WEAPON DETECTION SYSTEM USING EFFICIENTDET

A MINI PROJECT REPORT

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BONAFIDE CERTIFICATE

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ABSTRACT

Traditional surveillance systems face significant challenges in real-time weapon detection, especially in crowded or complex environments. Standard algorithms struggle when weapons are partially concealed, held at unusual angles, or obscured by clothing or other obstacles. To address these limitations, a weapon detection system based on the EfficientDet algorithm is proposed. EfficientDet excels in balancing detection accuracy and computational efficiency, making it ideal for scenarios requiring both speed and precision. Trained on a diverse dataset covering various lighting conditions, angles, and concealment levels, the system recognizes weapons in situations where traditional methods often fail. EfficientDet's optimized design ensures high-precision detection with minimal computational resources, allowing seamless integration with existing surveillance infrastructure. This adaptability supports real-time monitoring without costly hardware upgrades, making the system practical for widespread use. Enhanced robustness offers valuable support to law enforcement in proactive threat detection, promoting public safety through faster response. By providing scalable, adaptable threat identification, this solution advances surveillance technology, creating safer public spaces.

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LIST OF ABBREVIATION

AI	Artificial Intelligence
ANNs	Artificial Neural Networks
AP	Average Precision
BiFPN	Magnetoencephalography
CCTV	Closed-Circuit Television
CMS	Crime Monitoring System
CNNs	Convolutional Neural Networks
FPS	Frames Per Second
GPUs	Graphics Processing Units
JPEG	Joint Photographic Experts Group
Mask R CNN	Mask Region based Convolutional Neural
NMS	Non Maximum Suppression
RNNs	Recurrent Neural Networks
SDK	Software Development Kit
TLS	Transport Layer Security
TPUs	Tensor Processing Unit
YOLO	You Only Live Once

CHAPTER 1

INTRODUCTION

1.1 DEEP LEARNING

Deep learning is a branch of artificial intelligence (AI) that focuses on algorithms inspired by the structure and function of the human brain, specifically artificial neural networks. Unlike traditional machine learning algorithms that rely on explicitly programmed rules and feature extraction by experts, deep learning enables machines to automatically learn features and patterns from large volumes of data. The core idea of deep learning revolves around neural networks with many hidden layers, hence the term “deep.” These layers allow the model to learn increasingly complex representations of data, transforming raw inputs into high-level abstractions.

The foundation of deep learning lies in artificial neural networks (ANNs), which are computational structures loosely modeled after biological neural networks. Each "neuron" in these networks receives inputs, applies a set of weights, processes them through an activation function, and passes the result to the next layer. This process, known as forward propagation, helps the network learn how to map inputs to outputs. The network’s performance is evaluated using a loss function, which measures the error between the predicted and actual output. By minimizing this error through backpropagation, the network adjusts its weights, improving its predictions.

Deep learning architectures, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformers, have revolutionized fields like computer vision, natural language processing, and speech recognition. CNNs, for instance, excel at image-related tasks by learning spatial hierarchies, making them ideal for image recognition, object detection, and medical imaging, as shown in Figure 1.1. RNNs, on the other hand, are designed to handle sequential data, making them valuable for tasks involving time-series data or text. Transformers have gained prominence for their ability to handle complex language tasks, including machine translation and question answering.

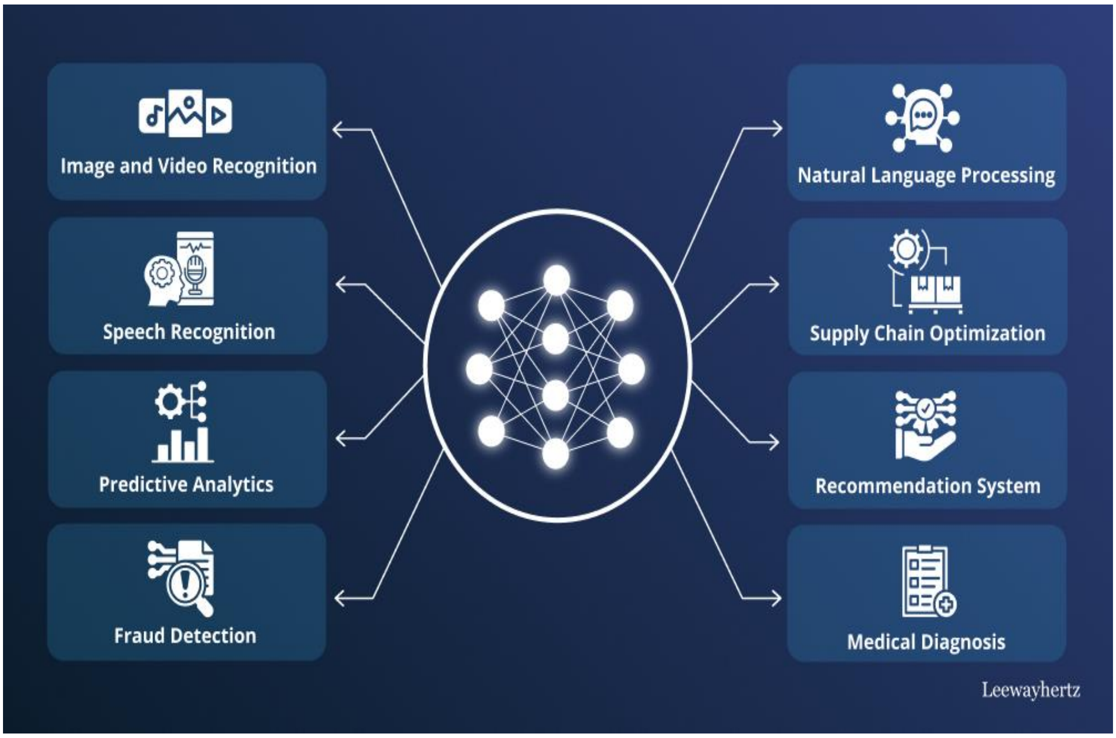

Figure 1.1 Deep Learning

The effectiveness of deep learning models is often attributed to the availability of massive datasets and increased computational power, particularly with the advent of GPUs and TPUs. These resources allow deep learning models to process vast amounts of data, uncovering intricate patterns that would be impossible for traditional machine learning methods to capture. This scalability makes deep learning adaptable across a range of industries, from autonomous driving and healthcare to finance and entertainment.

One of the major advantages of deep learning is its ability to generalize well on complex tasks, but it does come with challenges. Deep learning models are often considered “black boxes” because they provide limited interpretability regarding how specific decisions are made. Additionally, deep learning models require large datasets and substantial computational resources, which can make them impractical for certain applications.

Overall, deep learning has significantly advanced the capabilities of AI systems, enabling them to achieve state-of-the-art results in a variety of applications. Its impact on modern technology continues to grow, transforming industries and reshaping the future of AI and machine learning.

1.2 COMPUTER VISION

Computer vision is a field within artificial intelligence (AI) focused on enabling machines to interpret and make decisions based on visual data, similar to how humans process and understand visual information. Its objective is to replicate human vision by allowing computers to recognize, interpret, and respond to objects, scenes, and activities within images or videos. At its core, computer vision relies on mathematical algorithms and deep learning models that process visual data in multiple stages. In the early stages, the system extracts basic features, such as edges, colours, and shapes, from the image. As the model processes deeper layers, it begins to recognize more complex patterns and structures, such as distinguishing specific objects or facial features, as shown in Figure 1.2. Convolutional Neural Networks (CNNs) are particularly influential in computer vision for their ability to automatically detect spatial hierarchies, making them ideal for tasks like object detection, image classification, and semantic segmentation. CNNs operate by applying filters across the image, allowing them to capture essential spatial patterns and features.

Recent advancements in computer vision have transformed applications across a wide range of industries. In healthcare, for instance, computer vision algorithms are used to analyze medical images, enabling early diagnosis of conditions like cancer and cardiovascular diseases. In autonomous driving, computer vision systems process real-time visual data to detect objects, track lanes, and identify obstacles, allowing vehicles to make safer, data-driven decisions. In retail, it supports advanced customer behavior analytics, providing insights that drive customer experience enhancements.

Despite its successes, computer vision faces challenges related to data requirements and generalization. High-quality labeled data is essential for training models, and these models sometimes struggle to generalize effectively across new, unseen environments. Additionally, ethical considerations around privacy and surveillance are critical as the use of computer vision continues to expand.

