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Hybrid Motion Vector and Deep Learning Approach for Crime Event Detection and Face Identification in CCTV Feeds

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ABSTRACT: The identification of unusual occurrences is one of the primary goals of the research and use of video surveillance. In an attempt to improve public safety, surveillance cameras are being utilised increasingly often in public places including roads, intersections, banks, and shopping malls. Recognising unusual events, such crimes, traffic accidents, or unlawful activity, are one of the most crucial responsibilities in video surveillance. The frequency of abnormal events is often much lower than that of regular activities. Finding the window of time during which the anomaly is happening and promptly alerting users to conduct that deviates from expected patterns are the two main objectives of a practical anomaly detection system. Therefore, by separating anomalies from regular patterns, anomaly detection may be regarded as a basic technique for understanding films. Once an anomaly has been identified, classification techniques may be used to group it into one of the specialised tasks. This article gives an overview of anomaly detection with an emphasis on banking operations applications. The regular, recurring, and ad hoc activities and transactions that take place in banking operations include a wide range of stakeholders, including staff members, customers, debtors, and outside parties. Early discovery can greatly minimise any potential negative consequences and, in some situations, even totally eliminate them, even though things may take some time to sort out. To find people during undesirable times, anomaly detection based on time series is utilised. This research uses a machine learning-based anomaly detection approach to identify both common and rare occurrences. The biometric uniqueness of the face is captured and cross-referenced with faces of well-known criminal. If a match is found, it is easy to recognize and capture the offender.

KEYWORDS: Abnormal Event Detection, Movement Detection, Gaussian Mixture Model, Face Detection, Grassmann Algorithm, Criminal Detection

I. INTRODUCTION

One of the newest areas of image processing research is video surveillance. Analogue CCTV systems were used to gather data and keep an eye on people, locations, and activities when video surveillance first began. Current digital video surveillance systems rely totally on human operators to detect risks; they only supply the technology necessary to gather, store, and broadcast footage. It takes a lot of work to manually evaluate security footage. When done by hand, identifying many actions in real-time video is rather laborious. This led to the development of an intelligent video surveillance system. By examining video flow photos, the analytics application automatically identifies events and items (people, vehicles, and equipment) of interest for security reasons. Video surveillance is the process of keeping an eye on or assessing a certain region for security and business reasons. Concerns about crime prevention and safety are the driving forces for the installation of surveillance cameras. Public spaces, retail establishments, banks, automated teller machines, and banking institutions all employ video security cameras. These days, network surveillance research is constantly expanding. The tumultuous times that are taking place all across the world are the cause. For intelligent monitoring, a smart surveillance system is consequently essential. This system must be able to gather, transmit, process, and understand data pertaining to the monitoring objectives in real-time. Video footage may be forensically examined after a crime is committed. The use of video surveillance systems has increased as a result of the low cost of video cameras. Traffic tracking and human activity detection are only two of the many applications for video surveillance

systems. This is an illustration of how content-based searches and warnings may be generated in real-time when events occur in the monitored area using real-time activity analysis for video surveillance systems.

In reality, the phrase "multi-view face recognition" only describes scenarios in which a subject (or scene) is being concurrently recorded.

by numerous cameras, and an algorithm combines the gathered photos or videos. Nevertheless, the look has been widely utilised to identify faces in various poses. In terms of posture variations, a set of images shot concurrently with different cameras and a set of photos taken with the same camera but at various view angles are equivalent; this ambiguity has no influence on (still) picture recognition. The two situations are distinct, though, when it comes to video data. The capture of numerous perspectives is always guaranteed with a multi-camera system, but it is not always guaranteed that this can be accomplished with a single camera. In non-cooperative recognition applications like surveillance, these types of differences become crucial. However, the majority of currently deployed multi-view video face recognition algorithms rely on single-view recordings. They go through the collection after being given two face images to compare, trying to "align" the appearance of a facial component in one image with the same lighting and attitude in the second. In this method, it will also be necessary to estimate the lighting and poses for the two face photos. The "generic reference set" method was also used to create the holistic matching algorithm. The ranking of lookup results serves as its matching metric. Furthermore, some pieces compute the posture implicitly rather than explicitly, taking stance changes into consideration.

