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Integrated Human-Proximity and Recognition for Detecting Smart Object Ownership in Organizational Settings

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***Abstract* - In the evolving digital landscape, the emphasis on protecting essential assets within organizations has intensified. This research unveils a state-of-the-art surveillance system, meticulously crafted to bolster the security of prized possessions, notably laptops. The system epitomizes the harmonious fusion of Human Proximity detection with cutting-edge recognition algorithms. At its core, it harnesses the power of the Albumentations library for image augmentation, Google's MediaPipe for instantaneous facial detection, and the unparalleled object detection prowess of YOLOv8. The integration of the DEEPSORT algorithm ensures flawless object tracking across video sequences. A distinctive feature of this system is its forward thinking approach to human identification, moving beyond the conventional reliance on facial features to embrace holistic body feature recognition, achieved through the careful development and training of a specialized model. Furthermore, the system introduces a novel binding mechanism, enabling users to securely link their cherished assets, like laptops, to their distinct identity, while adeptly addressing multifaceted challenges, from privacy concerns to the imperative of real-time processing and steadfast system reliability.**

Keywords: Human Recognition, Advanced Proximity Detection, Next-gen Surveillance, Holistic Asset Protection, Body Feature Identification.

I. INTRODUCTION

In today's rapidly evolving digital era, the protection of valuable assets within organizational infrastructures has become more crucial than ever. The accelerated pace of technological advancements has heightened the need for sophisticated surveillance mechanisms. To address this pressing demand, we introduce the Integrated Human Proximity and Recognition System for Smart Object Protection, a system designed to redefine asset protection paradigms, especially in settings where assets like laptops play a pivotal role.

The primary aim of this system is to fuse human recognition capabilities with state-of-the-art proximity detection techniques. Traditional facial recognition, while robust, faces challenges when facial features are obscured or not directly visible [1]. Such situations highlight the need for a flexible recognition framework capable of identifying individuals based on various attributes, including body posture, attire, and gait. By integrating facial and body recognition techniques, our system promises unmatched accuracy, ensuring adaptability across a range of scenarios. Another fundamental component of this system is proximity detection. Utilizing advanced algorithms, the system can precisely detect the presence of individuals near valuable objects, playing a crucial role in preventing unauthorized access that could lead to significant data breaches or asset misappropriation [2].

Deep learning is the backbone of our system. The recognition algorithms benefit from the Albumentations library, which offers a wide range of transformations to the dataset, simulating the unpredictability of real-world scenarios [3]. Additionally, the system employs Google's MediaPipe for realtime face detection, ensuring that only images with clear facial features are considered, thus maintaining the integrity of the data for the recognition models [4].

In object detection, our system utilizes the YOLOv8 model, celebrated for its exceptional speed and accuracy [5]. This is further enhanced by the DEEPSORT algorithm, skilled in tracking objects across consecutive video frames, effectively handling challenges such as occlusions or overlapping objects. A notable feature of our system is its ability to link valuable objects to their rightful owners using cutting-edge pattern recognition techniques, ensuring that alert mechanisms are promptly deactivated once the legitimate owner is detected nearby [6].

In conclusion, as the landscape of surveillance systems undergoes transformation, the Integrated Human Proximity and Recognition System stands out as a beacon of innovation,

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symbolizing a future where assets, both tangible and intangible, are protected with an efficiency previously considered unattainable [7].

II. BACKGROUND AND LITERATURE REVIEW

In today's tech-driven world, protecting valuable assets, especially in organizations, is crucial. The unique blend of human recognition systems with proximity detection offers a new way to enhance the security of important items, like laptops.

A) Human Proximity Detection Systems

Human Proximity Detection Systems are gaining popularity in various fields, from healthcare to high-level security. These systems are designed to detect humans within a certain distance and can take specific actions based on this detection [8]. They are essential in places where human presence or absence affects operations or safety. Moreover, research by Liangsong Huang and others, discussed in their 'ScienceDirect' article, looks into flexible proximity sensors and their uses in environment monitoring, health tracking, and robotics [9]. While they focus on sensorbased detection, our study uses CCTV images for detection, introducing new possibilities. This review helps in understanding flexible detection, offering a fresh view beyond usual methods.

B) Human Recognition Systems

Human recognition, led by facial recognition, has shaped security and surveillance. But relying only on faces can be limiting. When faces are hidden or unclear, systems can struggle [10]. So, there's a push to create systems that identify people using other features, like body shape or walk.

