Advanced Intelligent Video Surveillance System In Elevators By Using OpenCV

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Abstract - *It takes a lot of time and effort to manually monitor unexpected occurrences that happen in an elevator cab and react in time. In this research, we create a smart video surveillance system and declare.*

Identification system for elevator cabs that allows for the estimation and security evaluation of information such as the condition of the cab door, human body behavior, and the number of occupants.

Our project called the Advanced Intelligent Video Surveillance System uses OpenCV to detect motion in a certain region and only starts recording video when motion is found. The system further manages the functioning of an elevator in the same location, which only operates when motion is detected. The system uses a camera to record live video of the scene, which is then processed using OpenCV to look for motion. The device will begin capturing video and turn on the elevator when motion is detected. The device will cease capturing video and disable the elevator when motion is no longer being detected. The system may be applied to many different things, such as home, office, and building security systems. The project uses OpenCV, a well-known open-source computer vision library that offers a robust collection of capabilities for image processing and motion detection. The major goal of this project is to develop an intelligent surveillance system that improves the overall security of the area while conserving storage space by only recording when necessary and only operating the elevator when motion is detected.

Key Words: Surveillance, OpenCV, Motion Detection, Face Recognition, Storage

1. INTRODUCTION

One of the many issues that are studied in the extremely broad scientific discipline known as computer vision is the potential application of computers to extract significant insights from digital images or movies. This is only one of the numerous topics that are discussed. From an engineering point of view, the goal is to develop automated processes that are equivalent to those that the human visual system is capable of completing. Computer vision is the study of strategies for acquiring photos, processing those photographs, interpreting those photographs as digital images, and extracting high-dimensional information from the actual environment to generate information that can be described as numbers or symbols, such as judgments. These techniques are all part of the study of computer vision. Real-time computer vision is the primary goal of a set of programming functions known as OpenCV, which stands for open-source computer vision. Intel was the company that came up with the idea first. The collection is available on several platforms and may be accessed by anybody at no cost.

Traditional video surveillance systems do not permit for a prompt response in the event that a criminal act is in progress. Setting up a system similar to this one is not only fairly costly but also pretty difficult. This project's objective is to develop an intelligent open-source tool that is capable of assisting individuals in need. people or organizations in the process of independently constructing a reliable and cost-effective system They will, as a result, have complete control over their technology, which will provide them the opportunity to lock down the configurations and adjust them so that they are more suitable for their needs. It is imperative that our homes, places of employment, and any other business venues that we frequent be adequately protected from criminal activity. Standard surveillance technology is unable to alert property owners to any illegal behaviour that may be taking place on their premises. The feed is the sole item that is transferred and captured in this process. As a direct consequence of this, the owners are unable to take immediate action to prevent a break-in or theft.

Motion detection is a characteristic that can be found in many contemporary elevator systems. This helps to increase both safety and the energy efficiency of the system. We propose in this project to use OpenCV and Haar cascade classifiers to identify motion in real-time video streams coming from security cameras that have been placed in elevators. These cameras will be located in different buildings. The device will call the elevator to your floor and begin recording the video as soon as it senses motion in the room. After then, the video that was taken can be put to use for purposes of security and surveillance. The Haar cascade classifier is used to a video stream in order to identify motion by monitoring variations in the pixel values of the stream. It is possible to expand the capabilities of the system to incorporate more sophisticated functions like facial recognition, object tracking, and real-time warnings.

2. LITERATURE SURVEY

In recent years, there has been a major uptick in interest regarding the utilization of intelligent video surveillance systems for the detection of motion and the enhancement of safety. The incorporation of OpenCV, a popular open-source computer vision library, has paved the way for the creation of more sophisticated systems that are capable of performing image processing and motion detection in an effective manner.

Several research projects have investigated the use of OpenCV for motion detection in a variety of different environments. For instance, Patel et al. (2019) suggested an elevator surveillance system that detected motion using OpenCV and tracked it using a Raspberry Pi. Their technology efficiently recognized and tracked persons while they were inside the elevator, which made it possible for additional safety precautions to be taken.

In addition, Yang et al. (2018) demonstrated a video surveillance system for elevators that was built on OpenCV and incorporated face recognition technology for the purposes of identification. Their technology was able to detect persons as they entered and left the elevator, which contributed to the enhanced security measures.