In essence, any collection of pictures that evolve over time is a video signal. The spatial intensity distribution of a stationary image doesn't change over time, but it does change over time for a time-varying image. One way to think of video signals is as a collection of frames, or pictures. By quickly changing the frame rate, also known as the frames, it is possible to provide the impression that the video is continuous. In fields including education, multimedia authoring systems, video teleconferencing, and video-on-demand systems, digital video is becoming more and more essential. I-frame, P-frame, and B-frame are the three primary types of video frames. 'I' stands for interceded frame, 'P' for predictive frame, and 'B' for bidirectional predictive frame. Future 'P' and 'B' type frames are projected from anticipated 'I' frames that are encoded without motion correction. In contrast, 'I' frames require a large number of bits to encode. Motion-compensated prediction is used to decode 'P' frames from a reference frame, which might be either a 'I' or a 'P' frame. Though they need less bits than "I" frames, "P" frames need more bits than "B" frames. While 'B' frames use fewer bits than 'I' and 'P' frames, they are computationally more complicated. Following the first "I" frame come the subsequent two "I" frames, which are together known as a group of pictures (GOP). The Republicans are depicted in Figure 3. Six "B" frames, two "P" frames, and a "I" frame make up the artwork. Many "B" frames are typically found between "I" and "P" frames or between "P" frame pairs. GOPs provide the implementation of features such as quick forward, random access, and regular and fast reverse playback. With devices like the Digital Versatile Disc (DVD), Digital Satellite System (DSS), high-definition television (HDTV), and digital still and video cameras, video processing technology has completely transformed the multimedia sector. They include (i) segmentation (iv), indexing (iii), compression (v), and tracking (v) among other techniques for processing movies. Machine learning based on anomalous detection has recently become a fascinating area of video analysis. This makes sense in real-time video surveillance (RVS), which shows different motion patterns that happen often or periodically in a busy traffic scenario. The objective is to analyse the motion pattern and get a high-level understanding. An event is considered abnormal if it appears unlikely or unexpected. In statistics, a "anomaly" is defined as an outlier data point in a data space or peculiar distributional behaviour. Behaviour comprehension is, of course, a sub domain of anomalous detection in RVS. An outlier is interpreted as abnormal behaviour by anomaly detection algorithms after they have been trained on a typical dataset. These systems usually cooperate to detect and locate anomalous behaviour. The anomalous pixels in each frame can be used to determine the location of an anomalous occurrence. For AED to react rapidly and accurately, an effective data representation approach is required. AED uses a spatiotemporal data space that encompasses both appearance and movement. Researchers use a range of methods to identify anomalous areas in a video clip. The most popular technique, known as "gridding," divides a series of frames into smaller, fixed-size 3D patches by imprinting a preset grid on them. The term anomaly refers to any departure from the usual behaviour. Abnormal detection abilities from a typical pattern are taught through training. In essence, it is accomplished by using a few particular learning techniques on the traits that have been retrieved. The main input for anomalous detection in video surveillance is a raw video, which is a collection of frames from which pertinent information are extracted. Pixel-level features and pattern-learning approaches form the foundation of the suggested study. The analysis of crowd scenes presents a number of challenges, such as object overlap, shadowing, and occlusion. Numerous methods have been proposed to solve this

problem, but each has advantages and disadvantages of its own. The motions of the scene elements might be interpreted in a variety of ways. Each and every object's orientation and velocity may be precisely simulated using these methods. However, these methods usually require a lot of time. The issue is made more complicated by the perspective distortion of urban surveillance footage, which creates various size and movement patterns depending on the positioning of objects and the camera. An adequate discriminative model is required to detect aberrant patches and frames since there are subtle differences between normal and abnormal instances, as well as variable lighting conditions. Deep neural networks are among the numerous machine learning models that require a substantial quantity of labelled data. However, because AED is an unsupervised learning issue, gathering a significant amount of labelled data is a time-consuming and tedious process. Among the most important methods for detecting anomalies in RVS are foreground modelling, adaptive learning, categorisation, and classifiers. A high number of objects in the traffic scene, an effective grouping centre, and unbalanced data (normal and abnormal occurrences) are some of the disadvantages of these systems. Figure 1 shows the video anomaly detection from datasets