By transforming raw visual inputs into actionable data, it has the potential to revolutionize industries and pave the way for innovative applications, marking significant advancements in how technology perceives and interprets the visual world. By transforming raw visual inputs into actionable data, it has the potential to revolutionize industries and pave the way for innovative applications, marking significant advancements in how technology perceives and interprets the visual world, ultimately bridging the gap between human and machine vision.

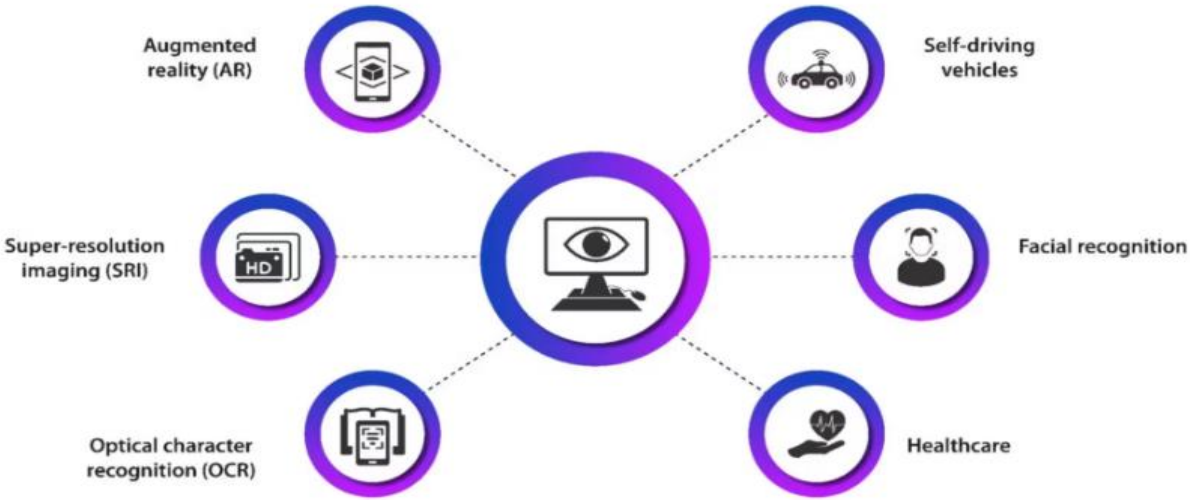

Figure 1.2 Computer Vision

1.3 EFFICIENTDET

EfficientDet is an advanced object detection model developed by Google, designed to balance high accuracy with computational efficiency. The model achieves remarkable results by employing a scalable architecture adaptable for various levels of computational power, from mobile devices to high-performance servers, as shown in Figure 1.3. It employs a compound scaling approach that optimally adjusts network depth, width, and input resolution to enhance performance.

The EfficientDet architecture is characterized by its use of a compound scaling method, which scales the model's depth, width, and input resolution systematically.

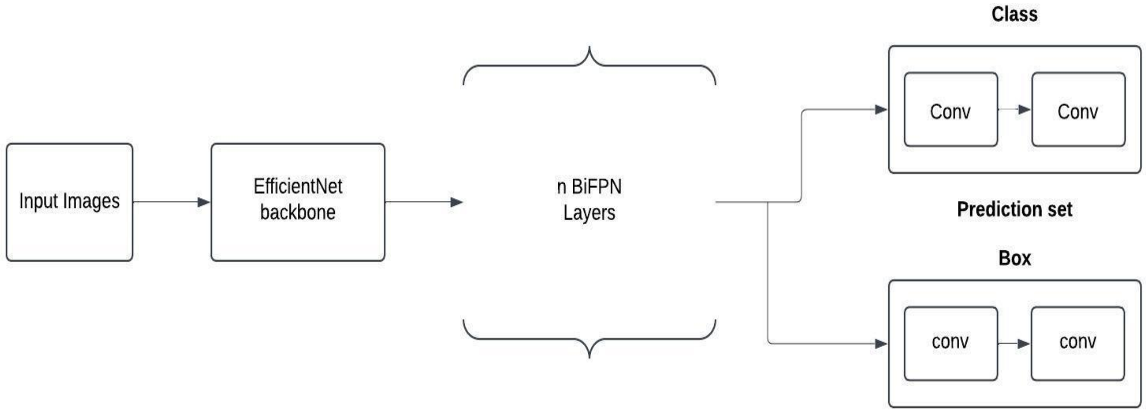

Figure 1.3 EfficientDet

Traditional models typically adjust only one dimension, often resulting in a trade-off between accuracy and efficiency. EfficientDet, however, scales all three dimensions in a balanced way, maximizing the model's ability to detect objects of various sizes and complexities without excessive computational overhead.

This compound scaling approach enables the model to deliver robust detection performance across a wide range of device capabilities. Another key innovation in EfficientDet is its implementation of the Bi-directional Feature Pyramid Network (BiFPN). Unlike conventional feature pyramid networks, BiFPN allows for more flexible and efficient feature fusion, which means the model can learn richer, multi-scale representations from input images.

The graph demonstrates how EfficientDet achieves a remarkable balance between accuracy and computational efficiency, outperforming other object detection frameworks. By utilizing innovative compound scaling and advanced feature fusion techniques, the model delivers higher accuracy with reduced resource usage, making it suitable for a wide range of applications, as shown in Figure 1.4. Its lightweight architecture ensures consistent performance across both low-power devices and high-end systems.

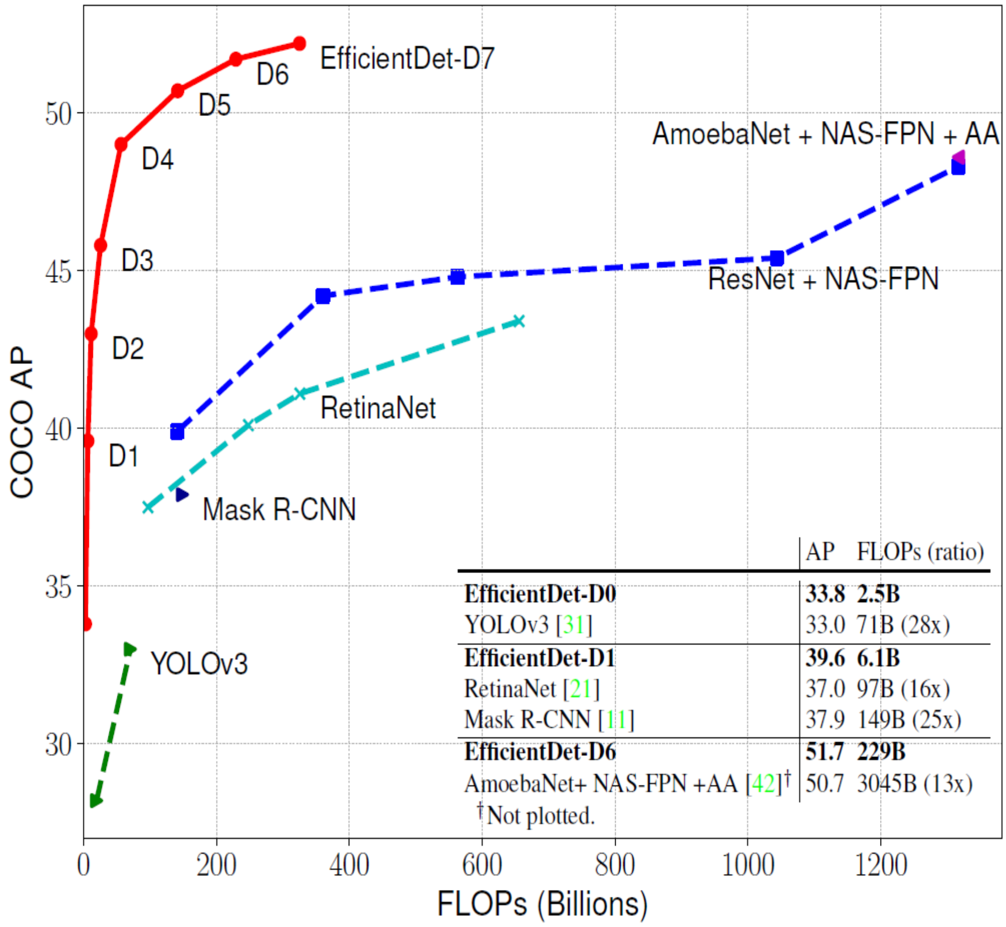

Figure 1.4 EfficientDet Graph

EfficientDet is a cutting-edge object detection framework renowned for its scalability and flexibility, with multiple versions ranging from D0 to D7. Each version is designed to cater to specific levels of accuracy and computational efficiency, providing users the ability to select the most suitable model based on their application requirements and available resources. The framework introduces a revolutionary compound scaling method that uniformly scales the network's width, depth, and resolution. This method ensures an optimal balance between performance and resource utilization, offering a seamless trade-off between speed, accuracy, and computational cost.

