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Automated Security for Lobby

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Abstract

Automated security systems are progressively adopted public areas such as building lobbies to enhance safety and restrict unauthorized entry. These systems play a decisive role in tracking visitor movements and ensuring secure access. This paper presents an innovative security framework designed for lobby environments, utilizing the Support Vector Machine (SVM) algorithm for intelligent data analysis. The proposed system integrates several components, including a network of surveillance cameras for image and video capture, environmental sensors to monitor surrounding conditions, and an SVM-based decision-making module. The choice of SVM is driven by its strong ability to classify data accurately by learning from labeled inputs, Optimizing its use for real-time security assessment and threat detection.

Keywords: Security; SVM; Regression Algorithms

Introduction

Automated lobby security using Support Vector Machine (SVM) and image processing is a sophisticated system developed to increase the safety and surveillance capabilities of buildings. This project combines both hardware and software components to create a responsive and intelligent security solution. The primary objective is to monitor the lobby area in real-time, detect any suspicious behavior or unauthorized access, and either alert the security personnel or initiate automated actions to address the threat.

At the heart of this system is the SVM algorithm, a supervised machine learning technique well-suited for tasks involving image analysis and pattern recognition. It is trained on labeled images consisting of both regular and irregular scenarios within the lobby environment. Once trained, the SVM model can accurately identify deviations from typical behavior by analyzing live video feeds. The hardware component includes high-definition cameras strategically installed to provide comprehensive coverage of the lobby. These cameras continuously capture images, which are processed by the image analysis module that uses SVM to detect anomalies such as unauthorized entries, the presence of unfamiliar objects, or erratic movements.

Upon detecting any unusual activity, the system is capable of taking immediate actions such as sounding alarms, notifying security staff, or activating additional security protocols. It can also be seamlessly connected to existing systems such as access control, fire alarms, and intrusion detection. There by offering a holistic and robust security framework. The advantage of using SVM in this context lies in its accuracy, ability to handle complex data, and effectiveness in recognizing subtle patterns that may signal a threat.

This approach to automated lobby security offers several benefits. It minimizes the need for constant human supervision, provides continuous and consistent monitoring, and significantly improves response times during potential security breaches. The system is also adaptable, allowing customization based on the unique requirements of different buildings or organizations. Such solutions are particularly beneficial in high-security environments such as airports, government facilities, corporate buildings, and public institutions where safety and vigilance are of utmost importance.

Looking ahead, the potential of this technology is vast. As advancements in AIML continue, the accuracy and intelligence of such systems are expected to improve further. Future developments may incorporate deeper learning models and real-time behavioral analysis, resulting in a more proactive and predictive security system. The incorporation of this solution with other evolving technologies will pave the way for more resilient, scalable, and intelligent building security systems.

