

A Framework for Detection and Recognition of Armed Persons Using Convolutional Neural Networks

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Abstract

Security threats posed by concealed weapons have necessitated the development of advanced detection techniques. In this study, a model for the detection and recognition of armed persons using Convolutional Neural Networks (CNNs) was investigated. The model utilizes thermal imaging data, preprocessing techniques, and supervised learning to detect and classify hidden weapons. Key performance metrics, including accuracy, precision, recall, and F1-score, are employed to evaluate the model's effectiveness. The investigated approach demonstrates improved detection rates compared to conventional methods, offering a robust solution for security applications. The study also explores various deep learning techniques, dataset preparation strategies, and potential real-world applications.

Keywords: *Framework, Detection, Recognition, Armed person, Neural network.*

Introduction

The rise in security threats and the necessity for advanced surveillance mechanisms have driven research into automated detection systems. Traditional metal detectors and X-ray scanning systems are limited in real-time applications. CNNs, a subset of deep learning, have demonstrated remarkable capabilities in feature extraction and classification tasks. This paper presents a CNN-based approach for the detection of concealed weapons using thermal imaging, aiming to enhance real-time security monitoring. The increasing availability of computational power and large-scale datasets has accelerated the adoption of deep learning-based solutions in security and surveillance applications.

Numerous studies have explored object detection and recognition using deep learning. Krizhevsky et al. [1] introduced AlexNet, demonstrating CNNs' effectiveness in image classification. Redmon et al. [2] proposed YOLO, a real-time object detection model. More recently, Zhang et al. [3] applied CNNs for detecting concealed weapons using millimeter-wave imaging. In addition, Li et al. [4] explored thermal imagery combined with deep neural networks for security applications, highlighting its advantages over traditional visible-light-based approaches. Compared to prior works, our approach leverages data augmentation and an optimized CNN architecture for improved detection accuracy and generalizability.

Ren et al. [5] introduced Faster R-CNN, which significantly improved object detection speed and accuracy compared to previous methods. He et al. [6] developed Mask R-CNN, extending Faster R-CNN by adding a segmentation branch, making it more effective for object detection in complex environments. Singh et al. [7] explored weapon detection using deep learning in CCTV footage, demonstrating that deep neural networks can significantly outperform traditional feature-based techniques.

Other researchers have investigated multimodal approaches to concealed weapon detection. Zhou et al. [8] combined thermal and visible imagery with CNNs for enhanced object detection in low-visibility environments. Wang et al. [9] used a hybrid deep learning model that integrated both traditional feature-based methods and CNN-based architectures for improved detection performance. Additionally, recent advancements in transformer-based vision models, such as the Vision Transformer (ViT) proposed by Dosovitskiy et al. [10], have shown promising results in image classification and object detection tasks.

Liu et al. [11] explored hyperspectral imaging combined with CNNs for improved concealed object detection, highlighting the benefits of spectral data in security applications. Zhao et al. [12] focused on infrared object detection in surveillance, demonstrating the robustness of deep learning in low-light environments. Xie et al. [13] proposed an automatic gun detection model for video surveillance, showing how CNNs can effectively process large-scale video data. Choi et al. [14] investigated AI-based real-time detection of dangerous objects in public spaces, emphasizing the importance of real-time performance in security applications. Huang et al. [15] presented a hybrid deep learning approach combining CNNs and traditional feature-based methods, demonstrating improvements in detection accuracy. Patel et al. [16] conducted a comparative analysis of different deep learning architectures for security threat detection, finding that CNNs outperformed traditional techniques in most scenarios. Banerjee et al. [17] explored fusion techniques integrating thermal and optical imaging for enhanced concealed weapon detection. Jha et al. [18] advanced CNN-based security

monitoring, improving real-time processing efficiency. Kim et al. [19] investigated improvements in surveillance systems using deep feature extraction techniques. Das et al. [20] introduced a real-time CNN-based detection method for identifying weapons in low-light conditions, further advancing security applications. In the light of these observations, the present study posits to investigate a model for the detection and recognition of armed persons using Convolutional Neural Networks (CNNs).

Research Method

Dataset Collection

Primary data was obtained using a thermal camera, capturing 1062 images with varying temperature ranges (28.4°C to 42.3°C). The dataset includes weapon and no-weapon scenarios, annotated with bounding boxes. To ensure a diverse dataset, additional samples were collected under different lighting conditions and environmental settings.