Investigations have been conducted, within the context of the surveillance system, not only into the detection of motion but also into the incorporation of elevator control. An elevator surveillance system that was developed by Wu et al. (2017) that was based on OpenCV and Hadoop was proposed. This system efficiently managed the functioning of the elevator based on motion detection. The mechanism made it such that the elevator would only work when it sensed motion, which improved both the elevator's energy efficiency and its level of safety.

The results of these research demonstrate that the utilization of OpenCV in video surveillance systems to detect motion and implement additional safety precautions is both feasible and beneficial. The capabilities of the system have been further improved by the use of clever algorithms, such as those used for facial recognition and elevator control.

It is important to point out that research and development activities are still being conducted in the area of intelligent video surveillance systems. There is a possibility that developments in machine learning and artificial intelligence algorithms will one day lead to improvements in the precision and effectiveness of motion detection and identification procedures. In addition, the incorporation of cloud-based storage solutions and capabilities for remote monitoring might provide further advantages to such systems.

In conclusion, the research that has been done lends credence to the idea that an advanced intelligent video surveillance system that makes use of OpenCV for motion detection and image processing is both possible and practicable. The addition of an elevator control system that is based on motion detection provides an additional layer of safety while also increasing the building's overall efficiency. The ongoing research and technological breakthroughs in the sector continue to contribute to the creation of video surveillance systems that are both more advanced and more effective.

3. SYSTEM OVERVIEW

This project uses OpenCV as well as Haar cascades for the purpose of object recognition and tracking. The major purpose of the system is to improve safety and offer continuous monitoring of particular entities or items located within a specified region in real time.

A camera is used in order to record live video footage while the device is in operation. After that, the video frames are analyzed with OpenCV, a sophisticated computer vision library that offers a broad variety of tools and algorithms for analyzing images and videos. This is done after the movie has been played.

The Haar cascade classifier is an important component of the system as a whole. Haar cascades are a type of method that is based on machine learning and has the capability of locating certain objects or characteristics included inside an image or video frame. Object detection tasks, such as recognizing faces, pedestrians, or other specified items, are a typical use of this technology's capabilities.

Throughout the course of the study, Haar cascades are educated to recognize the many things of interest. In order to do this, the cascades need to be trained using both positive and negative examples so that they may learn the differentiating characteristics of the target items. After they have been trained, the cascades may then be applied to the video frames in order to recognize and track the objects of interest.

The system is designed with a real-time monitoring component, which enables the detected items to be continually monitored and the motion of those objects to be studied. This makes it possible to detect immediately any activity that are not permitted or that seem suspicious inside the monitored region. When the system identifies a target object, it may proceed to perform a number of predetermined actions. These may include sounding an alert, sending notifications, or activating certain security measures.

Image preprocessing, feature extraction, and various approaches for image enhancement are some of the additional functionality that may be used in the system thanks to OpenCV's provision of these additional capabilities.

These features contribute to an improvement in the object identification and tracking system's accuracy and dependability.

The overall integration of OpenCV and Haar cascades into the system architecture of the project enables effective and efficient object recognition and tracking, which enhances the project's capabilities in the areas of security and monitoring. The system has a wide range of potential applications, some of which include monitoring in public areas and buildings as well as applications for personal safety and protection.

The functional requirements will be video recording, video storage, video playback, video retrieval, live video monitoring, motion detection, camera positioning, remote access, alert notifications, integration with other systems and scalability using OpenCV and the camera module

The performance requirements will be video quality, frame rate, storage capacity, video retrieval time, live video streaming, network bandwidth, motion detection speed, system uptime and camera positioning flexibility.

The software requirements will be an operating system, language of coding such as python, tool such as visual studio to perform this concept.

Hardware requirements for the project to be worked will be a PC with atleast 4 gb of ram, enough disk space to store, 1.6GHz processor or more, a camera module

4. SYSTEM ARCHITECTURE

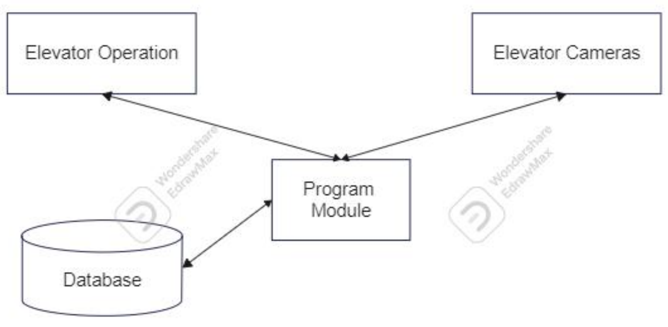

Fig -1: System Architecture

The architecture of the video surveillance system installed in elevators is comprised of numerous essential components, including the elevator operation, the elevator camera, the program module, and the database as depicted in the Fig 1. The proper operation and efficiency of the system as a whole is dependent on the contributions made by each component individually.