Literature Review

Davis et al. introduced a human detection system using Histogram of Oriented Gradients (HOG) features in 2016. Their approach utilized both RGB and depth images captured by an Asus Xtion Pro Live camera operating at 30 frames per second with a resolution of 640×480 pixels. Thermal imaging was also employed using an Omega OSXL-101 camera, recording at 1 frame per second. The synchronized camera setup ensured accurate data collection, and images were stored in PNG format via the Robot Operating System (ROS). Twelve classifiers were verified using features extracted from randomly shuffled training datasets. Among these, the SVM and k-Nearest Neighbors (k-NN) classifiers achieved the highest accuracy of 88.24% for depth images, with both models reaching a true positive rate of 81.81% and achieving 100% accuracy on negative samples. Ye et al. proposed a Piecewise Linear Support Vector Machine (PL-SVM) method for human detection in images. Their model outperformed conventional linear, kernel-based, and profile SVM classifiers across multiple datasets, with accuracy improvements ranging from 0.5% to 2%. The PL-SVM achieved average accuracies of 98.79%, 99.13%, and 98.53% on three benchmark datasets, showing superior performance particularly when both HOG and Bag- of-Features (BO) were used together. This demonstrated that combining local and global features enhances detection capabilities. Liu and Sun et al. (2012) developed a pedestrian detection system optimized for in-vehicle use to assist drivers. Their approach addressed the challenges of detecting pedestrians with varying appearances and complex backgrounds by implementing a C4 algorithm to extract CENTRIST features, processed on a NVIDIA GPU for real- time performance. Both IP and infrared cameras were utilized to improve detection reliability. The system, which used contour-based analysis and thresholding methods, achieved an accuracy of approximately 80%. Anfal et al. presented a biometric-based human detection and recognition system integrating Support Vector Machines and genetic algorithms. The study framed biometrics as the measurable study of human physical characteristics, rooted in the Greek origins of the terms ”bio” (life) and ”metria” (measure). Their hybrid approach aimed to enhance accuracy and adaptability in human recognition tasks using evolutionary algorithms alongside machine learning. Krishna et al. proposed an enhanced model for Human Motion Recognition (HAR) in 2021, merging multiple feature extraction methods with an optimized SVM classifier. Their methodology integrated Bag-of-Words, Spatio-Temporal Interest Points (STIP), and optical flow descriptors. The use of HOG and Shape Context features proved effective for pedestrian detection, and motion-based descriptors such as Histogram of Optical Flow (HOF) and Motion History Images (MHI) were used for activity recognition. Feature reduction was further achieved through Principal Component Analysis (PCA), resulting in improved system performance. Abdourahman et al. addressed the limitations of using HOG-SVM alone for human detection by integrating it with background subtraction and a mixture of Gaussian models. Their study found that detection using only HOG-SVM often resulted in inaccurately wide silhouettes and lacked effective segmentation. By combining various methods—HOG for feature extraction, SVM for classification, Gaussian Mixture Models for background modeling, and contour subtraction—they achieved more accurate and well-defined human detection. Bhardwaj et al. explored emotion classification from EEG signals using both SVM and Linear Discriminant Analysis (LDA). Their work highlighted the viability of applying machine learning algorithms to neurological data for emotional state detection, offering a comparative evaluation of classifier performance. Shaafi et al. introduced enhancements in human activity recognition through the use of wireless body sensors combined with SVM and frame-difference methods. Their system showed improved accuracy in real-time scenarios by effectively fusing sensor data with intelligent classifiers, making it suitable for mobile health and behavioral monitoring applications. Davis and Sahin implemented a HOG feature-based detection system tailored for identifying human figures in various environments. Their model relied on classical feature extraction methods and demonstrated robust performance, validating the reliability of HOG in object detection tasks. Lastly, Dadi et al. developed a hybrid approach combining Gaussian Mixture Models (GMM), HOG features, and SVM for face recognition and human tracking in surveillance videos. By merging motion- based and appearance-based techniques, their method provided improved accuracy and adaptability for real-time surveillance systems. Nguyen et al. introduced a hardware architecture specifically optimized for human detection using HOG features and an SVM classifier. Their design emphasized real-time processing capabilities and low energy consumption, making it highly suitable for smart surveillance applications. The architecture featured a co- optimized approach where both feature extraction and classification were streamlined to enhance system efficiency. In a related study, Cai developed a human behavior recognition algorithm that integrated HOG descriptors with SVM for classification. The method demonstrated reliable accuracy in recognizing complex and dynamic actions, highlighting its applicability in behavior analysis systems and intelligent monitoring platforms. Furthering the hardware implementation aspect, Nguyen et al. also presented a real-world embedded vision system for human detection based on HOG-SVM. Their focus was on optimizing resource usage, facilitating deployment in environments that demand compact and power-efficient solutions. Sonia et al. proposed a novel one-class classification method for human detection using ultrasonic sensors. Unlike traditional camera-based techniques, their approach offers a cost-effective solution ideal for resource- constrained environments such as home automation and healthcare systems. Deshpande and Warhade proposed an advanced human activity recognition model that utilized an integrated feature extraction strategy in combination with an optimized SVM classifier. By fusing multiple feature sets, their method significantly improved recognition accuracy compared to conventional single-feature-based systems. Building on this, Deshpande, Agarwal, and Kamathe established an energy-efficient CCTV system that employs the YOLOv8 for real-time human detection. Their work focused on attaining high accuracy while reducing computational load, making the system suitable for embedded and low-power surveillance contexts such as smart cities and IoT networks. In a broader context, Deshpande et al. authored a comprehensive survey chapter on human detection techniques in video surveillance. This work covered both traditional approaches like HOG and Haar cascades, as well as modern deep learning models such as CNNs, YOLO, and SSD. It provided detailed insights into evaluation metrics, benchmark datasets, system feasibility in real-time applications, and emerging trends in the field, serving as a valuable source for future scholars and system developers. Earlier contributions by Deshpande and Rana involved the combination of the Wavelet Transform with SVM for intelligent video surveillance. The wavelet-based approach allowed for effective multi-resolution feature extraction, enhancing detection performance in noisy or low-resolution video frames. In a follow-up study, Deshpande, Rana, and Pawar utilized the Discrete Wavelet Transform (DWT) as a preprocessing step for human detection. Their method proved effective in distinguishing human shapes from complex backgrounds, which is particularly important in surveillance settings with high scene variability. Further, Deshpande, Pawar, and Rana proposed a real-time human detection system based on background subtraction, DWT, and classification techniques. Their focus was on achieving low-latency and high-efficiency processing, targeting real-time surveillance needs in public areas such as transportation hubs and city.