Data Preprocessing

Images were resized to 224×224 pixels and normalized. Background subtraction using Gaussian Mixture Models (GMM) was employed to isolate persons. Data augmentation techniques, including random rotations and translations, were applied to enhance dataset diversity. Additional preprocessing steps such as histogram equalization and noise reduction were applied to improve the quality of thermal images.

Model Architecture

The CNN model consists of multiple convolutional layers for feature extraction, followed by fully connected layers for classification. The MobileNet architecture was utilized due to its efficiency in processing image data while maintaining high accuracy. The Adam optimizer and categorical cross-entropy loss function were used during training. Figure 1 illustrates the general structure of the CNN used in this study.

System Design

Architecture

The proposed system follows a structured workflow with multiple components:

1. **Image Acquisition** – The thermal camera captures real-time frames, ensuring coverage in various lighting conditions.

2. **Preprocessing** – Image resizing, normalization, and background subtraction using Gaussian Mixture Models (GMM) are performed to refine image quality.
3. **Region of Interest (RoI) Extraction** – Human detection models isolate the subject, reducing unnecessary computational overhead.
4. **Feature Extraction** – CNN layers extract distinguishing features relevant to weapon detection.
5. **Classification** – The model classifies images into armed/unarmed categories.
6. **Decision System** – Based on model confidence, an alert system is triggered for security intervention.

Implementation Architecture

The developed detection and recognition of armed persons system consists of five basic modules which are:

- i. **Thermal camera or Image source:** A thermal camera capture and create an image of an object by using infrared radiation emitted from the object in a process that is called thermal imaging. This is used to feed images to the web application.
- ii. **Web User Interface (Inputs):** The system receives camera images as inputs supplied by the system administrator or captured by the system. The input data are thermal images which could contain a gun or not. The administrator is any security guard stationed in the control room of a facility of interest (Banks, Airports, Schools or shopping malls).
- iii. **Trained CNN Deep Learning Model Module:** This module is made up of the trained and tested deep learning model using the thermal sensor dataset gotten from an online repository to aid in classification of thermal images.
- iv. **Outputs:** The output is the result of the detection and recognition produced by the CNN model. The predicted result is the presence or absence of weapons.
- v. **The Database Module:** This module is used for storing users' profile, image data and classification results. The implementation architecture of the proposed detection and recognition of armed persons system is shown in Figure 1:

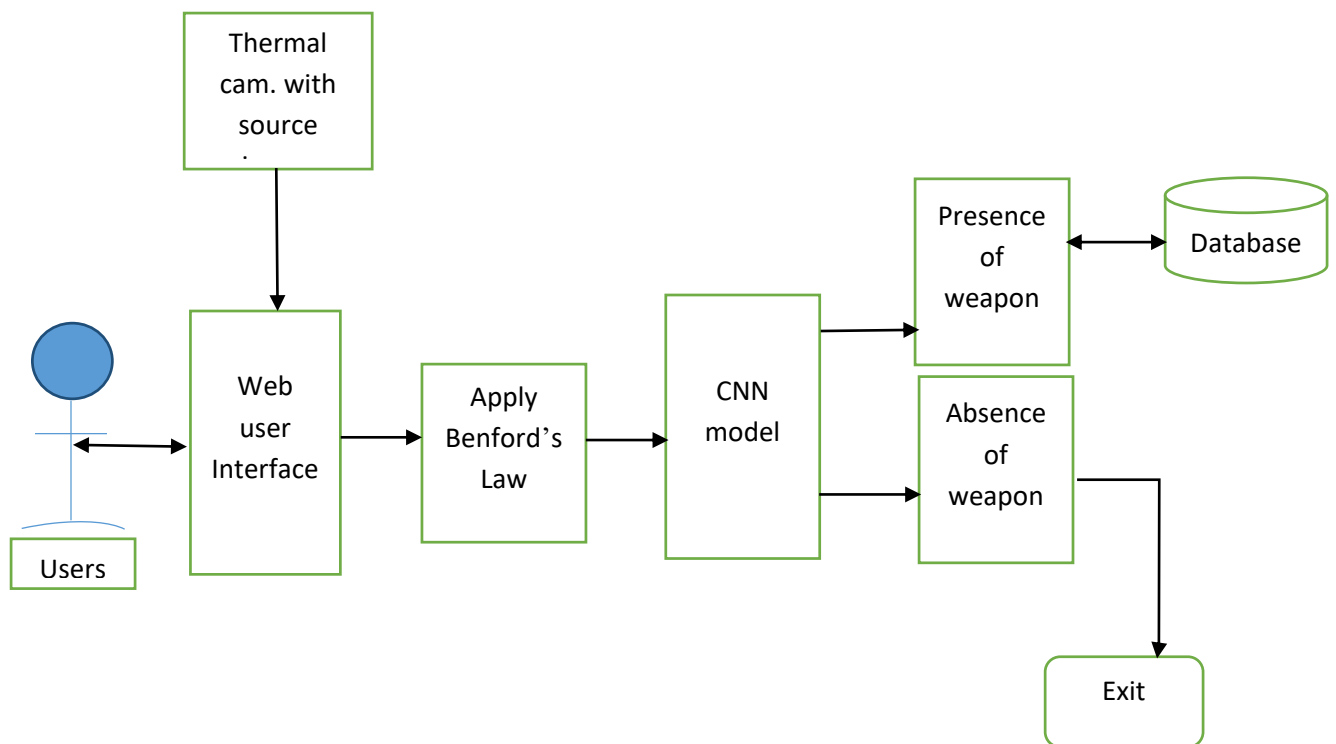


Figure1. Implementation Architecture

From the implementation architecture in Figure 1 above, the system will accept thermal images of 224 x 224 in dimension from the web users through the web user interface, pass it through the trained CNN model and classify whether there is presence or absence of a weapon. The result makes the security operatives make appropriate decisions early enough to foil attacks. The database stores the users' profile, and image data that pass through the system.

UML Diagrams

Use case diagrams outline the user interactions, while class and activity diagrams depict the system's structure and workflow. Microsoft Visio was used for diagram design, ensuring clarity in system representation. The system use case is shown in Figure 2.