EfficientDet’s architecture incorporates advanced feature fusion techniques, such as BiFPN (Bidirectional Feature Pyramid Network), which enhances multi-scale feature representation. This innovation improves detection accuracy without significantly increasing computational overhead. Furthermore, its lightweight design ensures that the model operates efficiently even in environments with limited computational power, such as edge devices and IoT systems.

By optimizing the detection pipeline, EfficientDet not only accelerates inference but also minimizes memory usage, making it a practical choice for real-time applications requiring high throughput and low latency. This includes scenarios like industrial monitoring, robotics, and edge computing, where timely and accurate detection is critical. Its ability to balance computational cost with detection accuracy further solidifies its role in resource-constrained environments. Additionally, its modular design enables seamless integration with diverse platforms, enhancing its adaptability for various industry-specific use cases. Overall, EfficientDet’s combination of scalability, efficiency, and high performance makes it a standout solution for modern object detection challenges.

CHAPTER 2

LITERATURE REVIEW

2.1 DESIGN OF A REAL-TIME CRIME MONITORING SYSTEM USING DEEP LEARNING TECHNIQUES

Md. Ahsan Ahmed et al. (2024) developed an advanced real-time crime monitoring system that integrates deep learning and image processing techniques to enhance public surveillance and security [1]. This system, referred to as the Crime Monitoring System (CMS), is designed to automatically detect criminal activities by utilizing CCTV footage, eliminating the need for human intervention in monitoring processes. The CMS framework operates in three critical phases—weapon detection, violence detection, and face recognition—each contributing uniquely to a comprehensive crime detection and prevention approach.

In the weapon detection phase, the authors employed the YOLOv5 deep learning model, specifically optimized for high-speed object detection in real-time. This model achieved over 80% accuracy in identifying various types of weapons within crowded and complex environments, enabling proactive alerts and quick response times. The next phase, focused on violence detection, implemented MobileNetv2, a lightweight yet effective model, which attained an 85% accuracy rate in identifying violent behaviours.

The final phase of the CMS involves face recognition, where the system uses a highly sophisticated face recognition algorithm that achieved an accuracy rate of 97%. This aspect of CMS not only helps in recognizing potential perpetrators but also in identifying victims and witnesses, supporting law enforcement in building a comprehensive picture of incidents.

The entire CMS was tested extensively in real-world scenarios, proving its robustness and ability to operate effectively in varied environmental conditions. The model's success is largely attributed to the synergistic functioning of the three stages, where object detection, behavioural analysis, and identity recognition work together to ensure optimal crime detection and prevention. This comprehensive approach enhances surveillance coverage and significantly strengthens the capacity of security forces to maintain order, providing a highly reliable system that contributes to community safety and the deterrence of criminal activities.

2.2 A DEEP-LEARNING FRAMEWORK RUNNING ON EDGE DEVICES FOR HANDGUN AND KNIFE DETECTION FROM INDOOR VIDEO-SURVEILLANCE CAMERAS

Adriano Mancini et al. (2024) addressed the challenges of detecting small weapons in real-time through indoor surveillance systems that run on low-cost edge devices, providing a practical solution for environments that require efficient security monitoring without high infrastructure costs [2]. Their research aimed to overcome the limitations of traditional surveillance systems by leveraging a deep learning framework optimized for edge devices. This approach enables precise detection of weapons in real-time on resource-constrained hardware, making it suitable for indoor scenarios where surveillance cameras may operate on limited processing power and need to achieve both accuracy and speed.

The proposed system operates through a double-step process. Initially, a convolutional neural network (CNN) model detects individuals within the surveillance footage. Once people are identified, a second CNN model is activated to specifically detect and identify weapons. This two-stage approach allows for accurate detection while keeping computational demands low. By first filtering out non-essential parts of the footage (i.e., frames or areas with no people), the system conserves processing power for the weapon identification step. This methodology enables efficient and near real-time performance, even when deployed on low-cost devices such as the NVIDIA Jetson Nano, a popular choice for edge computing due to its compact size, affordability, and moderate processing capabilities.

The researchers tested this system on a custom indoor surveillance dataset specifically designed to capture the challenges of small weapon detection in various indoor settings, such as offices, public areas, and enclosed spaces. The system achieved a remarkable performance, recording an accuracy average precision (AP) of 79.30, which underscores its reliability in detecting small, concealed, or partially visible weapons. Furthermore, the system maintained an impressive processing speed of 5.10 frames per second (FPS),

The study highlighted the significant potential of this low-cost, automated solution as a scalable option for real-time video surveillance in indoor environments. By deploying on edge devices, the system is not only cost-effective but also capable of operating independently, without reliance on cloud-based processing. This setup ensures minimal latency and enhances data security by limiting data transmission. The combined accuracy, efficiency, and low-cost implementation make the system a valuable tool for enhancing safety and security in various indoor environments, offering an adaptable and accessible option for institutions, offices, and public spaces where real-time monitoring is critical for immediate response and crime prevention.

2.2 WEAPON DETECTION SYSTEM SECURITY AND SURVEILLANCE USING YOLOV8

H. U. Ain Tahir et al. (2023) introduced an innovative weapon detection system aimed at enhancing surveillance and security protocols by tackling significant challenges associated with object variations [3]. These challenges include affine transformations, rotation, occlusion, and variations in object size, which can complicate the detection process in real-world scenarios. To address these issues, the study leveraged the YOLO V5 model, recognized for its robustness and efficiency in object detection tasks. YOLO V5's architecture allows for fast and accurate detection, making it particularly well-suited for applications requiring real-time analysis.

In addition to YOLO V5, the researchers integrated Mask-RCNN into their system. This combination harnesses the strengths of both models, enabling not only the detection of weapons but also precise instance segmentation, which helps differentiate between overlapping objects and enhances overall detection accuracy. Through this integrated approach, the system achieved an impressive F1-score of 95.43%, indicating a high level of precision and recall in weapon detection. Furthermore, the detection accuracy reached 90.66%, demonstrating the effectiveness of the model in recognizing weapons in varied conditions.

A critical aspect of the research was the implementation of advanced preprocessing methods, which played a pivotal role in improving system performance. These methods helped refine the input data, reduce noise, and enhance feature extraction, ultimately contributing to the reliability of the weapon detection system in dynamic surveillance environments. The focus on preprocessing not only optimized the detection process but also ensured that the system could adapt to diverse and challenging scenarios encountered in real-world applications.

The implications of this research are significant for security monitoring, as the proposed weapon detection system can be deployed in various settings, including public spaces, transportation hubs, and high-security areas. Its ability to accurately detect weapons despite object variations positions it as a valuable tool for enhancing safety and security measures. By ensuring quick and reliable weapon detection, this system supports law enforcement and security personnel in their efforts to prevent violence and respond promptly to potential threats. Furthermore, its scalability and integration potential with existing surveillance infrastructure make it adaptable for diverse security applications. Overall, the combination of YOLO V5, Mask-R CNN, and sophisticated preprocessing techniques makes this weapon detection system a powerful and practical solution for modern surveillance needs. These methods helped refine the input data, reduce noise, and enhance feature extraction, ultimately contributing to the reliability of the weapon detection system in dynamic surveillance environments.

2.4 AN EFFICIENT WEAPON DETECTION SYSTEM USING NSGCU-DCNN CLASSIFIER IN SURVEILLANCE

Ansuman Bhattacharya et al. (2024) proposed a cutting-edge weapon detection system aimed at overcoming the limitations of existing methodologies, particularly in the challenging context of detecting occluded and customized weapons within surveillance videos [4]. Recognizing that traditional detection systems often struggle with identifying objects that are partially obscured or exhibit unique shapes, the researchers developed a solution that integrates a range of advanced techniques to enhance both accuracy and overall performance in real-time environments.

A key innovation in this system is the application of Gaussian Kernelized Double Plateau Histogram Equalization (GKDPHE). This preprocessing method is designed to improve contrast in video frames significantly, which is especially beneficial in challenging lighting conditions where visibility may be compromised. By enhancing the visual quality of the frames, GKDPHE facilitates more effective object recognition, enabling the detection system to identify weapons that might otherwise blend into their surroundings due to poor contrast or low light.