HOG (Histogram of Oriented Gradients)

The Histogram of Oriented Gradients (HOG) is a widely used feature descriptor in the field of computer vision, particularly effective for human detection in still images. This technique analyzes the structure and appearance of objects by examining the distribution of edge directions. The core idea behind HOG is to capture local shape information by computing gradient orientation and magnitude across an image. The image is initially divided into small regions, typically 8×8 pixel cells. Within each cell, the gradient of every pixel—representing changes in intensity and direction—is calculated. These gradients are then sorted into a predefined number of orientation bins, commonly nine, covering angles from 0 to 180 degrees. Each bin accumulates the magnitude of gradients that fall within its direction range, effectively summarizing the edge orientation patterns in that region. By aggregating these histograms over larger blocks and normalizing them, the HOG descriptor becomes robust to lighting and contrast variations. This makes it especially useful in object detection tasks where the shape and structure of an object, such as the human form, are key features for recognition.

The HOG algorithm effectively captures the shape and edge characteristics of objects in an image by analyzing the local gradients. HOG can be viewed as an advancement derived from the Scale-Invariant Feature Transform (SIFT), focusing specifically on representing shape information through localized gradient orientation histograms. The process begins by dividing the image into overlapping blocks, with each block typically consisting of four smaller cells. Within each cell, the gradient information of every pixel is computed. Specifically, for a given pixel at position I(x,y), the orientation θ(x,y) and gradient magnitude m(x,y) are calculated. These values are then used to construct histograms representing the distribution of edge directions in that local region. By aggregating and normalizing these histograms across the image, the HOG descriptor forms a comprehensive and robust feature set that effectively encodes the object's shape, making it extremely suitable for recognition tasks in varying visual conditions.

$$dx = I(x+1,y) - (x-1,y)$$
$$dy = I(x,y+1) - (x,y-1)$$
$$\theta(x,y) = \tan^{-1}\left(dym(x,y) = \sqrt{\ dx^2 + \quad dy^2}\ \right)$$

SVM (Support Vector Machine)

Support Vector Machine (SVM) is a two class classifier and strong machine learning algorithm widely used for classification of two classes human and non-human. In this paper of automated lobby security using image processing, SVM plays a very important role in distinguishing between authorized and unauthorized individuals or objects. This is accomplished by training the model on a labeled dataset, where each image is categorized as either "authorized" or "unauthorized." During training, the SVM algorithm determines the optimal hyperplane that classify the two classes. This hyperplane is chosen to maximize the margin—the distance between the nearby data points of each category of class and dividing boundary—ensuring the most distinct separation possible.

The trained SVM model can then be deployed to analyze previously unseen lobby images By evaluating the position of these input features relative to the hyperplane, the algorithm accurately classifies them into the appropriate category. A major advantage of SVM lies in its capacity to deliver high prediction accuracy while avoiding overfitting, even with high-dimensional datasets. This his characteristic makes SVM ideal for high-dimensional data such as image- based security systems, where precision and generalization are essential for reliable threat detection and access control.