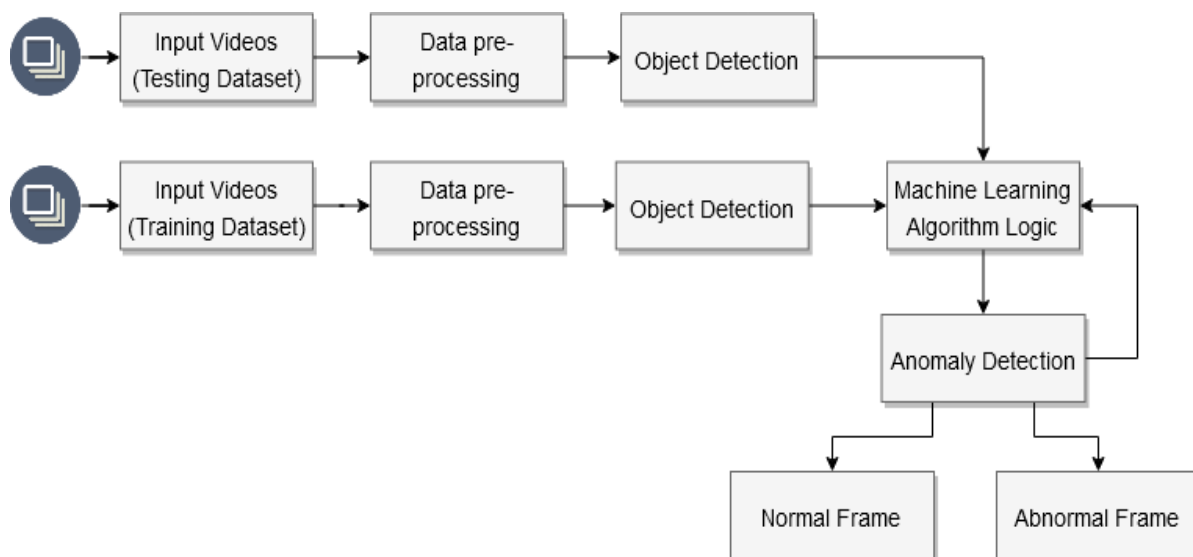


Fig 1: Video anomaly detection

II. RELATED WORK

Ahmed abbasi, Abdul rehmanjaved, et.al,...[1] serve as a vital instrument for protecting both private and public property and improving personal safety. A custom dataset was made by combining 15 background audio samples from the TUT Acoustic Scenes 2016 dataset with uncommon occurrences in order to categories strange sound events and identify anomalous audio. This study experimented using several audio data aspects to find abnormalities in the data. After extracting several features for feature engineering from the audio stream, this study use the PCA feature selection approach to choose the fewest number of best-performing features for optimal performance. Based on the chosen feature set, a number of machine learning approaches are used to detect seven unique anomalous occurrences in fifteen diverse background scenarios. Experiments showed that the proposed method for detecting abnormalities in audio data consistently beat the state-of-the-art research. The amount of multimedia data produced by various smart devices has significantly increased with the introduction of new digital technologies. A number of difficulties have arisen for data analysis in order to extract meaningful information from multimedia data. One of these difficulties is rapidly and reliably identifying abnormalities in multimedia data. In this study, an effective method for classifying uncommon occurrences and detecting abnormalities in audio data is proposed.

Lin Wang, et.al,...[2] The DF-ConvLSTM-VAE model, which learns the training data distribution for video anomaly detection, combines ConvLSTM and VAE. Additionally, the ConvLSTM-VAE (Asymmetric) model is recommended. The decoder is made weaker to construct the ConvLSTMVAE (Asymmetric) model. The ConvLSTM-VAE (Asymmetric) model outperforms the ConvLSTM-VAE (Symmetric) model in a number of ways, including training time and difficulty. The DF-ConvLSTM-VAE model performs better than the ConvLSTM-VAE (Asymmetric)

model, according to experiments. Tests on several publicly available benchmark data sets confirm the reliability and competitiveness of the proposed DF-ConvLSTM-VAE compared to other conventional techniques. Since the market for video monitoring sites is growing so quickly, the security industry has recently demonstrated a lot of interest in video anomaly detection. In unlabelled video footage, normal and aberrant data are now distributed unevenly. A prominent deep generative model for unsupervised anomaly detection is the variation autoencoder (VAE). This paradigm, however, struggles to analyze time-series data, particularly video data. Additionally, many auto encoder-based algorithms over-reconstruct anomalous behavior because to their excellent generalization capacity, which makes it difficult to detect abnormalities.