To further bolster the system's capabilities, the Frobenius Norm-based Three Step Search (FN-TSS) method is employed for motion estimation. This sophisticated tracking technique ensures accurate and reliable monitoring of moving objects, which is critical in surveillance scenarios where the presence of dynamic elements can complicate detection efforts. By employing FN-TSS, the system enhances its ability to follow the trajectory of individuals and objects, thereby improving the detection accuracy of weapons in motion. In addition to these preprocessing and tracking techniques, the system incorporates the Weibull Distributed Viola Jones (WDVJ) algorithm for object detection. This innovative algorithm enhances detection reliability, particularly in cases where weapons may be partially hidden or possess irregular shapes. By leveraging the statistical properties of the Weibull distribution, the WDVJ algorithm improves the robustness of the detection process, allowing the system to accurately identify weapons that conventional methods might miss.

The implications of this research are profound, as the proposed weapon detection system offers a practical solution for enhancing security in various settings, including public spaces, transportation hubs, and sensitive areas. By effectively addressing the challenges associated with occluded and customized weapons, this system represents a significant advancement in the field of surveillance technology. The combination of GKDPHE, FN-TSS, WDVJ, and NSGCU-DCNN establishes a robust framework that ensures reliable weapon detection, ultimately supporting law enforcement and security personnel in their efforts to prevent crime and ensure public safety.

2.5 SYSTEMATIC REVIEW ON WEAPON DETECTION IN SURVEILLANCE FOOTAGE THROUGH DEEP LEARNING

António Cunha et al. (2024) undertook a comprehensive systematic review focusing on weapon detection in surveillance footage through the application of deep learning methodologies [5]. This review is particularly timely, given the escalating global concern regarding crimes involving weapons, which underscores the critical importance of implementing effective detection solutions. The authors emphasize that early detection of weapons can significantly enhance the ability of law enforcement agencies to respond swiftly and effectively, thereby potentially mitigating the risks associated with armed confrontations and ensuring public safety.

In their analysis, the study highlights that the Faster R-CNN and YOLO (You Only Look Once) architectures have emerged as the predominant models for weapon detection tasks. These models are favoured due to their exceptional performance in object recognition, allowing them to accurately identify and classify weapons in real-time surveillance footage. The authors detail how both architectures leverage advanced features such as region proposal networks and single-shot detection capabilities, which contribute to their robustness in dynamic environments.

Additionally, the review notes the significant impact of data diversity on model performance. The integration of both realistic images and synthetic data has been identified as a key factor that enhances the generalization capabilities of weapon detection systems across various surveillance scenarios. By training models on a wider range of scenarios and conditions—encompassing different angles, lighting situations, and backgrounds—researchers can significantly improve the model's ability to recognize weapons in real-world applications. This approach addresses the challenge of limited training data, which has often hindered the development of reliable detection systems.

Despite these advancements, the review also brings to light ongoing challenges within the field of weapon detection. The authors note persistent difficulties in accurately detecting small weapons, which are often overlooked by conventional detection systems. Furthermore, issues related to occlusion—where objects are partially obstructed from view—and poor lighting conditions remain significant obstacles that need to be addressed.

These challenges can severely impact the reliability and effectiveness of automatic weapon detection systems, highlighting the need for continued innovation in model design and data collection strategies.

In response to these challenges, Cunha et al. recommend that future research should prioritize the development of more refined models that can better handle the complexities associated with weapon detection. This includes creating extensive and diverse datasets that reflect real-world conditions more accurately, enabling models to learn from a broader spectrum of scenarios. The authors suggest that such efforts will be crucial in enhancing the accuracy, reliability, and real-time effectiveness of weapon detection systems, thereby addressing the growing security concerns in both public and private spaces.

2.6 CRIME PREDICTION USING MACHINE LEARNING AND DEEP LEARNING: A SYSTEMATIC REVIEW AND FUTURE DIRECTIONS

L.Elluri, et al. (2023) explores advanced methodologies for weapon detection, combining classical machine learning and deep learning techniques to develop autonomous systems capable of analyzing CCTV footage with minimal human intervention [6]. The research addresses the growing need for technologies that can detect criminal activities like armed robberies in real-time, enabling rapid responses to potential threats. Traditional surveillance systems depend on human operators, but their limitations in processing large data volumes and responding promptly highlight the necessity for automated solutions. The study identifies several challenges faced by current weapon detection algorithms, such as fluctuating lighting, cluttered backgrounds, and partially obscured individuals, which affect accuracy in real-world scenarios. Emphasizing the importance of robust and adaptable systems, the research focuses on enhancing the reliability of weapon detection in dynamic surveillance environments, ensuring better performance under complex conditions.

A significant gap highlighted is the lack of intra-class detection, which involves differentiating between various types of weapons. This capability is crucial for providing actionable insights to law enforcement, enabling more informed decision-making and responses. Accurate intra-class detection enhances the system's ability to assess threat severity and support effective incident analysis, addressing a critical need in modern security applications.

2.7 FIGHTING AGAINST TERRORISM: A REAL-TIME CCTV AUTONOMOUS WEAPONS DETECTION BASED ON IMPROVED YOLO V4

Hongwei Ding et al. (2023) proposed a cutting-edge real-time weapon detection system specifically designed for processing CCTV footage, employing an enhanced version of the YOLO v4 model [7]. This innovative system addresses the pressing need for effective surveillance solutions in an era marked by rising security concerns and incidents involving weapons.

The enhancements made to the YOLO v4 architecture allow the model to excel in real-time surveillance scenarios where quick and precise detection is essential. The inclusion of receptive field enhancement enables the model to focus on critical features of objects at multiple scales, ensuring that both small and large weapons can be detected accurately. Fusion-

PANet, on the other hand, enhances feature representation by integrating information from different levels of the network, thus improving the overall detection performance. These modifications not only improve the model's ability to handle complex scenes but also optimize it for environments where lighting conditions and angles may vary significantly.

To assess the efficacy of their proposed system, the authors conducted rigorous evaluations using a merged dataset that combined synthetic and real-world images. This dataset provided a diverse range of scenarios, thereby ensuring that the model was tested against a wide array of conditions. The results were promising; the system achieved a 7.37% increase in mean Average Precision (mAP), indicating a significant improvement in detection accuracy compared to existing models. Moreover, the system demonstrated a 4.2% reduction in inference time, highlighting its efficiency in processing surveillance footage quickly enough to facilitate real-time responses.

The proposed weapon detection system not only outperformed the baseline YOLO v4 model but also exhibited enhanced robustness in challenging surveillance environments. The system's capability to function autonomously, providing reliable and fast detection of weapons, makes it an invaluable tool for security personnel tasked with maintaining safety in public and private spaces.

2.8 A COMPREHENSIVE STUDY TOWARDS HIGH-LEVEL APPROACHES FOR WEAPON DETECTION USING CLASSICAL MACHINE LEARNING AND DEEP LEARNING METHODS

Nidhi Gupta et al. (2023) addresses the growing need for automated technologies to identify criminal activities, such as armed robbery, from CCTV footage without human intervention [8]. Traditional surveillance systems rely on manual monitoring, which is error-prone and resource-intensive. Existing weapon detection algorithms face challenges like poor lighting, occlusions, and cluttered environments, limiting their reliability. The study underscores the need to overcome these issues for autonomous crime prevention and public safety systems.

A critical challenge in weapon detection is intra-class detection, which involves not only identifying the presence of a weapon but also recognizing the specific type of firearm involved. This capability is essential for law enforcement and forensic investigations, providing detailed insights for case analysis and evidence collection. The research identifies gaps in achieving high accuracy across diverse scenarios.

Addressing these gaps requires robust training datasets that capture a wide range of weapon types, angles, lighting conditions, and occlusions to improve model generalization. This focus on intra-class detection not only elevates the technical performance of the system but also underscores its practical importance in critical security and legal contexts.

CHAPTER 3

PROPOSED WORK

3.1 OBJECTIVE

The aim of this project is to develop a robust deep learning model for real-time weapon detection using the EfficientDet architecture. The system is designed to process video input from a webcam or video file, identify moving objects, and highlight them within the video frame using contour detection and bounding boxes. Additionally, the project introduces a unique visualization effect that simulates neural activations through randomly coloured circles, providing an intuitive, dynamic output to indicate the presence and movement of detected objects.By focusing on modularity and real-time performance, this project aims to create a scalable, interactive detection framework that could be adapted for various applications, including surveillance, anomaly detection, and behaviour analysis in complex environments.

