process of training a model for Helmet Detection, the initial steps involve loading the dataset using Tensor Flow's image dataset from the directory utility. The dataset is organized into training (**train_ds**) and validation (**val_ds**) sets, each containing 300 images belonging to two classes: "with-helmet" and "without-helmet Convolutional Neural Network (CNN) model is constructed using Tensor Flow's Keras Sequential API. The model consists of several layers, including Rescaling, Conv2D, MaxPooling2D, Flatten, and Dense layers. This architecture is designed to learn hierarchical features from the input images. The model is then compiled, specifying the optimizer, loss function, and evaluation metric. In this case, the Adam optimizer is chosen, Sparse Categorical Cross entropy is used as the loss function, and accuracy is monitored during training. Finally, the model is trained using the **fit** method on the training dataset (**train_ds**), with validation data provided from the validation dataset (**val ds**). The training process is set to run for 50 epochs.

```
[ ] model = tf.keras.Sequential(
        [
         tf.keras.layers.Rescaling(1./255),
         tf.keras.layers.Conv2D(32, 3, activation="relu"),
         tf.keras.layers.MaxPooling2D(),
         tf.keras.layers.Conv2D(32, 3, activation="relu"),
         tf.keras.layers.MaxPooling2D(),
         tf.keras.layers.Conv2D(32, 3, activation="relu"),
         tf.keras.layers.MaxPooling2D(),
         tf.keras.layers.Flatten(),
         tf.keras.layers.Dense(128, activation="relu"),
         tf.keras.layers.Dense(3)
        ]
    )
```

```
[ ] model.compile(
        optimizer="adam",
        loss=tf.losses.SparseCategoricalCrossentropy(from_logits = True),
        metrics=['accuracy']
    )
```

```
[ ] model.fit(
        train_ds,
        validation_data = val_ds,
        epochs = 50
    )
```

```
Epoch 1/50
10/10 [==============================] - 8s 328ms/step - loss: 0.8373 - accuracy: 0.5100 - val_loss: 0.7318 - val_accuracy: 0.5000
Epoch 2/50
10/10 [==============================] - 5s 333ms/step - loss: 0.7166 - accuracy: 0.4750 - val_loss: 0.6745 - val_accuracy: 0.5250
Epoch 3/50
10/10 [==============================] - 4s 314ms/step - loss: 0.6647 - accuracy: 0.6000 - val_loss: 0.6439 - val_accuracy: 0.7900
Epoch 4/50
10/10 [==============================] - 5s 262ms/step - loss: 0.6467 - accuracy: 0.6600 - val_loss: 0.6199 - val_accuracy: 0.6450
Epoch 5/50
10/10 [==============================] - 3s 214ms/step - loss: 0.5972 - accuracy: 0.6950 - val_loss: 0.5481 - val_accuracy: 0.7750
Epoch 6/50
10/10 [==============================] - 4s 313ms/step - loss: 0.5242 - accuracy: 0.7600 - val_loss: 0.4594 - val_accuracy: 0.8350
Epoch 7/50
10/10 [==============================] - 4s 214ms/step - loss: 0.4165 - accuracy: 0.8750 - val_loss: 0.3384 - val_accuracy: 0.9150
Epoch 8/50
10/10 [==============================] - 4s 312ms/step - loss: 0.3154 - accuracy: 0.8900 - val_loss: 0.3082 - val_accuracy: 0.8700
Epoch 9/50
10/10 [==============================] - 4s 313ms/step - loss: 0.3109 - accuracy: 0.8750 - val_loss: 0.1917 - val_accuracy: 0.9550
Epoch 10/50
10/10 [==============================] - 4s 210ms/step - loss: 0.2200 - accuracy: 0.9250 - val_loss: 0.2089 - val_accuracy: 0.9400
Epoch 11/50
10/10 [==============================] - 3s 212ms/step - loss: 0.1737 - accuracy: 0.9550 - val_loss: 0.1595 - val_accuracy: 0.9750
Epoch 12/50
10/10 [==============================] - 4s 314ms/step - loss: 0.1413 - accuracy: 0.9550 - val_loss: 0.1077 - val_accuracy: 0.9700
Epoch 13/50
10/10 [==============================] - 6s 336ms/step - loss: 0.1183 - accuracy: 0.9600 - val_loss: 0.1262 - val_accuracy: 0.9550
Epoch 14/50
10/10 [==============================] - 4s 216ms/step - loss: 0.1001 - accuracy: 0.9800 - val_loss: 0.0810 - val_accuracy: 0.9800
Epoch 15/50
10/10 [==============================] - 5s 343ms/step - loss: 0.0900 - accuracy: 0.9750 - val_loss: 0.0811 - val_accuracy: 0.9800
```