Keval Doshi, et.al,...[3] provided a novel, sizable dataset and a distinctive framework for more research in the area of video anomaly detection. With the revised issue statement (Sec. 3) and updated dataset (Sec. 4), it is expected that future VAD research would concentrate on workable and replicable solutions. Additionally, a cutting-edge video anomaly detector that can learn continuously through experience replay and incremental learning was demonstrated. The proposed technique beats two of the state-of-the-art methods in continual learning and in terms of the common frame-level AUC measure, according to thorough testing on the proposed NOLA dataset and known benchmark datasets. In the first instance, the abnormality was a person walking down a busy street with a snake in their hand. The third shows a couple fighting with the proprietors of the eatery. A VAD algorithm requires a far better comprehension of the complex interactions between each observed object and how it impacts its surrounds in order to identify such abnormalities. However, this also demonstrates how extensive the suggested NOLA dataset is and how it may be used to further VAD algorithms.

Mohana, et.al,...[4] developed a smart surveillance system that enables real-time object tracking and detection for security purposes. Today, most domains rely on a manually controlled method that is too time-consuming to implement efficiently in real-time. It is now required to build an automated system that operates in real time and without human intervention in order to boost its efficiency. The revised background subtraction method is developed using the Xilinx ISE software and the VHDL programming language. The footage is recorded with an OV7670 camera and the Zynq XC7Z020 FPGA board. FPGA systems are five to six times more efficient than DSP boards because they provide both temporal and spatial parallelism and provide module design flexibility based on system needs. Researchers are now concentrating on simultaneously identifying and monitoring unusual behaviors in people or things since FPGAs can perform algorithms in parallel. Using contour data to improve object categorization efficiency. The justification for effective monitoring is further strengthened by the ease with which abnormal behavior in huge groups may be identified after proper categorization. Following that, artificial intelligence will be included into the system to eliminate the need for human interaction in any aspect of the surveillance process. The idea of partial face detection with several key point descriptors can also be incorporated into the system to improve the surveillance system's overall efficiency.

Vinaya Kesar, et.al,...[5] have identified the credit card discrepancy, from which the incorrect information number was selected, and have illustrated the procedures for removal. Big data analysis is presently being used by several financial industries to assist them develop both active and passive security measures as well as to enhance the services they provide to their internal and external clients. Although doing input validation with the consumer in mind is undoubtedly more successful and lucrative, staff members should also be able to do this. Real-time applications need to be able to swiftly evaluate ephemeral data sources in order to make judgements or respond promptly. If decisions are made after the deadline has passed, they are no longer relevant. Because of the expansion of big data, examiners can now rapidly request their results from massive datasets.

III. EXISTING METHODOLOGIES

Finding unusual occurrences has grown in importance in the fields of computer vision and pattern recognition in recent years. Creating a variety of settings that depict unusual events is the most challenge. Defining an interface that encompasses the whole range of potential anomalous occurrences is challenging. In order to statistically understand anomalous events, it is standard procedure to classify them as low likelihood events in comparison to regular events. Behaviours that are inconsistent with samples and differ from norms are considered disordered thinking events. Event encoding and anomaly detection models are the two main phases of the detection process used to identify unusual occurrences. These procedures align with the most commonly recognised concepts in the fields of pattern recognition and machine vision. To illustrate an incident, the pertinent video components must be chosen. The event may be defined by characteristics at the pixel or object level due to the event description's ambiguity. Due to the imprecise

definition of an anomaly and the variety of visual circumstances in actual video data, anomaly identification in videos is still a difficult issue. Since abnormal occurrences frequently deviate from normality in appearance and/or motion behaviour, our research explores a unique permutation auto-encoder architectural design that may detach the spatio-temporal depiction to separately contain the time data and the distant sensing data. This is in contrast to previous studies that either used predictions as a support assignment or tried to rebuild the data in order to understand the temporal regularity. In particular, the spatial auto encoder learns to recreate the insight of the first frame (FIF) to model the data is normally distributed only on appearance feature space, whereas the temporal auto encoder efficiently replicates the movement of optical flow using the input of the first four consecutive frames and the output of the RGB difference.