C) Image Augmentation with Albumentations

Deep learning models' strength in image tasks depends on the quality and variety of training data. Image augmentation, especially with the Albumentations library, adds transformations to images. This expands the dataset and makes the model more adaptable [11].

D) MediaPipe for Face Detection

MediaPipe, created by Google, is a top tool for real-time face detection. It's efficient in identifying faces quickly, even in challenging conditions [12].

E) Object Detection with YOLOv8

The YOLO series has transformed object detection. YOLOv8 is known for its fast speed and accuracy in spotting multiple objects in images. It's valuable in surveillance where quick detection matters [13].

F) DEEPSORT for Image Tracking

Tracking objects, especially humans, in video sequences is complex. DEEPSORT, which combines deep learning with the SORT method, offers a strong solution. It ensures accurate tracking across video frames [14].

G) Challenges and Future Directions

Combining these advanced systems offers many benefits but also has challenges. Privacy, system strength, and real-time processing are concerns. Future research might include using sound cues or heat images to improve system performance [15].

III. METHODOLOGY

The methodology underpinning the proposed Integrated

Human-Proximity and Recognition System for Smart Object Protection is meticulously structured into two pivotal environments, each serving a distinct yet interconnected purpose. The Pre-deployment Environment is the preparatory stage, dedicated to the assembly and refinement of essential datasets, the development of robust recognition models, and the establishment of foundational algorithms. It sets the stage for the system's capabilities, ensuring that it is primed for real-world challenges. In contrast, the Live Environment is the operational stage, where real-time surveillance, object detection, and owner verification processes come into play. This environment is characterized by its dynamic interactions, swift decisionmaking, and the application of the tools and models crafted in the pre-deployment phase. Together, these environments form a cohesive methodology, ensuring comprehensive asset protection in organizational settings

A) Pre-Deployment Environment

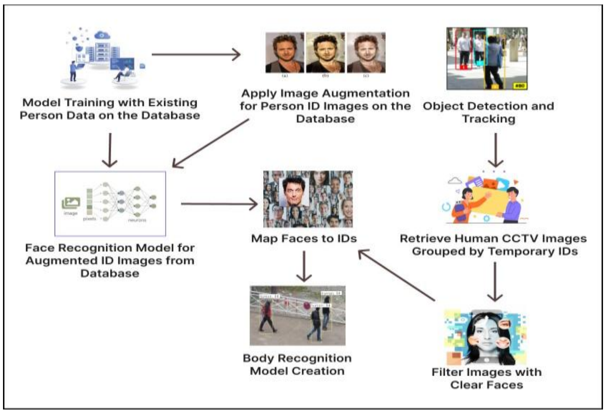

Figure 1: Integrated Human Proximity and Recognition System: Pre Deployment Environment Schematic

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The pre-deployment environment lays the groundwork for the entire surveillance system. It is a meticulous process that ensures the recognition models are robust, accurate, and ready for real time operations in the live environment. The steps undertaken in this phase are detailed below:

1) Dataset Collection for Face Recognition Model:

- Gathering ID Images: A comprehensive database of ID images is assembled. These images serve as the primary source of facial data, representing a diverse range of individuals.
- Augmentation with Albumentations: To bolster the dataset and introduce variability, the Albumentations library is employed. This ensures the model is exposed to a variety of facial orientations, lighting conditions, and expressions, enhancing its generalization capabilities.

Figure 2: Augmented Images generated through Albumentations

2) Face Recognition Model Creation:

- Training the Model: Using the augmented ID images, a deep learning model is trained to recognize faces. The model undergoes rigorous training cycles to ensure it achieves optimal accuracy.

3) Retrieve Human Images:

- Image Request: The secondary system, responsible for capturing real time CCTV footage, is queried to provide images of humans.
- Image Grouping: The received images are grouped based on unique IDs. These IDs, while not necessarily unique in a real world context, help in organizing the data for subsequent processing.

4) Filter Images with Clear Faces:

Figure 3: Illustration of Facial Keypoints Detected using MediaPipe

- MediaPipe Filtering: While the standard approach is designed to detect up to 52 facial keypoints, the methodology tailored for CCTV images takes a different route. Given the inherent limitations and quality of CCTV footage, not all keypoints are consistently detectable. Through extensive experimentation, it was determined that a subset of 37 keypoints serves as the optimal threshold for reliable face detection. The image arrays are sifted through, and only images where these 37 keypoints are visible are retained, ensuring that the data used for recognition is of the highest quality.