Fig.5. Model Training

D. Tensor Flow Deep Learning Framework

Following the successful training of the Guardian Helmet detection model, the subsequent step involves converting the trained model into the TensorFlow format, a versatile and open-source end-to-end machine learning platform. TensorFlow is renowned for its prowess in symbolic mathematics and dataflow programming, providing a robust framework for deploying machine learning models seamlessly.

TensorFlow serves as a comprehensive ecosystem, offering tools and resources that streamline the entire machine-learning workflow. As a deep learning framework, it empowers developers to construct and train intricate machine-learning models with ease. Its capabilities extend beyond model creation; TensorFlow excels in implementing rapid iterations, facilitating efficient model testing, and simplifying the debugging process.

With the model successfully trained, the conversion to TensorFlow format is pivotal for compatibility with mobile applications. Tensor Flow's versatility makes it an ideal choice for deploying machine learning models on a wide range of devices, including mobile platforms. This conversion ensures that the trained Helmet detection model can be seamlessly integrated into a mobile application, providing real-time object detection capabilities.

E. Android mobile application

The TensorFlow Lite model is seamlessly integrated into an Android Studio project. This involves incorporating the model files, along with any necessary dependencies, into the Android application development environment. This step ensures that the trained model is ready to be utilized within the Helmet detection application on Android devices.

Enhancing Safety Compliance: The TensorFlow Lite model is leveraged for real-time safety helmet detection within the Android application. As construction site workers wear helmets, the model identifies compliance with safety regulations. This functionality enhances safety monitoring by automating the process of ensuring adherence to safety protocols.

Real-time Communication Platform: The Android application serves as a communication hub between construction site workers and supervisors. It enables workers to seek safety guidance, report incidents, and make safety-related inquiries in real time. The integration of the TensorFlow Lite model enhances communication by providing immediate insights into safety helmet compliance.

Weather Information Integration: The Android application, utilizing real-time weather data, empowers workers and supervisors with essential information for informed decision-making related to safety and work planning. This feature, enhanced by TensorFlow Lite, contributes to improved situational awareness on construction sites.

Efficient Working Time Monitoring: The application's user-friendly time tracking tool, powered by TensorFlow Lite, facilitates accurate monitoring of working hours. It simplifies the process of recording and calculating cumulative hours worked, contributing to efficient time management for construction site workers.

SMS Notifications and Audible Alarms: In response to safety violations detected by the TensorFlow Lite model, the application sends SMS notifications to safety managers for swift action. Simultaneously, audible alarms are triggered to alert workers, reinforcing safety protocols and creating an immediate response mechanism for addressing safety issues.

Data Recorded in Firebase: The database captures a range of essential information, including timestamps, location data, and detailed descriptions of safety violations. Each entry in the database corresponds to a specific safety-related event, forming a comprehensive and continually updated record of the safety activities of individual workers on construction sites.