IV. CRIMINAL ACTIVITIES AND FACE DETECTION

Finding patterns in data that deviate from anticipated behaviour is known as anomaly detection. In a variety of application domains, these non-conforming patterns are occasionally called anomalies, outliers, discordant discoveries, exceptions, aberrations, surprises, oddities, or contaminants. The two words that are most frequently used in the context of anomaly detection are anomalies and outliers; however they are occasionally used interchangeably. Defect identification in safety-critical systems, intrusion detection for cyber-security, fraud detection for credit cards, insurance, or healthcare, and military monitoring for hostile activities are just a few of the many uses for anomaly detection. Concerns about crime prevention and safety are the driving forces for the installation of surveillance cameras. Video security cameras are used in banks, ATMs, public areas, and businesses. Malls are included in this. These days, network surveillance research is constantly expanding. The cause is the occurrence of instability on a worldwide scale. Therefore, intelligent monitoring necessitates the installation of a smart surveillance system. This system must be able to gather, transmit, process, and understand data pertaining to the monitoring objectives in real-time. Video footage may be forensically examined after a crime has been committed. Thus, these systems provide robust security in public areas, which is often a very difficult problem. The use of video surveillance systems has increased as a result of the low cost of video cameras. Traffic tracking and human activity detection are only two of the many applications for video surveillance systems. This is an illustration of how content-based searches and alerts may be generated in real-time based on actions that take place in the monitored area using real-time activity analysis for video surveillance systems. Computer software that can recognise or validate a person from a digital photo or a video frame from a video source is called a face recognition system. One way to do this is to compare certain facial traits in the image with a database of faces. When the right conditions are fulfilled, face print-based facial recognition systems may swiftly and effectively identify the target persons. Face recognition research is being conducted in large quantities for Smartphone applications.

Gaussian Mixture Model

Let us denote with $x = [x_1, x_2, \dots, x_L]^T$ the generic image pixel, L being the number of sensor channels. Anomaly detection is viewed as a statistical binary decision problem, where by observing x one must decide if it is a background pixel (H_0 hypothesis) or a target pixel (H_1 hypothesis). Further, it is assumed that background consists of N different clusters C_i ($i = 1, 2, \dots, N$) corresponding to different ground cover types. The generic cluster C_i is modeled as Gaussian distributed and its p.d.f. f_{C_i} is:

$$f_{C_i}(x) = f_G(x; \mu_i, \Gamma_i)$$

$f_G(x; \mu_i, \Gamma_i)$ denotes the multivariate Gaussian p.d.f. with mean vector μ_i and covariance matrix Γ_i .

V. GRASSMANN ALGORITHM

A Grassmann manifold $G_{n,p}$ is a set of p -dimensional linear subspaces of R^n (p -planes in R^n) for $0 < p \leq n$. This Grassmann manifold has a natural quotient representation $G_{n,p} = V_{n,p} / O_p$, where $V_{n,p}$ is a Stiefel manifold (a set of $n \times p$ orthonormal matrices) and O_p is the orthogonal group. This representation states that two matrices belong to the same equivalence class if their columns span the same p dimensional subspace. Hence, the entire equivalence class can be represented as the subspace spanned by the columns of a given matrix Y .

$$[Y] = \{YQ_p : Q_p \in O_p\}$$

In other words, a point on the Grassmann manifold is a linear subspace which may be specified by any arbitrary orthogonal basis.

- Use eye coordinates to determine the initial affine registration parameters for each image.
- Sample the affine registration manifold by perturbing the affine parameters
- Compute the k nearest neighbours from the registration manifold
- Apply color equalization and filter features values
- Construct the tangent space
- Embed the approximated tangent space and compute canonical angles
- Compute the subspace distance