5) Map Faces to IDs:

- Face Recognition: The previously trained face recognition model is employed to match images to known faces in the database.
- Image Confirmation: If a match is found, it confirms the identity of the individual in the entire image array, streamlining the data labeling process.

6) Body Recognition Model Creation:

- Training on Confirmed Arrays: With a dataset of confirmed image arrays, a new model is trained. This model, unlike the previous one, focuses on recognizing individuals based on body features, ensuring recognition even when faces are obscured.

7) Rationale for YOLOv8 Model Selection:

- The YOLOv8 model is a highly efficient real-time object detection system that processes images in a single pass, ensuring accuracy without compromising speed. Its transfer learning capabilities enable it to use pre-trained weights from vast datasets, even with limited data like obscured CCTV footage. Its adaptability makes it suitable for diverse scenarios.

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8) Comparative Analysis:

YOLOv8 vs. Traditional Models: The table below provides a detailed comparison, highlighting the reasons for selecting YOLOv8 over traditional models for body recognition in obscured CCTV footage:

Table I: Comparative Analysis: YOLOv8 vs. Traditional Models

Features	YOLOv8	Traditional
Speed	Single-shot for fast real-time detection.	Two-step: slower.
Accuracy	Multi-scale predictions; extensive dataset.	Varies with training data.
Complexity	Simplified architecture.	Multi-stage architectures.
Dataset Aug.	Advanced techniques for diversity.	Basic methods.
Size	Optimized for size.	Heavier models.
Integration	Streamlined for surveillance.	Can be challenging.
Scalability	Adaptable to scenarios.	Less adaptable.

Upon the successful culmination of the aforementioned procedures, the pre-deployment phase guarantees that the surveillance infrastructure is fortified with two state-of-theart recognition models. These models are primed and ready, laying the foundation for their seamless real-time deployment in dynamic live scenarios.

B) Live Environment

The Live Environment represents the active deployment phase, where the system is put to the test in real world settings to safeguard valuable assets such as laptops. In this phase, the system operates in real time, continuously monitoring and making decisions based on the data it receives. It leverages the robust recognition models and methodologies meticulously crafted in the pre-deployment phase. This ensures not only the identification of individuals based on facial and body features but also the detection of any unauthorized proximity to valuable assets. Furthermore, the live environment integrates advanced object detection techniques, such as YOLOv8, and precise image tracking mechanisms, like DEEPSORT, to maintain a vigilant watch over the monitored area. The culmination of these tools and techniques ensures that the system operates with maximum efficiency, accuracy, and reliability, offering unparalleled asset protection in organizational contexts.

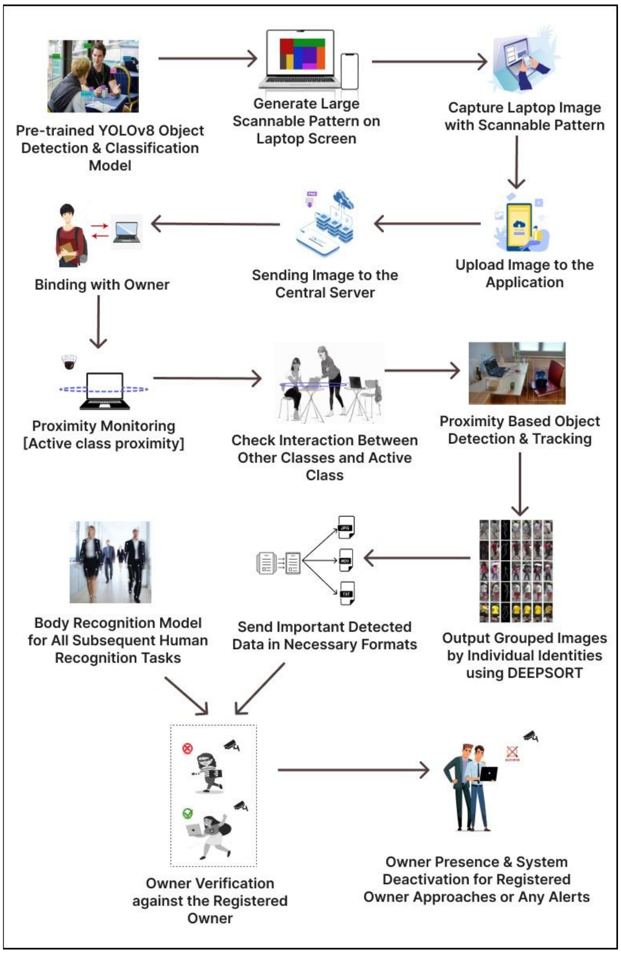

Figure 4: Integrated Human Proximity and Recognition System: Live Environment Schematic

1) Object Detection and Classification:

- YOLOv8 Integration - The system employs the YOLOv8 model, known for its rapid and precise object detection capabilities, to identify and classify various objects within the surveillance area, including but not limited to laptops and humans.