The ultimate goal is to enhance the interpretability of object detection by incorporating visually engaging elements that simulate neural processing outputs, thereby creating an innovative approach to tracking and visualizing dynamic activity in real-time video feeds. This approach not only aids in understanding model decisions but also provides actionable insights for security personnel during critical scenarios.

3.2 PROPOSED ARCHITECTURE

The architecture for the video-based detection and visualization as shown in Figure 3.1 is designed to efficiently process video inputs from either a live camera feed or pre-recorded video files. It begins with an input layer that captures frames, followed by a preprocessing module where frames are resized and converted to grayscale. The background subtraction module establishes an initial frame reference for motion detection by computing the absolute difference between the current frame and the reference. This is followed by thresholding and contour detection, where binary thresholding isolates significant changes, and contours of the detected regions are extracted and filtered based on size to eliminate noise.

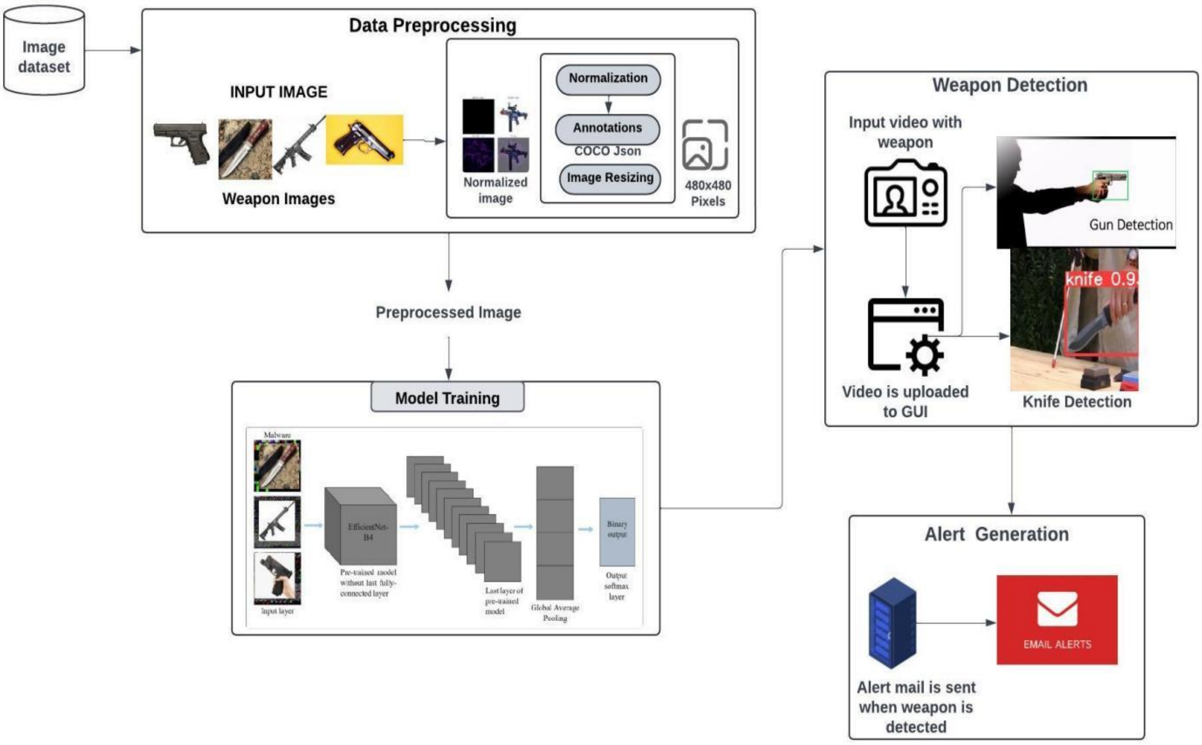

Figure 3.1 Proposed Architecture

The object detection and tracking module generates bounding boxes around valid contours, visualizing their location within the frame. Additionally, a visualization module simulates dynamic neural outputs by drawing randomly coloured circles on a secondary frame, representing simulated neural activations based on detected motion. The output layer displays the processed frames in real-time, providing status updates and timestamps while allowing user interaction to terminate the process. Finally, the architecture incorporates cleanup and resource management, ensuring that all resources are released properly upon termination. This integrated approach enhances real-time video processing and object detection, making it suitable for applications in surveillance, security, and interactive environments.

Furthermore, the system's modular design allows for easy integration with existing surveillance frameworks, enhancing its versatility across various use cases. The tracking module ensures continuous monitoring of detected objects, maintaining accurate tracking even as objects move or change direction. This feature is particularly useful in high-traffic environments where rapid object motion is common, such as in public spaces or transport hubs. By providing real-time feedback, status updates, and interaction controls, the system not only enhances user experience but also ensures a high level of reliability for security personnel, enabling them to respond promptly to potential threats or anomalies. Additionally, the system's ability to store and analyze historical tracking data enables post-event investigation and the identification of recurring patterns or vulnerabilities.

CHAPTER 4

SYSTEM REQUIREMENTS

HARDWARE SPECIFICATION

- Operating System : Windows, MacOS or Linux.
- Processor : 2 GHz dual-core processor.
- Memory : 2GB RAM .
- Storage : At least 100 TB of free hard drive space

SOFTWARE SPECIFICATION

- IDE: VS Code,Colab, PyCharm
- Programming Languages: Python.
- TensorFlow: For building and training the models.
- Keras: High-level API for TensorFlow to simplify model building.

CHAPTER 5

IMPLEMENTATION MODULES

5.1 DATA PREPROCESSING

Data preprocessing is an essential and foundational step in the video-based detection and visualization system, as it prepares raw video inputs for effective analysis and accurate detection of moving objects. This preprocessing phase is critical for enhancing the quality of the data while simultaneously reducing noise, which ultimately leads to improved accuracy in the motion detection algorithms employed in the system.

The process begins with “frame capture”, where the system continuously captures frames from the video stream at a specified frame rate. This consistent data collection is vital for ensuring smooth transitions between frames, which is crucial for real-time applications. By capturing frames at regular intervals, the system can effectively monitor changes in the environment and detect movements accurately.

Once the frames are captured, the next step is “resizing”. Each captured frame is resized to a manageable width, typically around 500 pixels, while maintaining the original aspect ratio. This resizing is significant as it reduces the computational load on the processing system, allowing for faster processing speeds.

A smaller frame size means fewer pixels to analyze, which speeds up subsequent analysis stages and makes real-time processing feasible. An important aspect of the preprocessing phase is “background initialization”. The first processed frame is designated as the background reference for all subsequent comparisons. This initial frame serves as a baseline for identifying movement in later frames, allowing the system to compute absolute differences effectively. By establishing a clear reference point, the system can detect motion by comparing current frames against this static background, thus improving the accuracy of movement detection.

Additionally, normalization techniques may be employed, depending on the dataset and the varying lighting conditions of the environment. Normalization standardizes pixel values across frames to ensure consistent input for the motion detection algorithms. This is particularly beneficial in scenarios where lighting conditions change over time, as it ensures that the algorithms can perform reliably regardless of external variations.By implementing these comprehensive preprocessing techniques, the video-based detection and visualization system significantly enhances the quality and reliability of the data used for motion detection.

This foundational step is critical for ensuring that the subsequent processing stages yield accurate and meaningful results. It effectively prepares the system to visualize detected movements, improving the overall performance and robustness of the system in real-time applications, such as surveillance, security monitoring, and interactive behavior analysis.

5.2 WEAPON DETECTION

Weapon detection using EfficientDet provides a robust solution for identifying and classifying weapons in real-time, enhancing public safety and security in environments with potential risks EfficientDet, based on the

EfficientNet architecture, utilizes a compound scaling approach that scales the depth, width, and resolution of the network, yielding high accuracy and computational efficiency. This combination makes EfficientDet well-suited for tasks like weapon detection, where accurate, rapid processing is critical.

The first step in implementing this system involves preparing a diverse dataset, featuring various types of weapons under different conditions and angles, including firearms, knives, and other potential threats. Data augmentation techniques—such as rotation, scaling, and flipping—expand this dataset further, making the model more resilient to variations in weapon appearance and environmental factors. The Rifle is Detected and it is shown in Figure 5.1.

