SmartGuard: Advanced Security with Real-Time Alerts in Banking Sector

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Abstract: *In today's world, basic surveillance is no longer enough—security systems must be intelligent, responsive, and proactive. While traditional CCTV systems are commonly used in banks, hospitals, and public spaces, they simply record footage and allow for post-incident review. They don't prevent crimes or offer real-time alerts. SmartGuard is an advanced security system designed specifically for the banking sector. It uses AI-powered video surveillance to recognize individuals in real time, distinguish between employees and unknown visitors, and track entries and exits. The system also includes night vision, fire and shadow detection, stolen object tracking, and even mask detection. By combining monitoring with intelligent analysis and instant alerts, SmartGuard moves beyond passive surveillance—offering a smarter, safer, and more responsive solution for modern bank security.*

Keywords: Smart surveillance, real-time video analysis, facial recognition, fire detection, object theft detection, mask detection, bank security, AI-based monitoring.

1. Introduction

Security within the banking sector is of utmost importance, given the sensitive nature of customer data and the high value of assets being protected. Traditional surveillance systems—primarily based on basic CCTV setups—have long served as a passive safety net. However, these systems often fall short when it comes to actively preventing threats in real time.

SmartGuard aims to transform this passive model into a proactive one. Designed as an intelligent surveillance solution, SmartGuard blends facial recognition, object detection, fire and weapon alerts, and behavioral analysis into a unified system. It leverages machine learning and computer vision to provide fast, accurate, and adaptive responses—reducing false alarms while enhancing security.

In addition to its analytical power, the system supports features like night vision, mask detection, and stolen object tracking. Custom access control allows it to distinguish between authorized personnel and strangers, helping improve both security and convenience.

2. System Architecture

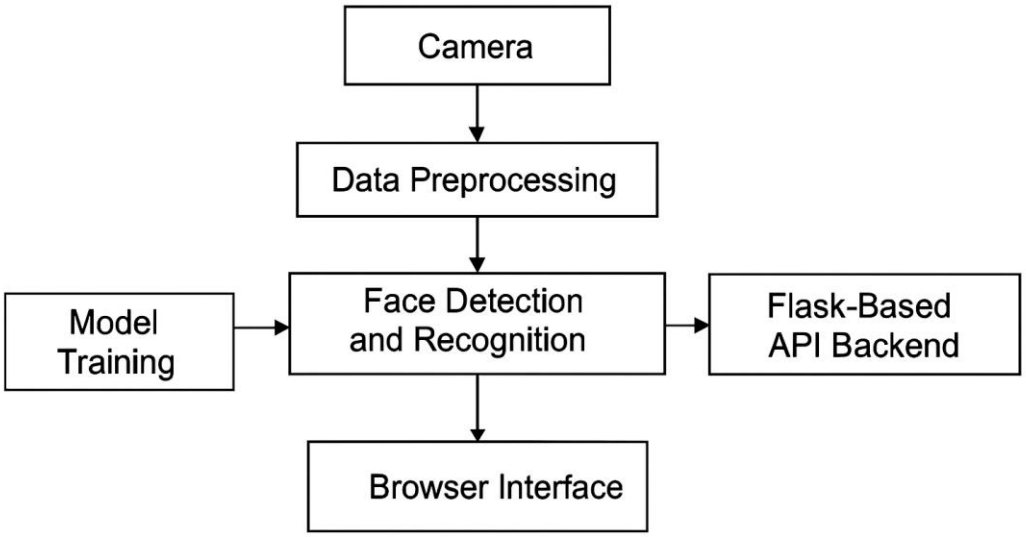

Figure 1. System Architecture of SmartGuard

SmartGuard's system architecture is thoughtfully designed to be both **modular** and **scalable**, ensuring reliable performance under real-time conditions. At its foundation is a constant video feed from surveillance cameras installed in and around sensitive areas like vaults, ATMs, and entry points. These video streams serve as the raw data input for the system.

The first stage of the pipeline is **data preprocessing**, where incoming frames are cleaned and formatted. This includes resizing images, converting them to grayscale to reduce processing complexity, and filtering out noise. These steps prepare the images for more advanced analysis.

The preprocessed frames are then passed to the **Face Detection and Recognition** module. Here, the system identifies individuals by comparing facial features against a trained database. This database is built during the **Model Training** phase using categorized images of employees and individuals flagged for potential threats.

Meanwhile, other classifiers handle additional tasks—such as identifying weapons, masks, and signs of fire—within each frame. If a suspicious event is detected, a **Flask-based API backend** takes over, acting as the brain of the operation. It processes the detection results and generates real-time alerts.

These alerts are delivered to a **browser-based interface**, allowing security personnel to monitor live video feeds, receive alerts, and access logs instantly from any authorized device. SmartGuard's design supports integration with existing surveillance setups and can operate on both local servers and cloud environments, providing institutions with the flexibility they need.

3. Dataset Preparation

To deliver reliable, real-time threat detection, SmartGuard depends heavily on a well-structured and diverse dataset. This dataset is divided into two primary categories: **'employees'** and **'criminals'**. Each category contains subfolders for individual identities, with numerous images representing different facial angles, lighting conditions, and expressions.