2) Binding with Owner:

- User Initiated Binding - Users can initiate the binding process through specialized applications on their laptops and mobile devices.
- Pattern Generation - The laptop, upon initiation, generates a distinct, large-scale pattern for scanning purposes. • Mobile Scanning - Users employ their mobile devices to scan the generated pattern, subsequently transmitting the captured image to a centralized server.
- Server-side Verification - The central server undertakes the responsibility of matching the transmitted pattern with patterns discernible in the CCTV footage, thereby establishing and confirming the ownership of the laptop.

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3) Operational Phase with Body Recognition Model:

- Real-time Human Recognition - The body recognition model, meticulously trained during the pre-deployment phase, is now in action, identifying individuals based on their body features, even in scenarios where facial features might be obscured.

4) Image Output and Tracking:

- Image Production - The system is capable of outputting images of detected classes or, alternatively, can provide coordinates for bounding boxes encapsulating the detected objects.
- DEEPSORT Application - The DEEPSORT algorithm is integrated to ensure images are systematically grouped based on individual identities, facilitating continuous tracking even in densely populated or crowded environments.

Figure 5: Demonstration of Object Detection and tracking using YOLOv8 and DEEPSORT

5) Proximity Monitoring:

- Interaction Surveillance - Advanced sensors, in tandem with sophisticated algorithms, continually monitor interactions between different object classes. Special emphasis is placed on scenarios where humans approach valuable assets, such as the bound laptop.

6) Proximity Monitoring and Owner Verification:

- Continuous Surveillance - The system persistently captures images of individuals in proximity to the bound laptop.
- Owner Verification - These captured images are then processed by the body recognition model to verify if the individual matches the registered owner's profile.

7) Owner Presence and System Deactivation:

- Presence Monitoring - The system remains vigilant, monitoring the vicinity of the laptop, awaiting the registered owner's approach.
- Alert Deactivation - Upon successful verification of the owner's presence, the system promptly deactivates any active alerts or tracking mechanisms, ensuring a seamless and unobtrusive experience for the user.

IV. TESTING AND RESULTS

In this section, we delve into the comprehensive testing procedures undertaken to evaluate the performance and robustness of the proposed Integrated Human Proximity and Recognition System. Through a series of controlled experiments, we aim to understand the system's capabilities in real-world scenarios, especially its ability to detect and recognize individuals accurately. By analyzing key metrics and visualizing them through graphs, we provide a holistic view of the system's effectiveness and areas of improvement.

A) Experimental Setup

To evaluate the effectiveness of the proposed Integrated Human Proximity and Recognition System, an experimental scenario was set up involving four participants. The participants enacted a scene where they moved around a designated area, simulating typical behaviors observed in organizational settings, including the act of picking up laptops, which mimicked potential theft scenarios. 1) Data Collection:

- ID Images: Four distinct ID images, one for each participant, were collected. These images are representative of typical identification photos, capturing clear facial features of the individuals.
- Video Recordings: Multiple video recordings were captured, showcasing the participants' movements, interactions with the environment, and the simulated theft actions.

B) Model Training and Evaluation

The data we gathered played a pivotal role in both training and testing our models. This diverse dataset, encompassing various facial and body images, was instrumental in refining our models, ensuring they are both robust and adaptable to real-world scenarios.

1) Loss Analysis: The depicted graph is a testament to the model's continuous improvement. By the 50th epoch, the training loss had substantially decreased to a mere 0.025, showcasing the model's adeptness at learning from the data. Concurrently, the validation loss also showed a commendable reduction, stabilizing around 0.08. This convergence of training and validation losses indicates that the model is not only learning effectively but is also generalizing well to new, unseen data.