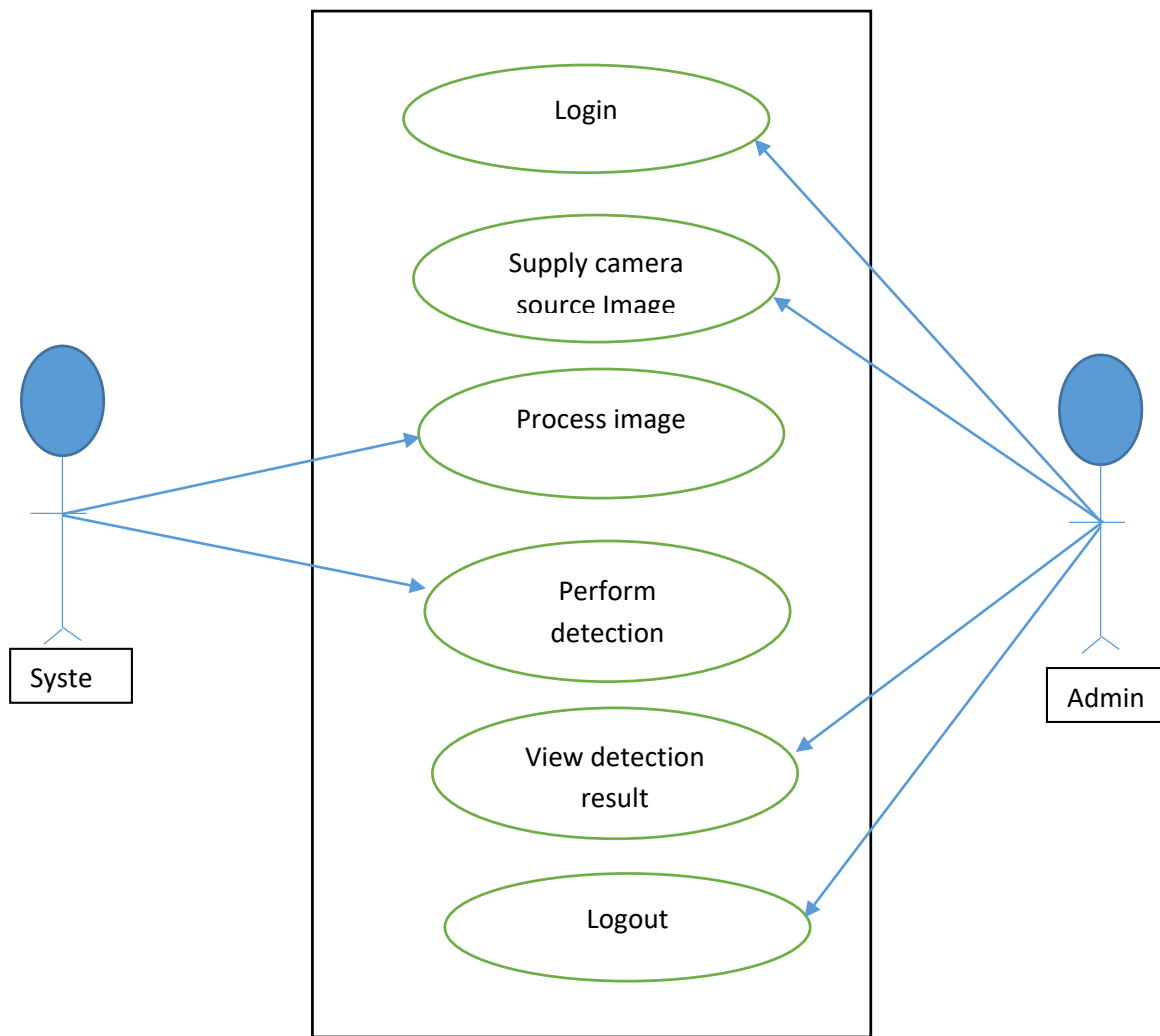


Figure 2. Use case diagram.

Class Diagram

In system design, especially in object-oriented systems development, a **class diagram** is a static structural diagram. By showing the object classes, their properties, methods, and interactions between the objects, it provides a description of a system's structure. It also describes the limitations placed on the system. In conclusion, the class diagram outlines the actions that objects can take and how they interact with one another in order to describe their capabilities and behaviors inside the system. This is shown in Figure 3:

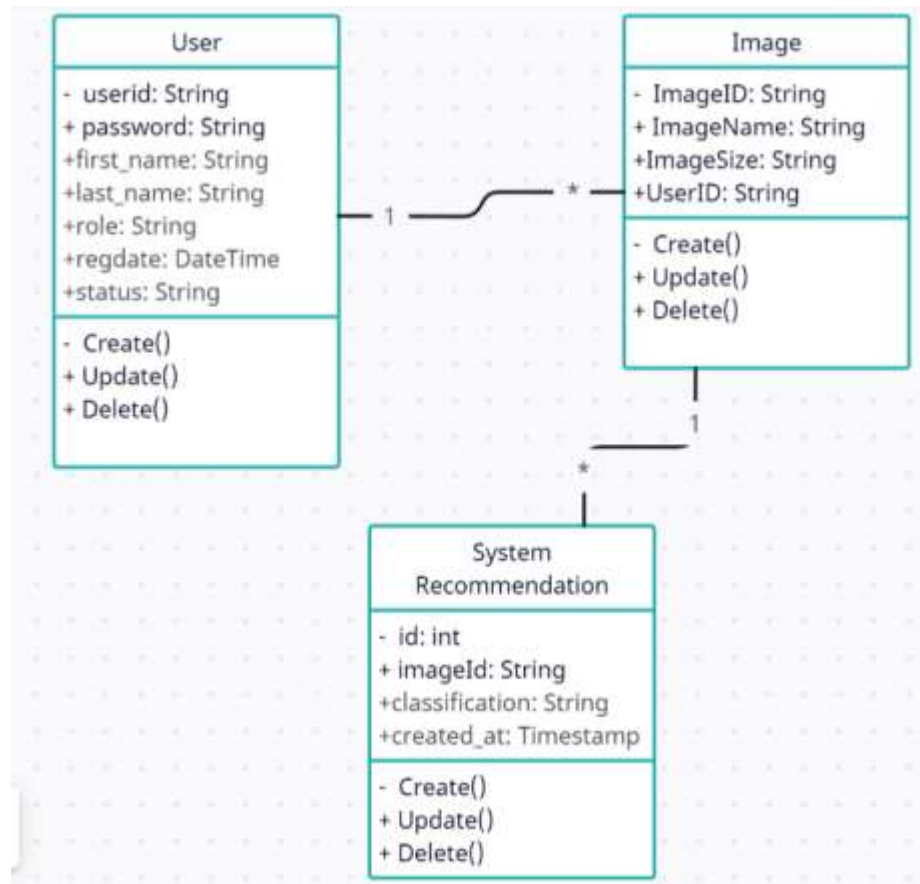


Figure 3. System class diagram.