This organized structure helps the system learn how to accurately distinguish between trusted individuals and potential intruders. But before these images can be used for training, they go through a series of **preprocessing steps**:

- **Resizing**: Ensures all images conform to a standard size for consistent model input.
- **Grayscale Conversion**: Simplifies image data while preserving essential facial details.
- **Encoding**: Translates facial features into numerical values that the model can interpret and compare.

To further extend its functionality, SmartGuard includes a specialized module for **weapon detection**. A custom image dataset was created for this task, featuring a variety of weapon types such as **knives, drilling machines** and **blunt objects**. These images were collected both from public sources and controlled environments to replicate real-world conditions found in banks.

Like facial images, these weapon images undergo preprocessing to enhance model training:

- **Resizing**: Standardizes the input dimensions.
- **Normalization**: Adjusts pixel values for better model convergence.
- **Augmentation**: Introduces variability (e.g., rotation, scaling, flipping) to improve the model's ability to generalize.
- **Label Encoding**: Assigns a unique identifier to each weapon category for supervised learning.

These datasets and preprocessing strategies ensure that SmartGuard is not only responsive but also **resilient** in identifying both known individuals and potential threats, even under challenging visual conditions.

4. Model Training

SmartGuard lies a combination of machine learning models purpose-built to recognize faces and detect potential threats such as weapons in real time. These models are trained on carefully prepared datasets that reflect real-world conditions inside a banking environment.

For facial recognition, SmartGuard uses the **Local Binary Patterns Histogram (LBPH)** algorithm—an effective technique known for its simplicity and speed. The model is trained using categorized images of employees and individuals flagged as threats. Each image is analyzed by comparing pixel patterns around every point on the face, turning those patterns into a histogram that uniquely represents a person's facial features. This method allows the system to recognize individuals even under varying lighting conditions, different facial expressions, or when viewed from slightly different angles.

The Local Binary Patterns Histogram (LBPH) algorithm is used for facial recognition. It encodes each pixel based on the intensity of its neighbors using the following equation:

$$LBP(x_a, y_a) = \sum_{p=0}^{P-1} s(i_p - i_a) \times 2^p \quad (1)$$

Where:
- i_a *is the intensity of the center pixel,*
- i_p *are the surrounding pixels,*
- $s(x) = 1$ *if* $x \geq 0$*, else 0.*

The goal is not only to recognize employees but also to flag unauthorized individuals in real time. When someone enters a monitored area, the system captures their face, encodes it, and compares it with the stored profiles. If a match is found, their identity is confirmed; if not, an alert is triggered for further verification.

Alongside facial recognition, a **custom object classification model** has been trained to detect weapons such as knives, pistols, and blunt objects. These images are gathered under various lighting and perspective conditions to simulate real-life situations. During training, the model learns to differentiate weapons from harmless objects based on shape, texture, and context within the image. This is crucial in environments like banks, where even a moment's delay in detecting a threat can have serious consequences.

Importantly, the weapon detection system is optimized to reduce false alarms—ensuring that it reacts only when there is a clear risk, without causing unnecessary panic or disruption.

Table 1. Model Comparison

Model	Accuracy	Speed	Ideal Use Case
LBPH	High	Fast	Facial recognition (real-time)
CNN (custom)	High	Medium	Weapon detection

Together, these models form the brain of SmartGuard: continuously learning, adapting, and enabling proactive decision-making that enhances safety and peace of mind for both staff and customers.

5. Deployment and Results

Once the SmartGuard models for facial and object recognition are trained, they are deployed using a **Flask-based server** that acts as the system's control center. This server exposes multiple endpoints that enable real-time interaction with surveillance cameras, typically through a webcam or IP camera feed.

When the system is live, it continuously processes video frames and checks for faces, weapons, or suspicious activities. The recognition results are returned through **JSON responses**, which include crucial details such as the identified person's name (if matched from the dataset) and their corresponding threat level (e.g., employee, unknown individual, or flagged person).

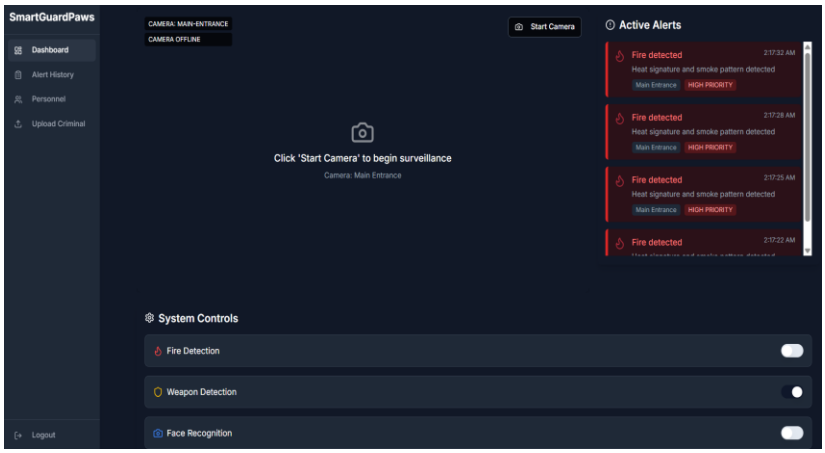

Figure 2: This is the UI dashboard named SmartGuardPaws for the project. It includes real-time video monitoring, detection status for fire, face, and weapons, identity classification (employee/criminal), and a simplified alert display to support timely response and decision-making.