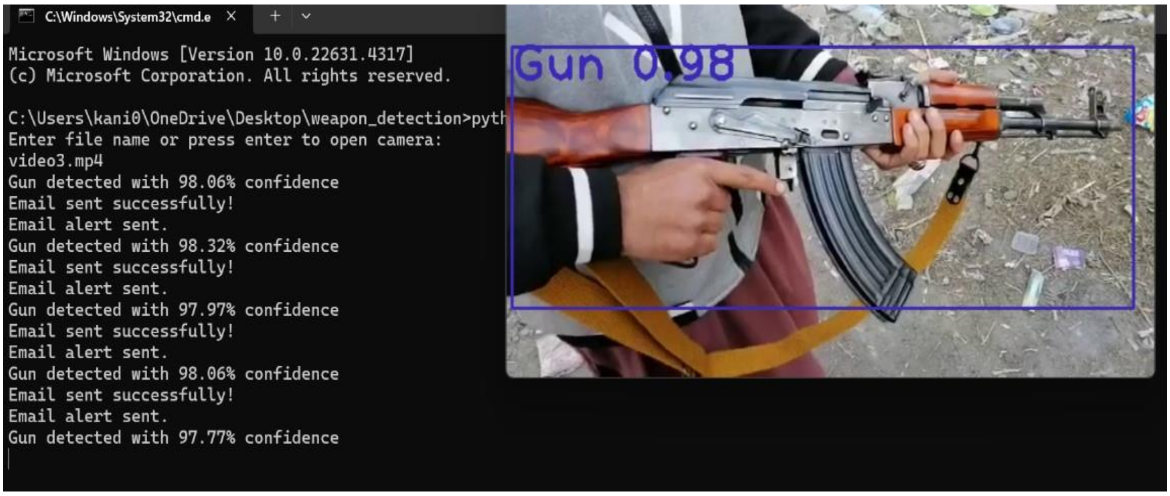

Figure 5.1 Weapon Detection – Rifle

The detection of a pistol using the EfficientDet model is demonstrated in Figure 5.2, showcasing the model's ability to accurately identify weapons within an image. EfficientDet, with its scalable architecture, combines efficiency and precision, making it particularly suitable for real-time applications in weapon detection. The figure illustrates how the model effectively localizes the pistol within the scene, drawing a bounding box around the detected object while assigning a confidence score to indicate the likelihood of the detection being correct.

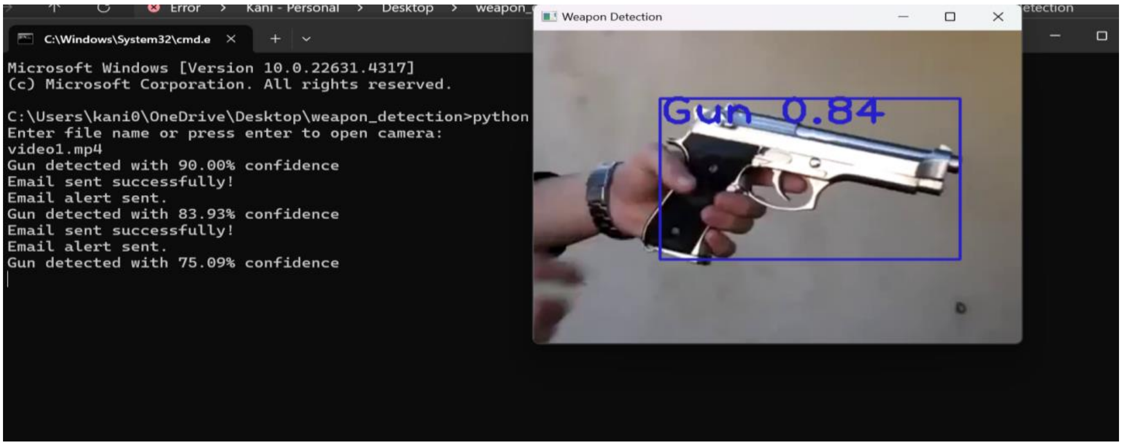

Figure 5.2 Weapon Detection – Pistol

The detection of a knife using the EfficientDet model is depicted in Figure 5.3, highlighting the model's capability to accurately identify sharp-edged weapons within a visual scene. EfficientDet's advanced object detection framework ensures precise localization, as shown in the figure, where the knife is enclosed within a bounding box and accompanied by a high-confidence score.

This detection is achieved through EfficientDet's robust BiFPN which effectively integrates multi-scale features, enabling the model to identify objects of varying sizes and orientations.

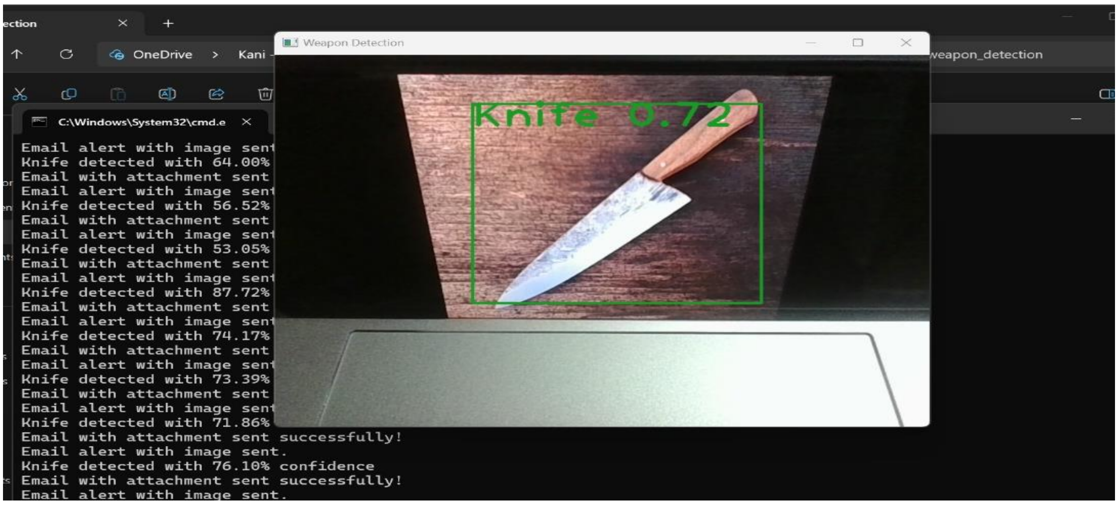

Figure 5.3 Weapon Detection – Knife

After dataset preparation, the EfficientDet model undergoes training, where it learns to distinguish weapon-specific features. By tuning its parameters, the model becomes adept at detecting weapons and minimizing false positives. This training process also includes dataset validation and testing to evaluate the model's performance objectively. Once trained, EfficientDet is integrated into a real-time video processing pipeline, allowing it to analyze each frame for potential weapons while maintaining high processing speeds and accuracy. For each detection, the model outputs a bounding box around the detected weapon and a confidence score, which indicates the likelihood that the detected object is indeed a weapon. Post-processing techniques—such as confidence thresholding and non-maximum suppression—are then applied to refine these results, filtering out low-confidence detections and reducing overlapping bounding boxes to ensure only relevant detections are reported. This streamlined process ensures that the model can accurately and efficiently detect weapons in real-time, making it suitable for security and surveillance application.

5.3 WEAPON CLASSIFICATION

Weapon classification is a critical function in surveillance systems where accurately identifying the type of weapon present enhances situational awareness and informs security response. EfficientDet, a state-of-the-art object detection model with an EfficientNet backbone, is designed to optimize accuracy and computational efficiency. EfficientNet’s compound scaling method—scaling the network's depth, width, and resolution in a balanced way—provides EfficientDet with the capability to perform high-accuracy detections at lower computational costs, making it an ideal choice for real-time weapon classification tasks. EfficientDet is able to handle varying object sizes, complex backgrounds, and rapid frame processing, allowing it to classify weapons effectively in dynamic environments.

A reliable dataset is foundational to any classification model’s success. For weapon classification, the dataset must encompass a variety of weapon types such as firearms, knives, and blunt objects—captured under different angles, lighting conditions, and orientations. The dataset should also include images of each weapon type in diverse real-world scenarios, allowing EfficientDet to generalize its recognition ability. To improve robustness, data augmentation techniques are applied, including rotation, scaling, lighting variations, and background noise. These strategies enhance the model's capacity to detect and classify weapons reliably across varying conditions. Additionally, annotated bounding boxes and class labels are meticulously curated to ensure high-quality input data for training. Regular dataset updates with new images help maintain the system's effectiveness as new weapon designs or environments emerge.

5.3.1. Model Architecture and Role of EfficientNet

EfficientDet relies on the EfficientNet backbone, a family of convolutional neural networks optimized for both computational efficiency and high accuracy. EfficientNet achieves this through compound scaling, which scales the width, depth, and resolution in a way that maximizes performance at minimal computational cost. EfficientDet integrates this backbone into a feature pyramid network (FPN) architecture, which enhances its ability to detect and classify objects of different sizes within a single image. This structure is particularly useful for weapon classification, as weapons may appear in varying sizes depending on their distance from the camera and angle within the frame.