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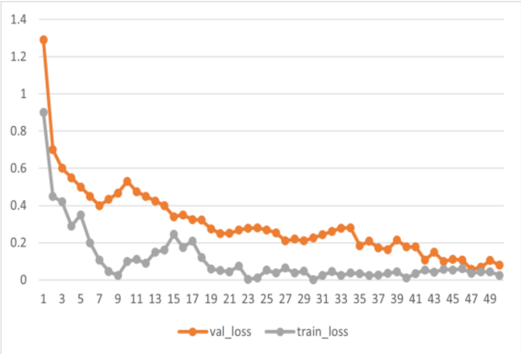

Figure 6: Graph illustrating the evolution of training and validation losses across epochs

2) Precision and F1 Score Analysis: The steady ascent in both precision and F1 score underscores the model's increasing accuracy and reliability. By the 50th epoch, the precision had impressively climbed to 0.9286, indicating a high rate of true positive identifications. Simultaneously, the F1 score, a harmonic mean of precision and recall, reached a notable 0.9050, further emphasizing the model's balanced performance.

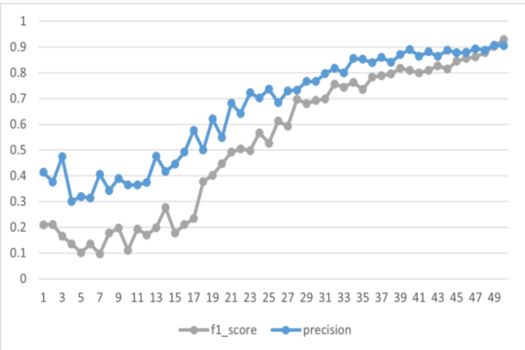

Figure 7: Graph delineating the progression of precision and F1 score across epochs

In conclusion, the rigorous training regimen, combined with the quality of data used, has culminated in a model that not only exhibits stellar performance metrics but also holds immense promise for effective deployment in real-world surveillance scenarios.

C) Bounding Box Adjustments

Given the 2D perspective of CCTV cameras, floor lines can appear slanted. Bounding boxes were adjusted to align with the camera's perceived floor angle.

D) Recognition Results

The system successfully recognized the participants from the video recordings using both facial and body features. The recognition was consistent, even in instances where the face was partially obscured or not directly visible.

E) Overall Performance

The system exhibited commendable performance in realtime scenarios. The integration of advanced algorithms, coupled with the modifications made to the bounding boxes, ensured that the system could accurately detect and recognize individuals in diverse scenarios.

Figure 8: Illustration of the adjusted bounding boxes aligned with the floor angle

The simulated theft actions were promptly detected, and the system was able to correctly identify the individuals involved, validating the system's efficacy in real-world applications. The graphs showcasing the training and evaluation metrics further attest to the robustness and reliability of the proposed system.

V. CONCLUSION

The realm of surveillance technology is undergoing a transformative phase, with the integration of sophisticated recognition systems and proximity detection mechanisms. The research presented in this paper introduces the Integrated Human Proximity and Recognition System for Smart Object Protection, a pioneering solution designed to address the challenges of safeguarding valuable assets, particularly in organizational settings.

Our primary objective is to devise a surveillance system that transcends traditional methodologies, focusing on the protection of valuable assets like laptops. The system's foundation was laid with the creation of a robust face recognition model, trained meticulously using a diverse database of ID images. To enhance the model's performance and adaptability, the dataset was augmented using the Albumentations library, ensuring the model's exposure to varied facial orientations and conditions.

The retrieval of human images, grouped by unique IDs, set the stage for the subsequent filtering process. Leveraging

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the capabilities of MediaPipe, images with clear and discernible facial features were isolated, ensuring the integrity of the data. This meticulous filtering process was pivotal in mapping faces to their corresponding IDs, a step that further solidified the system's recognition capabilities.

However, recognizing the limitations of relying solely on facial features, the research ventured into the domain of body recognition. A dedicated model was trained, capable of identifying individuals based on distinct body features, independent of facial attributes. This dual recognition capability, encompassing both face and body, was rigorously tested in real world scenarios, proving its efficacy and adaptability.

The live environment showcased the system's prowess in real time operations. The integration of the YOLOv8 model facilitated swift object detection and classification. Coupled with the DEEPSORT algorithm, the system adeptly tracked individuals across video frames, ensuring continuous recognition even in dynamic scenarios.

A standout feature of the system was its binding mechanism, allowing users to link their belongings to their identity. Through a seamless process involving scannable patterns and centralized servers, the system established ownership, ensuring that alerts were deactivated once the rightful owner was in proximity.

In conclusion, the Integrated Human Proximity and Recognition System for Smart Object Protection is not just a technological marvel but a beacon of innovation in the surveillance domain. It epitomizes the fusion of advanced recognition systems with proximity detection, promising enhanced security and asset protection. As the landscape of surveillance technology continues to evolve, systems like these will undoubtedly set the benchmark, offering unparalleled protection and peace of mind.

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