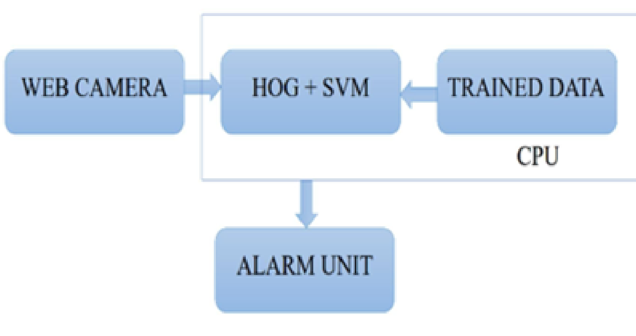

Fig 1. Architecture of automated lobby security

Figure 1 shows the architecture of automated lobby security Web Camera captures images of individuals attempting to enter the lobby. The web camera captures the image and read it. It performs the background subtraction method. The web camera captures live video footage of the lobby, which can be analyzed using image processing algorithms.

The HOG algorithm works by first dividing an image into small cells, typically 8x8 pixels in size. For each cell, HOG computes the gradients i.e., the direction and magnitude of changes in color intensity of the pixels within the cell.

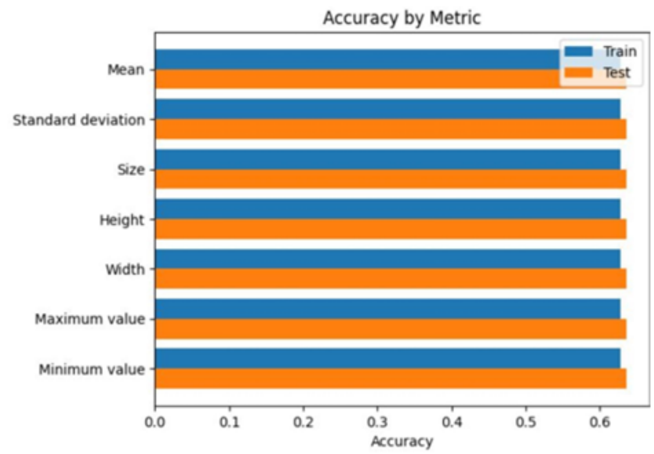

Fig 2. Accuracy obtain for different feature vectors

The Figure 2 graph represents the accuracy of the SVM model trained on the human detection dataset using Histogram of Oriented Gradients (HOG) features. HOG features capture local gradients in image patches and are commonly used for object detection tasks. Upon analyzing the graph, we observe that the accuracy values for the HOG features vary across the different metrics. Each metric captures different aspects of the HOG features, resulting in varying performance.

The y-axis displays different extracted features, including Mean, Standard deviation, Size, Height, Width, Maximum value, and Minimum value, while the x-axis represents the accuracy achieved by the SVM model.

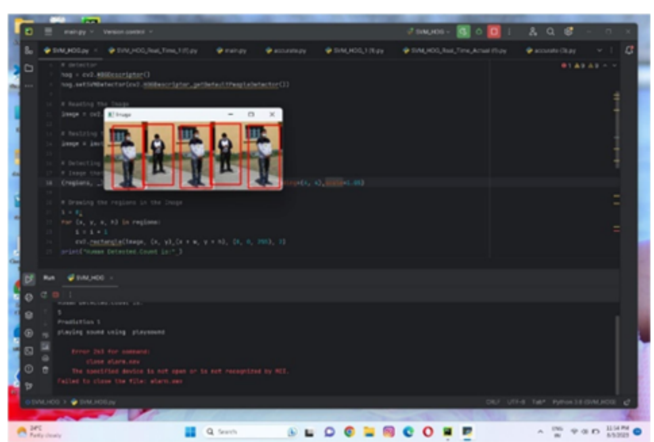

Fig 3. Bounding Box formation across detected human

If one or more humans are detected, rectangles will be drawn around the detected individuals, and the text ”Prediction-1” along with ”Human Count =” followed by the actual count of detected humans will be displayed.

In conclusion, the graph visualizes the performance of the SVM model utilizing HOG features across different metrics. It highlights the varying accuracy achieved by the model for each metric, providing insights into the significance of different HOG feature characteristics for human detection.