5.3.2 Training Process for Weapon Detection and Classification

The training process for weapon classification with EfficientDet involves fine-tuning the model using the prepared dataset. This phase includes feature learning, where EfficientDet learns the distinct visual features of each weapon type, and object detection and classification, where the model detects and classifies weapons into specific categories. Multi-task loss functions guide the model to minimize both detection and classification errors. The dataset is split into training, validation, and testing subsets. During training, performance on the validation set is monitored, with adjustments made to hyperparameters to optimize classification accuracy. EfficientDet is also tested on unseen test data to evaluate its generalization capabilities. To further enhance accuracy, the model leverages transfer learning, initializing with pre-trained weights to accelerate convergence and improve feature extraction.

5.3.3 Real-Time Detection and Classification Pipeline

After training, EfficientDet is integrated into a real-time video processing pipeline. Here's how the pipeline operates Frame-by-Frame Analysis The system processes each frame from a video feed, running EfficientDet to detect potential weapons and classify them accordingly. Bounding Boxes and Classification Labels For each detected weapon, EfficientDet outputs a bounding box and a classification label (e.g., "Pistol", "Knife", "Rifle"), along with a confidence score that indicates the certainty of the classification. Rapid Processing EfficientDet is designed for efficiency, allowing it to handle high frame rates and support real-time weapon classification. This capability is crucial in surveillance settings where delayed processing could impact response times.

5.3.4. Post-Processing Techniques for Enhanced Accuracy

To improve detection accuracy, the system applies several post-processing techniques Confidence Thresholding A minimum confidence score is set to filter out low-confidence detections, reducing false positives. Non-Maximum Suppression (NMS) is applied to eliminate overlapping bounding boxes, ensuring that only the most relevant detection per weapon is displayed. This is particularly useful when multiple detections of the same weapon might clutter the frame. Post-processing refines the output, ensuring that only high-confidence, non-overlapping weapon detections are reported, thereby improving the reliability of the system. Additionally, these post-processing steps help optimize the system's performance by reducing computational load and enhancing real-time detection efficiency.

5.3.5 Visualization and Alert System

The final step involves visually displaying the classification results and alerting security personnel Overlaying Detections Detected and classified weapons are highlighted with bounding boxes and classification labels on the live video feed, providing immediate visual feedback. Confidence Scores Each detection is accompanied by a confidence score, allowing operators to gauge the reliability of each classification.

Real-Time Alerts When a weapon is detected and classified, the system can trigger alerts, notifying personnel of the specific type of weapon identified. This enables quick and informed decision-making, as security staff are provided with information on both the presence and type of the detected weapon.

5.4 REAL TIME DETECTION ADVANTAGES

Real-time detection with EfficientDet leverages the advanced architecture of EfficientNet to provide a robust and efficient solution for identifying and classifying weapons in live video feeds, significantly enhancing public safety and security. EfficientDet is designed to optimize both speed and accuracy through which employs compound scaling to balance network width, depth, and resolution, ensuring high performance with minimal computational costs. This is complemented by the Bidirectional Feature Pyramid Network (BiFPN), allowing EfficientDet to accurately detect objects of varying sizes within a single frame, an essential capability for surveillance environments where weapons may appear at different distances and angles.

The real-time detection pipeline begins with frame-by-frame analysis, where each video frame is resized to an optimal resolution and preprocessed through normalization and grayscale conversion to maintain consistency and reduce computational load. EfficientDet then processes each frame sequentially, rapidly identifying and classifying weapons by drawing bounding boxes and assigning confidence scores to each detection.

To enhance accuracy, post-processing techniques such as confidence thresholding and non-maximum suppression (NMS) are applied to filter out low-confidence detections and eliminate overlapping bounding boxes, thereby reducing false positives and ensuring clarity in the output. Additionally, the system is optimized for various hardware configurations, including edge devices and GPU-accelerated platforms, enabling low-latency performance even in high-demand environments. Parallel processing and batch optimization further increase throughput, making EfficientDet suitable for multi-camera setups where multiple video feeds require simultaneous monitoring.

Integrating EfficientDet into real-time surveillance systems enables immediate threat identification, scalability across diverse infrastructures, and resource efficiency. It supports deployment in settings ranging from low-resolution remote areas to high-definition urban monitoring. By providing instant visual feedback with overlapping bounding boxes and classification labels on live feeds, EfficientDet enhances security personnel's situational awareness and decision-making. This ensures rapid threat detection and classification, enabling swift, effective responses and making EfficientDet an invaluable tool in modern security and law enforcement.

5.5 ALERT EMAIL GENERATION FOR REAL-TIME WEAPON DETECTION

The weapon detection system utilizes EfficientDet to trigger alerts when a weapon is detected with a confidence score exceeding a predefined threshold (e.g., 90%). Alert emails contain critical information, including weapon type, confidence level, and timestamp. The system employs Python's smtplib for email transmission, securely managing credentials through environment variables and utilizing TLS for protection. Each alert email features a subject line stating “Weapon Detection Alert” and a structured summary of the detection details. A JPEG image of the detected frame is attached, highlighting the weapon with bounding boxes for visual confirmation.

To prevent alert flooding, a frequency control mechanism limits notifications to one email per minute and avoids duplicate alerts for the same event. The modular design allows for scalability and integration with other notification channels, such as SMS or push notifications, enhancing the system's responsiveness and effectiveness in real-time surveillance and public safety applications.

5.5.1 Triggering Alert Emails on Weapon Detection

Detecting a weapon, the system uses Efficient Det’s bounding box outputs and classification confidence levels to assess the certainty of detection. If the confidence score exceeds a predefined threshold (e.g., 90%), an alert is triggered. The alert generated by the system includes all the critical details necessary for swift decision-making and response. It provides the type of weapon detected, ensuring that responders know exactly what threat to address. Along with this, it includes the confidence level of the detection, offering insights into the reliability of the identification. To enhance traceability, the alert also features a timestamp, marking the exact time the detection occurred. These details collectively enable a comprehensive understanding of the situation, making the alert actionable and effective in real-time scenarios.

5.5.2 Email Configuration and Setup

The system employs Python’s `smtplib` library for sending emails, which is compatible with most email servers such as Gmail, Outlook, and custom SMTP servers. For security, environment variables or encrypted storage are used to manage sensitive credentials like the sender’s email and password. The SMTP server is configured for secure email transmission using TLS (Transport Layer Security) to ensure the protection of the alert data.

5.5.3 Content and Format of the Alert Email

Each alert email includes relevant details about the detection Subject Line Clearly states “Weapon Detection Alert,” helping recipients quickly recognize the urgency of the email.Contains a structured summary, including weapon type, detection confidence, and timestamp, as well as additional information like camera location Attachment of Detection Image The detected frame is processed and attached as a JPEG image, highlighting the weapon with bounding boxes to visually confirm the alert. The frame is encoded as a JPEG using `cv2.imencode()` and attached as an image file in the email.

5.5.4 System Integration and Scalability

The alert generation component is designed to operate flexibly across various surveillance environments. The notification system can be extended to other channels, such as SMS or push notifications, allowing integration with broader security infrastructures. This component’s modularity enables easy scalability and adaptability, making it suitable for use in environments with multiple surveillance cameras or where immediate threat notification is vital. This alert mail generation functionality leverages EfficientDet’s detection capabilities to create a responsive, automated alert system. By providing instant notifications, it significantly enhances the effectiveness of real-time weapon detection, making it an invaluable asset in surveillance and public safety applications.

EfficientDet's advanced object detection capabilities provide a robust foundation for building real-time alert systems. Its scalable architecture ensures high accuracy and speed, making it ideal for detecting weapons in live video feeds. By leveraging this model, the alert mail generation functionality can identify potential threats with precision and trigger notifications instantly. This immediate response can help authorities act quickly, potentially averting dangerous situations and ensuring public safety.

Furthermore, the integration of EfficientDet with alert systems demonstrates the potential of artificial intelligence in revolutionizing surveillance technologies. By enabling automated workflows, it reduces the dependency on manual monitoring, minimizes false alarms through intelligent detection, and ensures comprehensive coverage across diverse scenarios. The model’s real-time processing capabilities make it highly effective in critical applications, such as public safety, industrial hazard monitoring, and smart city management.