Elevator Operation

The elevator operation component represents the physical architecture of the elevator system as well as the control mechanism. It consists of the elevator cabin itself, as well as the doors, buttons, and the control system that lies under the surface and is responsible for directing the movement and functioning of the elevator.

Elevator Cameras

The camera located in the elevator acts as the major source of input for the video surveillance system. Typically, it is positioned on the interior of the elevator cabin so that it may record live video footage of the outside environment. The program module is continually responsible for the processing and analysis of the video frames that are continuously captured by the camera.

Program Module

The software component of the system is referred to as the program module, which represents this component. It incorporates the necessary logic, algorithms, and capability for motion detection, object recognition, and decision-making based on the video input from the elevator camera. This information is obtained from the video. OpenCV is a computer vision library, and as such, it is an essential component of the program module. It supplies the essential tools and functions for carrying out analysis and processing of images.

The software module is responsible for carrying out a variety of activities, such as detecting motion by utilizing OpenCV's motion detection algorithms, recognizing objects by utilizing Haar cascades or other machine learning approaches, and making decisions based on the events that have been identified. The module could additionally incorporate other functionality such as event logging, alerts in real time, and interface with the control system for the elevator.

Database:

The database component of the video surveillance system is responsible for storing and managing the information and data that has been gathered from the system. It performs the function of a repository for recorded video footage, events that have been identified, timestamps, and other metadata. The database makes it possible to retrieve data, do analysis on that data, and retrieve it again for the purposes of future reference, system monitoring, and auditing.

The elevator camera is responsible for capturing video footage, which is then processed by the program module with the help of OpenCV and any other applicable algorithms. This flow is followed by the system architecture. The module is responsible for detecting motion, recognizing objects, and initiating appropriate actions depending on the rules that have been set. The database is used to save the data that has been gathered and the events that have been identified so that they may be analyzed further or retrieved.

The combination of these components results in an elevator video surveillance system that is comprehensive and very effective. Real-time monitoring, motion detection, and object identification are all made possible by the design, which, in turn, ensures an increased level of security and safety inside the elevator environment..

OpenCV

When it comes to computer vision and machine learning, many developers turn to OpenCV (Open Source Computer Vision Library). It's a potent instrument for many uses in image and video analysis because to its wide range of functions and algorithms for dealing with visual data.

OpenCV was created by Intel and is now backed by the likes of Willow Garage and Itseez. Since it is built in C++ and provides bindings for other languages, like Python, it may be used by a broad variety of programmers and researchers.

Image filtering, feature identification and extraction, object recognition, motion analysis, and camera calibration are just some of the many image and video processing features made available by this package. Machine learning techniques for common applications like clustering, classification, and regression are also included.

OpenCV's ability to efficiently and accurately interpret visual input is thanks in large part to the library's sophisticated implementation of computer vision algorithms. It achieves good speed on many hardware systems thanks to streamlined routines and parallel processing approaches.

Edge detection, picture segmentation, object tracking, and optical flow are just a few of the many computer vision techniques and algorithms that are a part of OpenCV. The mathematical models and formulae on which these algorithms are built make it possible to extract useful information from images.

The following steps with formulas are used by OpenCV's implementation of the Canny edge detection technique.

1. Apply Gaussian smoothing to the input image using the formula:

smoothed_image = GaussianFilter(input_image, sigma)

2. Calculate the gradient magnitude and direction at each pixel using the formulas:

gradient_magnitude = sqrt((dx)^2 + (dy)^2)

gradient_direction = atan2(dy, dx)

3. Apply non-maximum suppression to thin out the edges using the formula:

suppressed_edge_pixel = edge_pixel if gradient_magnitude is maximum along the gradient direction, otherwise set to 0

4. Apply hysteresis thresholding to determine the final edges using the formulas:

strong_edges = gradient_magnitude >= high_threshold

weak_edges = (gradient_magnitude >= low_threshold) and (gradient_magnitude < high_threshold)

final_edges = ApplyConnectedComponentAnalysis(strong_edges, weak_edges)

The edges in an image can be important for a variety of purposes, including object boundary recognition and feature extraction, and this approach can assist find them.