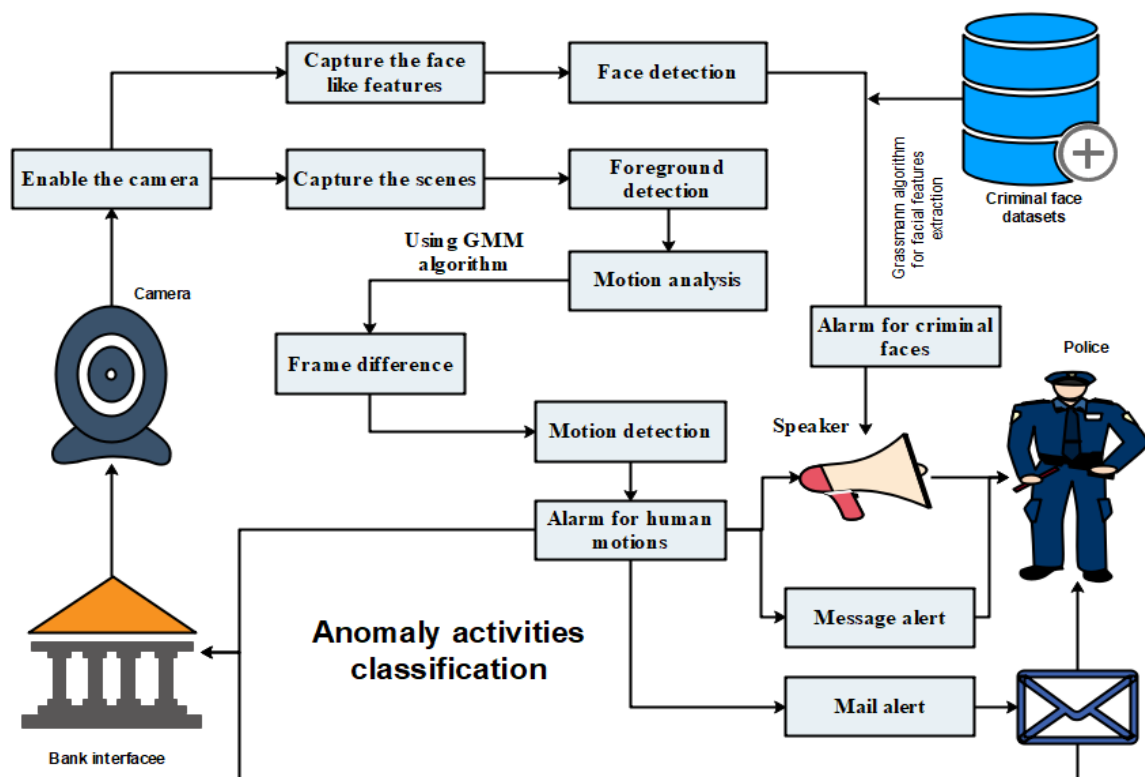


Fig 2: Proposed architecture

VI. EXPERIMENTAL RESULTS

Using the Grassmann method to extract facial characteristics, we can create a framework for face detection in this study. The performance is then calculated in terms of the false rejection rate using real-time face datasets. False reject rate is an effort by a trained individual to violate the rules. FRR, or the ratio of false rejections to recognition attempts, is frequently used to characterise a system.

$$\text{FALSE REJECT RATE} = \text{FN} / (\text{TP} + \text{FN})$$

FN = Genuine Scores Exceeding Threshold
TP+FN = All Genuine Scores

The proposed system can provide less number of rejection rate than the existing algorithms such as Support Vector Machine, Random forest, Adaboost classifier and Grassmann algorithm with Convolutional neural network algorithm. Performance can be shown in table 1.

Algorithms	FRR
Random Forest	0.42
Adaboost Classifier	0.35
Support Vector Machine	0.28
Grassmann algorithm	0.14

Table.1: Performance table

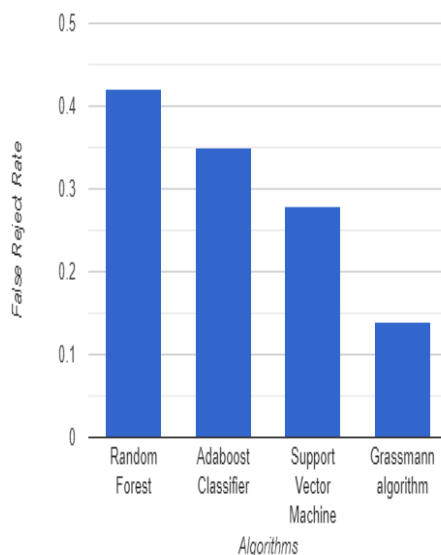


Fig.3: Performance chart

From of the illustration above, shows suggested Grassmann algorithm provides the poor number of erroneous denial rate in face detection system

VII. CONCLUSION

The proposed solution is centred on developing an anomaly detection system that uses smart cameras to monitor bank activity and spot any odd behaviour. The criminals would then be located using facial recognition software and motion detection techniques based on undesired time intervals. If any suspicious behaviour of this type is detected at an inconvenient time, the smart camera will automatically notify the security department. The message comprises the type of alert that has been sent, the moment the detection was made, a web link to the live image, and the image of the thief's face so that the security personnel may arrive prepared.

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