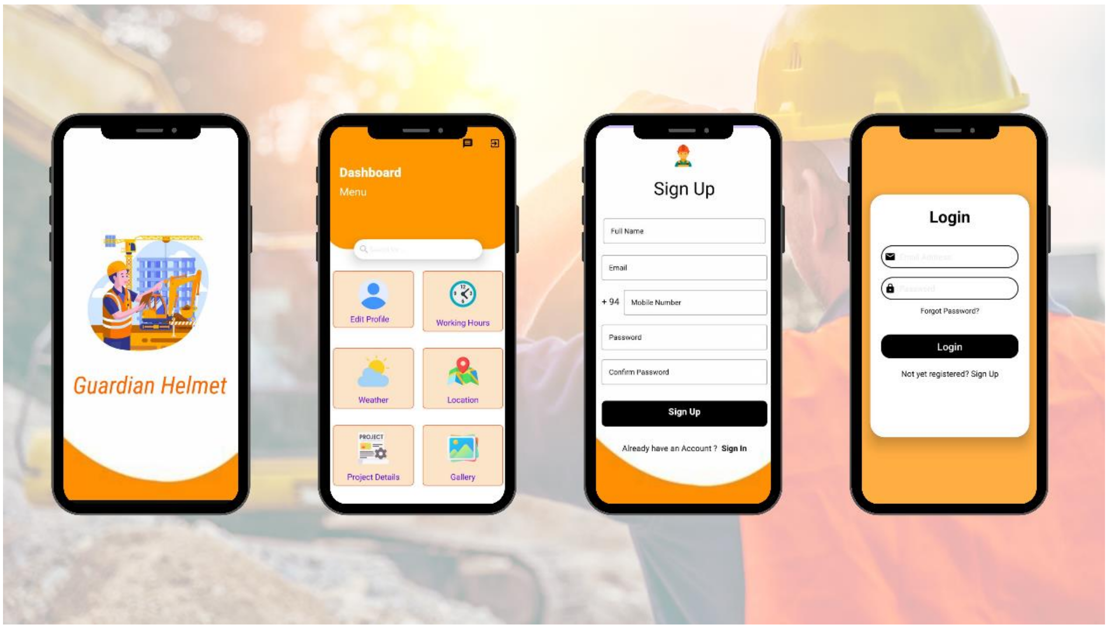

Fig.6. Mobile Application Interface

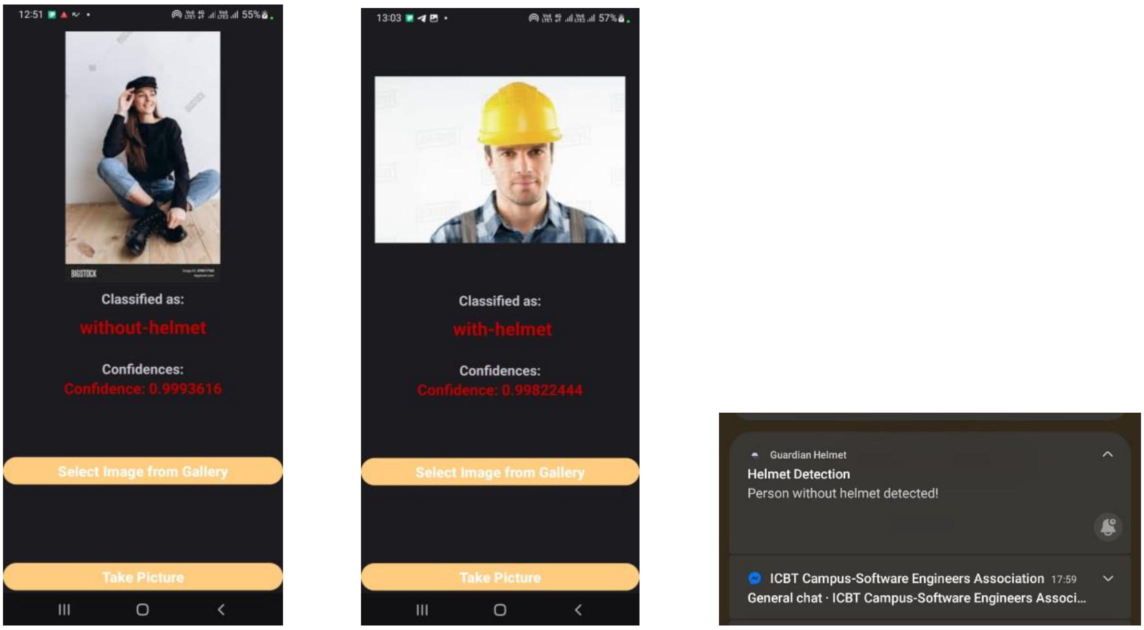

Fig.7. Helmet Detection & Notification Alerts

6 Experiments & Results

The culmination of the research effort yields a transformative outcome, empowering construction workers with the capability to monitor both live images and those stored in a database. The focal point of this achievement lies in the model's proficiency in discerning whether individuals in these images are wearing helmets, thus enhancing safety protocols on construction sites.

Through the utilization of the Guardian Helmet detection model, construction site surveillance is elevated to a new paradigm. The live monitoring functionality provides real-time insights into the compliance of workers with helmet safety regulations. As workers move within the field of view, the model dynamically analyzes live images, promptly flagging instances of non-compliance and prompting timely corrective action.

Moreover, the integration of the model with a database extends this monitoring capability to historical records. By querying images stored in the database, construction supervisors can retrospectively assess adherence to safety protocols over time. This retrospective analysis serves not only as a compliance auditing tool but also as a valuable resource for identifying trends and patterns related to helmet usage among workers.