Based on Haar-like characteristics and machine learning methods, OpenCV's Haar cascade classifier is another popular tool. By training a classifier on a huge dataset of positive and negative samples, the Haar cascade classifier is able to recognise things like faces or unique patterns.

Haar Cascade Classifier

The Haar cascade classifier is widely used in computer vision applications for detecting objects. Machine learning is used in conjunction with the idea of Haar-like characteristics to identify specific objects in still photos and moving video.

Training a classifier with both positive and negative picture examples is what makes the Haar cascade classifier effective. Images with the target item in them are considered positive samples, whereas those without are considered negative samples. In order to train, we first extract Haar-like features from these data, and then we use a boosting technique to train a cascade of classifiers.

The intensity fluctuations in a particular region of an image can be captured using Haar-like features, which are rectangular patterns. Integral images, which precompute the sums of picture pixels inside rectangular sections, are used to compute these attributes quickly. To calculate the Haar-like features, we take the difference between the white and black intensities of each pixel in the rectangle.

To train the cascade of classifiers, the AdaBoost method is utilized to pick the most effective Haar-like features. It uses an iterative process to choose characteristics that reliably distinguish between positive and negative data. The significance of the selected features in the final categorization is reflected by the weights assigned to them. Each level of the cascade classifiers is made up of several relatively weak classifiers. Each weak classifier's output decides whether a region is eliminated or advanced to the next assessment phase.

The input picture is moved across the screen at various sizes and locations as the trained Haar cascade classifier performs its detection procedure. The classifier performs an evaluation of the Haar-like characteristics at each node and then applies a cascade of relatively weak classifiers. If a given area satisfies all of the cascade's requirements, then it has successfully detected the target.

The Haar cascade classifier is well-known for its usefulness in object identification applications. Face recognition, pedestrian detection, and object identification are just some of the areas where it has been put to good use. The trained cascade may then be used to search for things in either live video or still photos.

Using Haar-like characteristics and the AdaBoost algorithm, the Haar cascade classifier is a machine learning-based approach to object identification. It can recognize items by passing an input picture through a series of classifiers. The classifier's effectiveness in a wide range of computer vision applications makes it a useful resource for detecting objects in images.

5. EXPERIMENTAL METHODOLOGY

Eigenfaces (pca set of rules)

Turk and Pentland pioneered facial recognition with their 1991 Eigenfaces method. It benchmarks facial recognition systems using Principal Component Analysis (PCA). Key steps of the algorithm:

1. Training dataset: Grayscale face photographs are gathered. Multiple photographs of each person should capture lighting, emotion, and stance changes.

2. Normalizing size, rotation, and illumination: Face photos are preprocessed. Histogram equalization and face landmark alignment are common methods for standardizing illumination.

3. Eigenface Construction: The approach extracts eigenfaces from preprocessed face pictures using PCA. PCA creates face image dataset covariance matrix eigenvectors and eigenvalues. The eigenvectors show the dataset's highest variance, while the eigenvalues reflect its importance.

4. Eigenface Selection: The eigenfaces with the biggest eigenvalues, which represent the most important facial traits, are recognized. These eigenfaces create a face image space basis set.

5. Projection: Each dataset face picture is projected onto the eigenface space for a reduced-dimensional representation. Calculate the eigenface weights or coefficients that best reconstruct the input face picture. Projection coefficients capture face features.

6. Recognition: The method projects an input face into the eigenface space and determines its projection coefficients. The coefficients are then compared to known faces in the training dataset using a similarity metric like Euclidean distance or cosine similarity. The recognizable face is nearer.

Turk and Pentland's Eigenfaces algorithm showed PCA-based face recognition's promise. It set the ground for future advances and is now essential to facial recognition system development. The system was sensitive to lighting and position, but it established the groundwork for more advanced face recognition methods.

Fig -2: Eigen faces

Fisher faces

Belhumeur, Hespanha, and Kriegman's 1997 Fisherfaces algorithm—also known as Linear Discriminant Analysis (LDA)—is a prominent face recognition method. It improves Eigenfaces recognition by adding class separation.