Another approach for accuracy used is to provide input images of humans to the classifier and it detects all humans present in image.

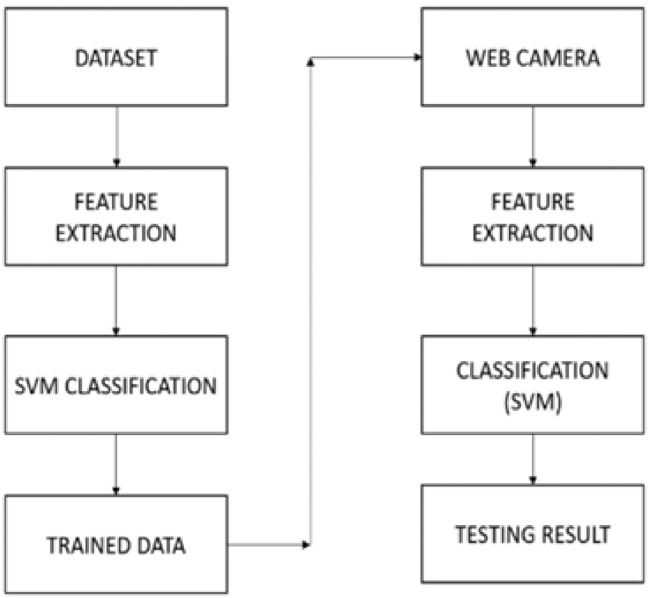

Fig 4. Flowchart of Automated lobby security

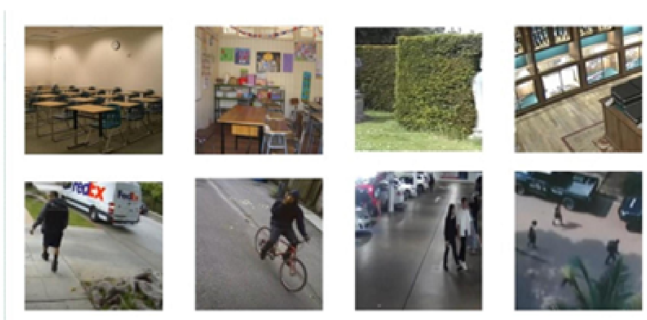

Fig 5. Sample images from dataset

First, we search for image dataset containing positive and negative images Figure 5 shows the sample images from dataset and then used HOG feature descriptor and resize the image and print the features. Then use this HOG features to train SVM model and calculate the training and testing accuracy. After this we used SVM trained SVM model to predict label 0 or 1 on test images.

The trained linear SVM classifier achieved a high training accuracy of 1.000, indicating a perfect fit to the training data. The model’s ability to classify the training samples with complete accuracy suggests a strong learning capability and effective discrimination between positive (human) and negative (non-human) instances.

When applied to the test image, which features a Female Scientist Analyzing Liquid Beaker Types, the model predicted a label of [1], indicating that the image contains a human. Figure 6 shows the results obtained for detected human

This prediction aligns with the objective of the human detection task, where positive labels are assigned to human images.

The extracted HOG features were fed into the trained SVM model, which successfully predicted the presence of a human in the test image with a label of] and for non-human test image it predict label 0. This demonstrates the effectiveness of the SVM classifier in generalizing its learning to new images and accurately classifying them.

Another approach is to use specified URL such as Ip Webcam mobile application to access a snapshot from the video feed at the specified IP address and port. and processes each frame to detect human figures using a HOG (Histogram of Oriented Gradients) classifier. The image is first rotated and resized for uniform processing. The HOG classifier detects people by identifying regions of interest within the image, which are then highlighted with red rectangles. If no individuals are detected, the output displays ”Prediction-0” with a count of zero. If people are detected, it plays a beep sound, shows ”Prediction-1” with the count of detected individuals, and updates the displayed image accordingly. The image display updates every second, and the process continues until manually stopped.

Results and Discussions

The trained SVM model is implemented in real time human detection process using web camera. When the camera captures the frame in which human is present then it predicts the 1 and When the human is not present in the frame then it predicts the 0 So in the first result the is human is captured in the frame, so the prediction is 1 as shown in Figure 6. In the second result the object is captured in the frame, so the prediction is 0 as shown in Figure 7. Figure 4 shows the detail flowchart of working of algorithm.