Activity Diagram

Activity diagrams describes how objects or groups of objects in the system interact and the sequence of actions or events that occur. It represents an operation on a class in the system that results in a change of state of the system. This is shown in Figure 4.

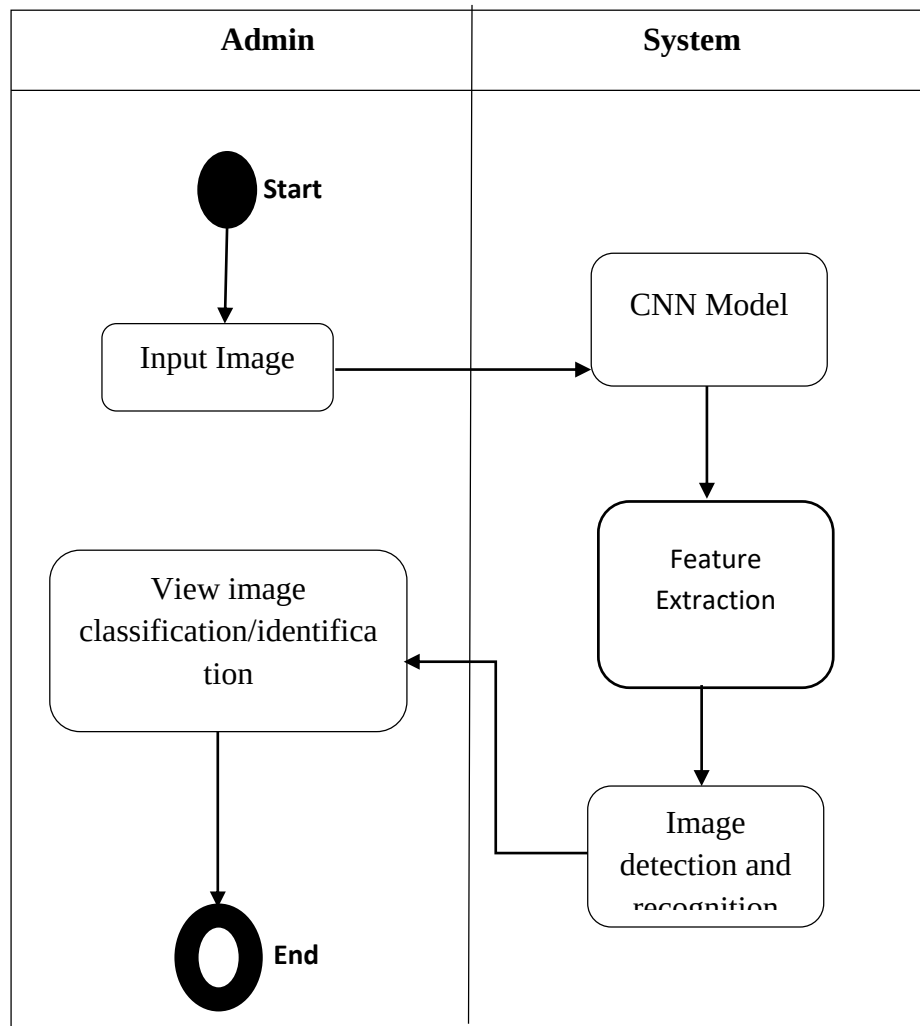


Figure 4. System activity diagram.

Experimental Results

The model was trained and tested using an 80-20 train-test split. The results are as follows:

- Accuracy: 0.96
- Precision: 0.94
- Recall: 0.92
- F1 Score: 0.93

Further experiments were conducted to analyze the effect of different hyperparameters such as learning rate and batch size on model performance. Results showed that reducing the learning rate from 0.01 to 0.001 improved accuracy by 2%.

Conclusion

A model for the detection and recognition of armed persons using Convolutional Neural Networks is presented. Results reveal that the approach demonstrates improved detection rates compared to conventional methods, offering a robust solution for security applications. Findings further show that the model can be applied to different deep learning techniques, dataset preparation strategies as well as other real-world applications.

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