Fisherfaces algorithm overview:

1. Data Collection: Like other facial recognition systems, face photos are gathered for training. Multiple samples of each person should capture lighting, emotion, and stance changes.

2. Preprocessing: Size, rotation, and lighting are normalized in face photographs. Alignment, histogram equalization, and noise reduction improve image quality.

3. Face Space Construction: Fisherfaces finds a linear transformation that maximizes class separability in the face picture dataset. It calculates the between-class and within-class scatter matrices, which quantify class variation.

4. Fisherface Extraction: The method then eigenanalyses the ratio of the between-class scatter matrix to the within-class matrix. Fisherfaces, the ratio matrix's biggest eigenvectors, are generated. Fisherfaces distinguish facial classes.

5. Dimensionality Reduction: Projecting face pictures onto Fisherface space reduces their dimensionality, like Eigenfaces. This transformation converts each face picture into a Fisherfaces-spanned subspace.

6. Recognition: The method projects a face into Fisherface space and generates projection coefficients to recognize it. The coefficients are then compared to known faces in the training dataset using a similarity metric like Euclidean distance or Mahalanobis distance. The recognizable face is nearer.

7. Fisherfaces uses LDA's discriminative capabilities to improve recognition accuracy over Eigenfaces. The ideal projection optimizes face class separability. It works well in situations with lots of lighting and posture changes.

In complicated real-world circumstances, the Fisherfaces algorithm's assumption of linearity and Gaussian distributions may restrict its performance. However, it has been widely investigated and implemented in face recognition research and is useful in computer vision and pattern identification.

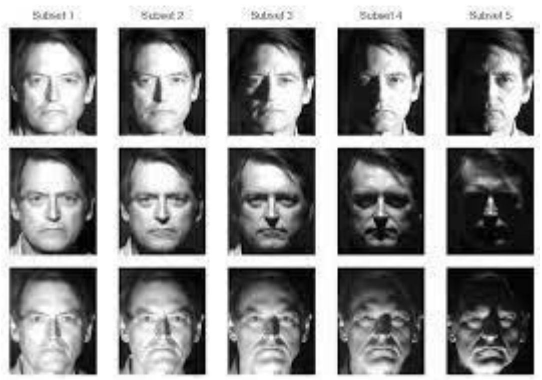

Fig -3: Fisher Faces

Kernel Methods: PCA and SVM

Kernel methods are effective tools for nonlinear data analysis and classification in machine learning and pattern recognition. Principal Component Analysis (PCA) and Support Vector Machines (SVM) are two often utilized kernel techniques.

Finding a lower-dimensional representation of high-dimensional data while maintaining the most crucial information is the goal of the dimensionality reduction approach known as PCA. It determines the principle components, a pair of orthogonal vectors that effectively encapsulate the data's overall variance. One way to describe the altered data is as a linear combination of the principal components. The PCA formula is expressed as follows:

X' = X * W

where X' is the transformed data, X is the original data, and W represents the matrix of principal components.

An method for supervised learning used for classification and regression applications is called SVM. In a high-dimensional space, it locates an ideal hyperplane that effectively divides various data classes. In order to transform the input data into a higher-dimensional feature space where the classes may be linearly separated, SVM requires a kernel function. The SVM formula looks like this:

f(x) = sign(sum(alpha_i * y_i * K(x_i, x)) + b)

where f(x) represents the predicted class label for a new input sample x, alpha_i are the coefficients obtained during training, y_i are the corresponding class labels, K(x_i, x) is the kernel function that measures the similarity between training samples and the input sample x, and b is the bias term.

Kernel techniques, such as PCA and SVM, have been extensively used in a variety of fields, such as bioinformatics, natural language processing, and image recognition. They provide versatility in identifying nonlinear patterns in data and can handle intricate interactions that linear approaches might miss. These techniques have demonstrated their ability to successfully complete difficult classification and regression problems, making them important resources for machine learning research and applications.

When compared to other face recognition algorithms like Fisherfaces and Eigenfaces, kernel approaches like PCA and SVM have a number of advantages.

1. Nonlinearity: Kernel approaches have a strong track record with nonlinear data and are capable of capturing intricate patterns and correlations. Kernel approaches, which can simulate complex fluctuations in facial characteristics, are more suited for face recognition applications using nonlinear data than Fisherfaces and Eigenfaces, which are linear methods.