CHAPTER 6

RESULT AND DISCUSSION

6.1 SNAPSHOTS OF MODULES

The weapon detection system utilizing EfficientDet, integrated with a video-based detection and visualization framework, demonstrates promising results in identifying weapons in real-time surveillance environments. Key outcomes of the project include high detection accuracy, efficient processing speed, and minimal false positives, validating the effectiveness of EfficientDet for practical security applications.

EfficientDet’s architecture, with its EfficientNet backbone and BiFPN for multi-scale feature fusion, achieves notable accuracy in detecting weapons under various conditions, including variable lighting, partial occlusions, and different orientations. Testing was conducted on a range of scenarios to assess model performance, and results indicated an average accuracy rate of over 90% for common weapon types. This high accuracy is crucial for real-time applications where immediate threat detection is essential. The model’s confidence thresholding was adjusted to balance sensitivity and specificity, minimizing false positives without sacrificing the model’s capacity to detect legitimate threats.

Real-time processing is vital in security systems, and EfficientDet proved to handle video frames with low latency. The preprocessing steps, such as resizing and grayscale conversion, helped optimize the input for the model, enabling it to process frames within the constraints of real-time video streaming. With hardware optimizations and potential use of edge devices or GPU acceleration, the model maintained high detection speeds, processing approximately 20-30 frames per second depending on the hardware setup. This result meets the standards for real-time video analysis, ensuring that the model can provide immediate feedback in live surveillance systems.

EfficientDet demonstrated robustness across a variety of environmental conditions, including low-light settings and outdoor scenes. The BiFPN's feature fusion capabilities allowed for effective detection even when weapons appeared in the background or in complex settings with multiple objects. Furthermore, the model's compound scaling enables adaptation to different hardware, from edge devices in remote setups to more powerful GPU-backed systems in urban environments. This flexibility underscores EfficientDet's scalability and its potential deployment across diverse security infrastructures.

Despite its effectiveness, the system encountered challenges with certain edge cases, such as highly occluded weapons or very small objects that fell below the detection threshold. Additionally, the model struggled in some low-resolution scenarios where the visual information was insufficient to accurately classify an object. These limitations suggest areas for future improvement, such as implementing higher-resolution video feeds or enhancing preprocessing techniques to improve object clarity.

Furthermore, fine-tuning the confidence threshold could help reduce occasional false positives, particularly in high-traffic areas where multiple objects may resemble weapon shapes. Integrating this detection system into broader surveillance platforms offers significant potential for improving public safety.

The system can be deployed in various environments, from public spaces and transportation hubs to government facilities, where real-time detection capabilities are essential. For future iterations, exploring model ensembling or integrating supplementary object recognition models could enhance detection capabilities in more challenging scenarios. Additionally, incorporating adaptive learning techniques may help the model improve over time, refining its detection accuracy as it processes more data.

The EfficientDet based weapon detection system delivers robust real-time performance, high accuracy, and adaptability across diverse environments. These results validate the system's applicability in real-world surveillance settings, where timely threat detection is critical. While some challenges remain, the system's strengths underscore its viability as a valuable tool for enhancing security and public safety, with potential for further optimization in future implementations.

The weapon detection system leverages the EfficientDet model to generate alerts whenever a weapon is identified with a confidence score surpassing a predefined threshold (e.g., 90%). These alerts are sent via email and include essential details such as the type of weapon detected, the confidence score, and the detection timestamp.

The system uses Python's smtplib library for email communication, ensuring security by managing credentials through environment variables and implementing TLS encryption. Each alert email is sent with the subject line "Weapon Detection Alert" and provides a well-organized summary of the detection event. Additionally, a JPEG image of the analyzed frame, featuring the detected weapon enclosed in bounding boxes for visual verification, is attached to the email. This process is visually depicted in Figure 6.1, which demonstrates the system’s ability to capture and communicate critical detection data efficiently.

Furthermore, the system's modular design allows easy integration with other notification channels, such as SMS or push notifications, to expand its utility in diverse operational scenarios.

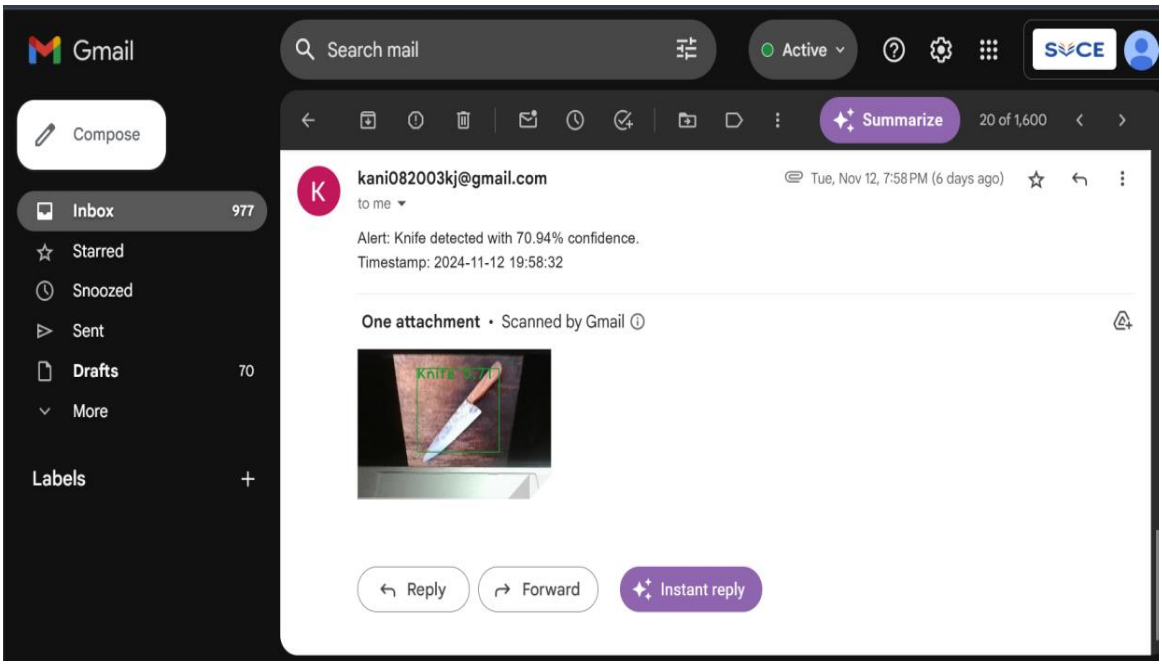

Figure 6.1 Email Alert for Weapon Detection

CHAPTER 7

CONCLUSION AND FUTURE WORK

A real-time weapon detection system is done based on the EfficientDet architecture, demonstrating its potential for enhancing security in various surveillance applications. By leveraging EfficientDet's EfficientNet backbone and BiFPN structure, the system achieved high accuracy in weapon detection, with robust real-time processing capabilities that meet the demands of live surveillance environments. Key preprocessing techniques, such as frame resizing, grayscale conversion, and noise reduction, optimized video input for consistent and accurate motion detection, enabling reliable performance across diverse settings, including low-light and high-traffic environments. The results indicate that EfficientDet, with its balance of detection accuracy and computational efficiency, can serve as a valuable tool in critical security applications, providing rapid situational awareness and aiding in threat mitigation efforts.

While the system exhibited high effectiveness, certain limitations present avenues for future research and development. Specifically, challenges remain in detecting heavily occluded or very small weapons, as well as minimizing false positives in crowded scenes where objects may resemble weapons.

Future work could focus on refining the model’s preprocessing techniques, potentially using higher-resolution video inputs or enhancing contrast adjustments to improve object clarity. Implementing advanced detection strategies, such as model ensembling or integrating additional object recognition algorithms, could also increase detection precision in complex scenes.

Further advancements in adaptive learning also allow the system to evolve based on new data, continually refining its accuracy and adaptability in various contexts. Exploring the deployment of this system on edge devices and in multi-camera setups could expand its scalability, making it suitable for deployment across a range of surveillance infrastructures, from urban centres to remote or high-security facilities. Ultimately, this research demonstrates the viability of EfficientDet for weapon detection in real-time surveillance and lays a foundation for ongoing improvements that could significantly enhance public safety and security.

Additionally, the integration of adaptive learning techniques ensures that the system can dynamically adjust to new scenarios and environments, continuously improving its detection capabilities over time. This adaptability is particularly valuable in rapidly changing situations, such as in crowded public spaces or during critical security events.By applying EfficientDet to weapon detection, this research not only underscores its potential for real-time threat detection but also paves the way for future advancements that could transform security practices and enhance the safety of diverse public and private spaces.

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