	ı Helmet	ıout Helmet
ɔgnition Correct		
ɔgnition error		

Table 1. Detection Results

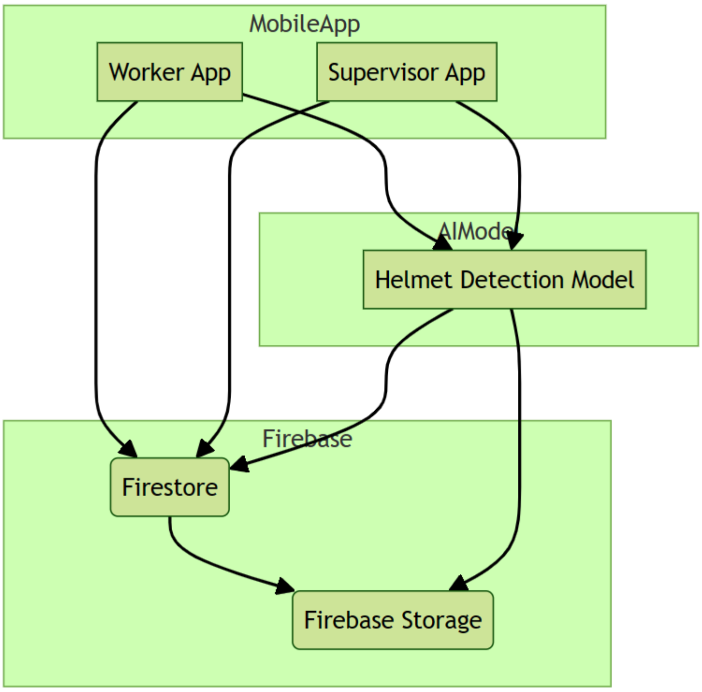

Fig.8. Deployment Diagram

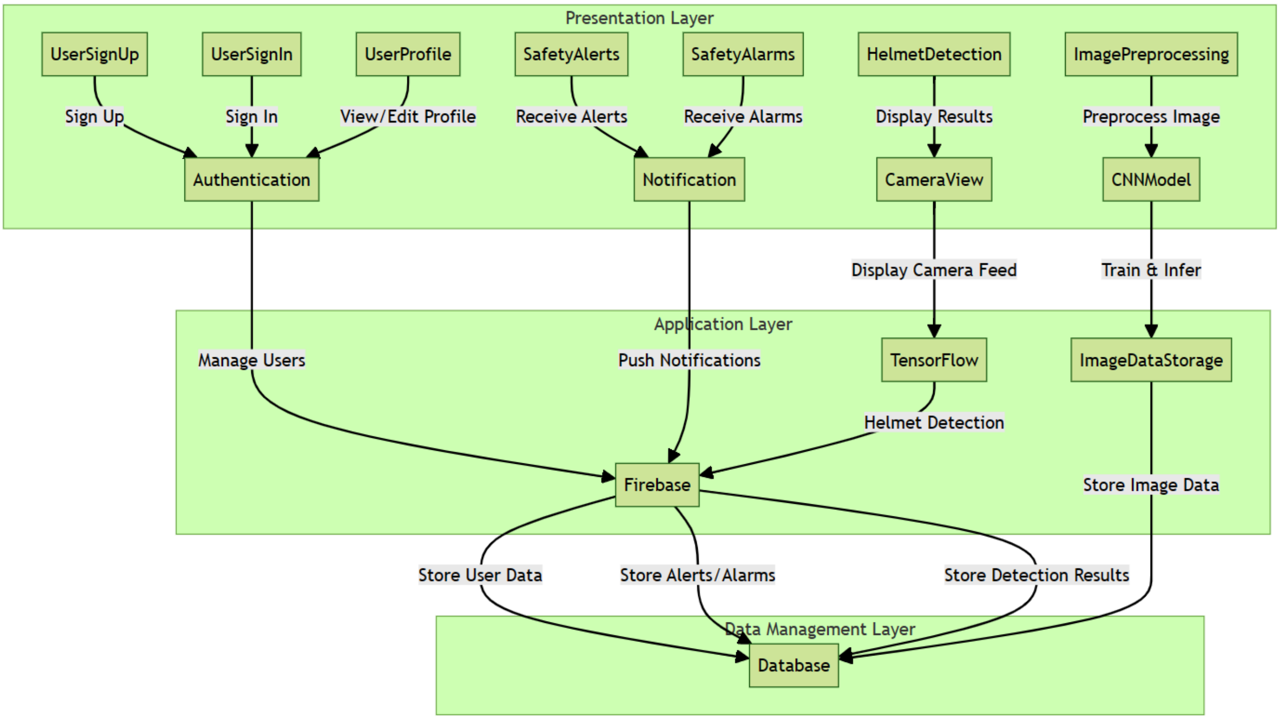

Fig.9. System Architecture

7 Conclusion

The developed model, trained and fine-tuned to recognize helmet compliance in both live images and historical databases, provides a sophisticated and proactive approach to safety monitoring.

The live monitoring capabilities of the model empower construction workers and supervisors with real-time insights, enabling swift interventions in instances of non-compliance. Beyond this, the integration with a database extends the utility of the model, allowing for retrospective analysis and trend identification over time.

The practical implications of these research findings are substantial. The construction industry, with its inherent risks, stands to benefit from the adoption of intelligent and automated safety monitoring systems. By providing a technologically advanced solution, this research contributes to the ongoing evolution of safety practices, aligning with the contemporary demands of a dynamic work environment.

Furthermore, the successful deployment of the Helmet detection model underscores the potential of machine learning and computer vision in addressing industry-specific safety challenges. The model's ability to discern safety compliance from visual data not only contributes to accident prevention but also sets a precedent for the integration of cutting-edge technologies in safety management.

8 LIMITATIONS

The Helmet detection project, while showcasing remarkable advancements in construction site safety, is not without its limitations. Firstly, the model's current configuration is tailored for binary classification focused on helmet detection. Extending its capabilities to recognize multiple objects or diverse safety hazards within the construction environment may necessitate further model modifications and training. Additionally, the model's training is influenced by specific environmental conditions present in the dataset, and variability in lighting, weather, and background settings could impact its generalization to different construction sites. Furthermore, the accuracy of the model is contingent on the quality of input images, posing challenges when faced with poor resolution, occlusions, or extreme angles. The real-time processing demands of the model may also impact its performance on resource-constrained devices, potentially leading to slower processing speeds and latency in live monitoring. Privacy concerns associated with live monitoring introduce a delicate balance between safety and individual privacy, requiring thoughtful consideration and implementation of privacy-preserving measures. Finally, the continuous optimization of the model is crucial for addressing changes in construction site conditions over time, such as evolving helmet styles, worker attire, or site-specific features. Recognizing and mitigating these limitations will be pivotal in ensuring the responsible and effective deployment of the Guardian Helmet detection system in real-world applications.