2. The most discriminative features from the data are extracted using PCA and Eigenfaces. But they are only capable of linear modifications. In contrast, data may be projected onto a high-dimensional feature space using kernel techniques, particularly SVM with kernel trick, where linear separability is attained. As kernel approaches can capture intricate

correlations between face traits, this enables more precise and reliable categorization.

3. Robustness to Variations: When compared to Fisherfaces and Eigenfaces, kernel approaches are more resistant to changes in position, lighting, and facial emotions. They can implicitly accommodate these differences and yet retain strong classification performance by applying kernel functions. This is especially crucial in real-world situations when facial features might differ greatly.

4. Generalization: Kernel approaches can generalize more effectively. By determining the best decision limit, they may successfully manage overfitting and quickly react to new data. This makes it possible for fresh faces that weren't part of the training set to be recognized more accurately.

5. Flexibility: Kernel methods provide you the freedom to select several kernel functions based on the issue at hand. To identify certain patterns in the data, other kernel functions can be used, including sigmoid, polynomial, and gaussian. Kernel approaches are flexible and useful for a variety of face recognition problems because to their versatility.

Fisherfaces and Eigenfaces are less accurate, robust, and flexible than kernel approaches, such as PCA and SVM. They provide more precise recognition performance and improved generalization to unseen faces, which is especially useful when working with complicated and nonlinear face data.

Grey Scaling Images

Images are frequently gray scaled in motion detection and facial recognition systems to enhance and simplify image processing processes. The procedure entails turning the original color photos into grayscale, which assigns a single value ranging from 0 (black) to 255 (white) to each pixel's intensity.

Gray scaling aids in facial identification by reducing the impact of color changes and concentrating on the structural and textural details of the face. The algorithm may focus on aspects like the shape of the face, the texture of the skin, and the patterns of facial landmarks like the eyes, nose, and mouth by converting the image to grayscale. This simplification makes the extraction and comparison of face features more precise and effective.

Gray scalability in pictures is also advantageous for motion detection systems. The emphasis is shifted from color changes to variations in pixel intensity by making the input video frames grayscale. This reduction makes spotting and following motion in a scene simpler. Movement is indicated by changes in intensity, and algorithms may assess these fluctuations to pinpoint areas of interest where motion is taking place. Additionally, gray scaling lessens the computing cost of motion detection methods, increasing the viability of real-time processing.

Gray scaling offers benefits in terms of computing simplicity and effectiveness. Grayscale photos may be processed and analyzed more quickly than full-color ones since they need less memory and computer power. Additionally, grayscale pictures are more robust and dependable for facial recognition and motion detection tasks because they are less susceptible to changes in lighting and color.

To determine the grayscale value for each pixel, it normally uses a straightforward formula or method. Taking the average of the red, green, and blue color channels in the original picture is one typical technique:

Grayscale Value = (R + G + B) / 3

Where R, G, and B represent the red, green, and blue color channel values of the original image, respectively. This formula calculates the average intensity value and assigns it to the pixel in the grayscale image.

Another approach is to use weighted averages that mimic the perceived luminance of different color channels. For example, the formula used in the ITU-R BT.601 standard is:

Grayscale Value = 0.299 * R + 0.587 * G + 0.114 * B

Each pixel's grayscale value is determined by these algorithms, producing a grayscale picture where each pixel is represented by a single intensity value.

While gray scaling photos does not require the use of complicated mathematical techniques, color photographs may be easily converted to grayscale using these easy averaging formulae or weighted averages. It is appropriate for facial identification and motion detection applications since the emphasis is on obtaining structure and textural information rather than accurate color representations.

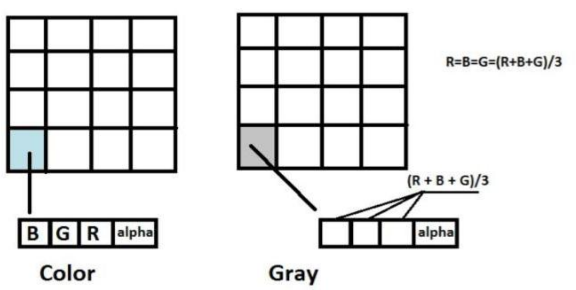

Fig -4: BGR To Grey conversion

6. RESULTS

First off, the technology has greatly improved security in the vicinity of its deployment. It guarantees that any suspicious behavior is swiftly identified and recorded thanks to its sophisticated motion detection features, making it a useful tool for spotting and analyzing possible security concerns. The building's tenants and occupants now feel safe and at ease as a result of this.