Furthermore, as shown in Figures 8 and 9 SVM is tested for real time images and if human is detected the algorithm is modified and displaying count of the human present in the image.

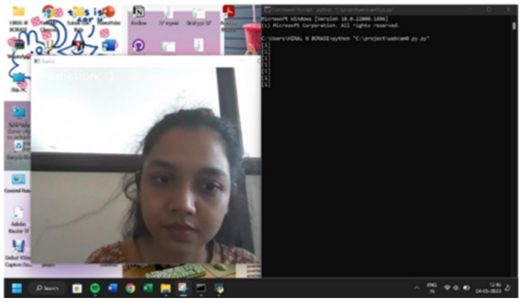

Fig 6. Results obtained for detected human

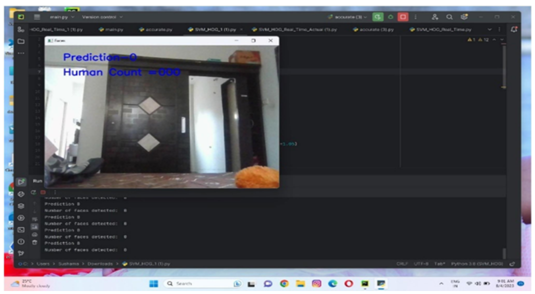

Fig 7. Results obtained for detected non-human

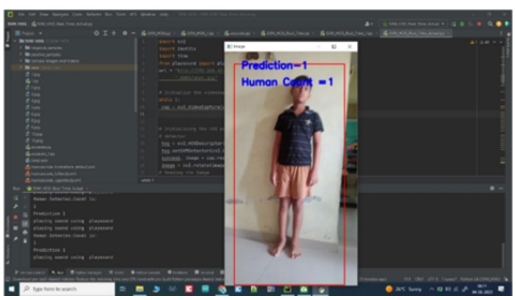

Fig 8. Results obtained for detected non-human

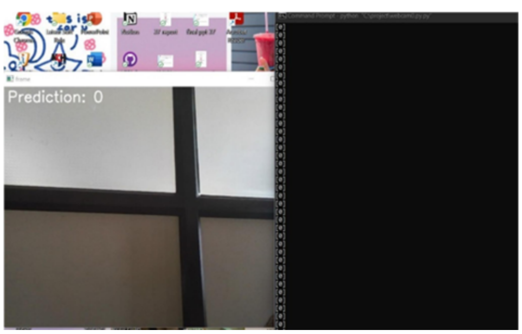

Fig 9. Results obtained for detected human with count

Future Scope

Transfer Learning and Few-Shot Learning: SVM models trained on large-scale datasets can be utilized as feature extractors or classifiers in transfer learning scenarios. By leveraging pre-trained SVM models, it becomes possible to train accurate human detectors with limited labeled data, a technique known as few-shot learning.

Privacy-Preserving Human Detection: As privacy concerns continue to rise, developing privacy-preserving human detection systems becomes crucial. Future research can focus on developing SVM-based methods that can detect humans without capturing or storing sensitive information, thereby ensuring privacy while maintaining effective detection performance.

Edge Computing and Deployment: With the advancements in edge computing, it is becoming increasingly important to develop lightweight SVM models suitable for deployment on resource-constrained devices. This would enable on-device human detection, reducing the need for transmitting sensitive data to centralized servers.

Explainability and Interpretability: SVM models are generally considered to be less interpretable compared to some other machine learning algorithms. Future research can focus on developing methods to enhance the explainability and interpretability of SVM-based human detection models, which would be particularly useful in critical applications where trust and transparency are essential.

Conclusion

The approach of research was based on ideas in image processing, using the Histogram of Oriented Gradients (HOG) features combined with Support Vector Machines (SVM) algorithm. The Automated Security System is an effective solution for organizations looking to enhance their security while saving time and resources. The system uses image processing techniques to identify individuals, which is faster and more accurate than manual verification. The system can also store visitor information for future reference, making it easier for visitors to access the lobby. The system's alarm function can alert security personnel in case of any unauthorized access attempts, which can help prevent security breaches.