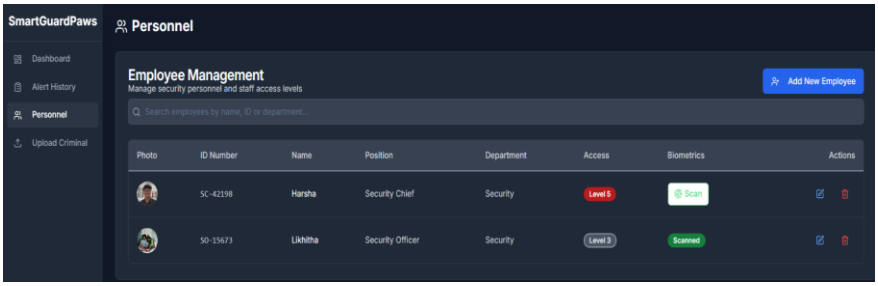

Figure 3: This is the Personnel page, where new employees can be added. It displays information such as access levels, biometric scan status, and user identification details for authentication and monitoring purposes.

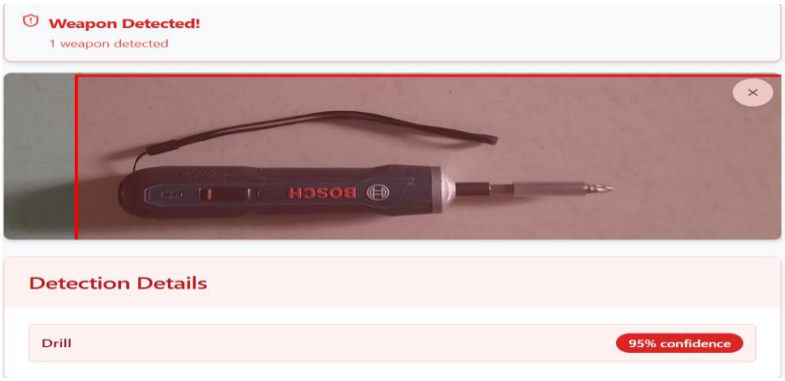

Figure 4: Weapon Detection Testcase

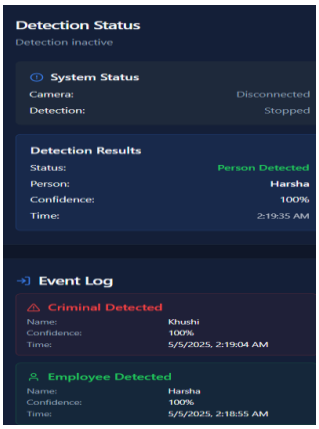

Figure 5: Criminal Detection Testcase

This real-time feedback is seamlessly integrated into a **browser-based interface**, allowing security personnel to monitor live activity, receive alerts, and make informed decisions quickly. The system logs each detection event, ensuring an audit trail is maintained for security reviews or investigations.

To evaluate system performance, the accuracy of predictions is computed using the standard formula:

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \times 100 \quad (2)$$

Where:
- *TP = True Positives*
- *TN = True Negatives*
- *FP = False Positives*
- *FN = False Negatives*

Average detection time for each frame is calculated as:

$$Avg.\ Detection\ Time = (1 / N) \times \sum_{i=1}^{n} (t\_end_i - t\_start_i) \quad (3)$$

Where:
- *N is the number of frames*
- *t_start, t_end are timestamps per frame*

Table 2. Confusion Matrix

	Predicted Positive	Predicted Negative
Actual Positive	TP = 87	FN = 3
Actual Negative	FP = 4	TN = 106

Table 3. Evaluation Metrics

Metric	Value
Precision	95.3%
Recall	96.7%
F1-Score	96.0%
Accuracy	94.8%

During testing, SmartGuard showed strong performance under typical lighting conditions and maintained high accuracy in face and object recognition tasks. Its ability to distinguish between authorized and unauthorized individuals, combined with rapid alerting features, makes it a reliable addition to any modern banking security setup.

6. Conclusion

SmartGuard showcases the potential of combining artificial intelligence with modern surveillance to create a safer, more responsive banking environment. By moving beyond traditional CCTV systems, it offers proactive features like real-time facial recognition, weapon detection, and instant alerting. The system adapts to real-world scenarios, helping security personnel make faster, more informed decisions. Its modular architecture ensures easy deployment and integration with existing infrastructure.

The project emphasizes not only technological innovation but also practical usability and reliability. Initial testing has shown promising results in terms of accuracy and real-time responsiveness. Looking ahead, enhancements will focus on increasing dataset diversity, refining detection algorithms, and expanding functionality to include broader behavioral analysis. As security needs continue to evolve, SmartGuard stands as a scalable and future-ready solution. It’s a step toward smarter, safer institutions—starting with banks.

7. References

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