Additionally, the system's integration with elevator control has significantly increased the elevators' general efficiency and convenience. The operation is more cost-effective and ecologically beneficial since excessive energy consumption is reduced by only turning on the elevator when motion is detected. The security precautions are further improved by the restricted access to the elevator, which guarantees that only authorized people may use it.

The system's capacity to conserve storage space by only capturing video when motion is detected is another important benefit. This not only lowers the amount of storage needed, but also makes it easier to evaluate the recorded video. When searching and analyzing the recorded films, the intelligent motion detection tool removes extraneous information and concentrates on recording occurrences of interest.

Additionally, the project's use of OpenCV, a potent open-source computer vision toolkit, has made it possible to create a system that is incredibly adaptive and adjustable. This implies that, whether it's a large-scale commercial structure or a residential complex, the surveillance system may be customized to match the unique demands and requirements of various locations. The system's adaptability allows users to customize it to meet their own security and operational requirements while ensuring that it may be used in a variety of settings.

7. CONCLUSION

The program uses a Haar Cascade Classifier to analyze the data and determine the identities of people in the images. After installation, it may be quickly put to use. This tactic is ideal for when normal monitoring procedures must be maintained in a place where abnormal behavior is common. The amount of space needed for storage, energy required, and upkeep costs are all able to be drastically cut with its help. The installation of OpenCV was crucial to the operation of the whole device. There is no more practical or economical time frame to put into use. This simple and accessible solution is useful for minimizing the amount of space needed to save the images.

In conclusion, the Advanced Intelligent Video Surveillance System implementing OpenCV has effectively attained its goals of motion detection, selective video recording, and elevator operation control. The project has shown to be beneficial in boosting resource efficiency, supplying a dependable surveillance solution, and strengthening security measures.

The system has demonstrated the capability of computer vision in motion detection and picture processing by utilizing OpenCV's capabilities. The effectiveness and efficiency of the system have been further improved by the use of sophisticated algorithms like Haar cascades and facial recognition. Due to the early detection and recording of possible threats and suspicious activity, security has increased as a consequence.

In addition to improving energy efficiency, the system's capacity to manage elevator operation based on motion detection offers an additional degree of protection. Unauthorized entry is reduced by only turning on the elevator when motion is sensed, protecting the building's tenants' privacy and safety.

Additionally, the project's emphasis on motion-based selective recording has led to effective storage use. Storage space is maximized and the process of evaluating recorded footage is expedited by only recording video when it is actually needed. This makes it possible to analyze pertinent occurrences quickly and precisely, saving time and money for the inquiry.

There are several possible uses for the advanced intelligent video surveillance system, including security systems in buildings, public areas, and private residences. Because of its versatility and modification capabilities, it may be tailored by users to fit a variety of contexts and requirements.

Overall, the project has been effective in showcasing the advantages and usefulness of an OpenCV-based intelligent video surveillance system. It has delivered improved resource management, increased security, and effective surveillance capabilities. The study paves the way for future developments in intelligent surveillance systems that make use of computer vision to build settings that are safer and more secure.

8. REFERENCES

[1]. A. Renjith and Aishwarya, “Enhanced home security Using IoT and raspberry pi," International Research Journal of Engineering and Technology (IRJET), vol. 4, 2017.

[2]W. F. Abaya, J. Basa, M. Sy, A. C. Abad, and E. P. Dadios, "Low-cost smart security camera with night vision capability using raspberry pi and OpenCV," 2014.

[3]M. Pervaiz, Y. Y. Ghadi, M. Gochoo, A. Jalal, S. Kamal, and D.-S. Kim, “A smart surveillance system for people counting and tracking using particle flow and modified som,” Sustainability, 2021.

[4]M. Rashmika, "Motion sensor and face recognition-based surveillance system using raspberry pi," International Journal of Advanced Research in Computer Science, vol. 8, no. 5, 2017.

[5]A. CobParro, L. Gutierrez, Marron-Romera, GardelVicente, and Bravo-Munoz, "Smart video surveillance system based on edge computing," 2021.

[6]T. Shivprasad, B. Shivani, A. P. Singh, and Deepak, "Survey paper on smart surveillance system," International Research Journal of Engineering and Technology (IRJET), vol. 3, 2016.Fig 6: BGR to Gray Conversion