9 RECOMMENDATIONS

Recommendations for the Helmet detection project encompass strategies to address identified limitations and enhance its overall effectiveness in construction site safety. Firstly, there is a need to explore the extension of the model's capabilities beyond binary classification to recognize multiple objects or diverse safety hazards commonly present in construction environments. This may involve augmenting the training dataset with additional object classes and refining the model architecture to support multi-object detection. Moreover, efforts should be directed towards diversifying the training dataset to account for various environmental conditions, ensuring the model's adaptability to different construction sites, lighting scenarios, and background settings.

Addressing image quality concerns should be prioritized by implementing image preprocessing techniques that handle variations in resolution, occlusions, and extreme angles. Additionally, the assumption of a stationary camera setup could be revisited to accommodate scenarios with moving cameras or dynamic perspectives. Future model updates should incorporate techniques to handle these dynamic conditions, enhancing the system's applicability across diverse construction site setups.

To tackle class imbalance challenges, continuous efforts should be made to collect and include a more balanced dataset. Augmentation techniques, such as oversampling minority classes or adjusting loss functions, can help improve the model's robustness in recognizing both helmet-wearing and non-helmet-wearing instances.

Considering the real-time processing demands of the model, optimization strategies should be explored to enhance its efficiency, especially on resource-constrained devices. This could involve model quantization, pruning, or exploring lightweight architectures suitable for mobile deployment. Balancing the trade-off between accuracy and computational efficiency will be crucial for achieving real-time performance.

Privacy considerations should guide the implementation of privacy-preserving measures, ensuring that the model can effectively contribute to safety monitoring without compromising individual privacy rights. This may involve anonymizing or aggregating data to mitigate concerns related to personal identification.

9 REFERENCES

[1] Bai, C., Dallasega, P., Orzes, G., & Sarki, J. (2020). Industry 4.0 technologies assessment: A sustainability perspective. *International Journal of Production Economics*, *229*, 107776.

[2] Zhou, F., Zhao, H., & Nie, Z. (2021). Safety Helmet Detection Based on YOLOv5. IEEE, China.

[3] Wang, X. (2023). Real-Time Safety Helmet Detection System for Construction Site Monitoring. *Construction Safety Journal*.

[4] Li, X., Hu, J., & Cao, J. (2021). A wearable IoT-based fatigue detection system for construction workers. *Automation in Construction*.

[5] Ren, D., Sun, T., Yu, C., & Zhou, C. (2021). Research on Safety Helmet Detection for Construction Site. Paper presented at the International Conference on Computer Information Science and Artificial Intelligence (CISAI), Kunming, China.

[6] Liu, Z., Wang, Q., & Meng, F. (2022). A benchmark for multi-class object counting and size estimation using deep convolutional neural networks. *Engineering Applications of Artificial Intelligence*, *116*, 105449.

[7] Dacong, R., Tongsheng, S., Cungui, Y., & Cheng, Z. (2021). Deep Learning-Based Safety Helmet Detection in Construction Sites. *International Journal of Environmental Research and Public Health*, *18*(4), 1850.

[8] Hayat, A., & Fernando, M.-D. (2022). Deep Learning-Based Automatic Safety Helmet Detection System for Construction Safety. *MDPI Applied Sciences*.

[9] M., J., et al. (2015). Factorized Appearances for Object Detection. *Computer Vision and Image Understanding*, *138*, 92-101.

[10] Heinrich, H. (1931). *Industrial Accident Prevention: A Scientific Approach*. McGraw-Hill.