Project Report On

Smart Surveillance with Anomaly Detection & Person Re-Identification

Submitted in partial fulfillment of the requirements for the award of the degree of

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in

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CERTIFICATE

This is to certify that the project report entitled ***"Smart Surveillance System with Anomaly Detection & Person Re-Identification"*** *is a bonafide record of the work done by* ***Nevil Biju Varghese (U2003150), Shreepad Sumesh P (U2003199), Romain Robert (U2003173) and Rayyan Fadi (U2003164)****, submitted to the Rajagiri School of Engineering & Technology (RSET) (Autonomous) in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology (B. Tech.) in Computer Science and Engineering during the academic year 2023-2024.*

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Abstract

Security cameras have undergone significant transformations to sophisticated devices integrated with digital technology and the internet. A notable advancement is the incorporation of artificial intelligence (AI), especially in tasks like traffic violation detection and deep learning applications. Deep learning models excel in extracting complex features for anomaly detection and person re-identification, enhancing accuracy in monitoring.
Anomaly detection and person re-identification are two important tasks that can be implemented in security cameras. Both tasks can be challenging due to the complexity and diversity of scenes, also due to the intense human work and time required, as well as the often noisy and low-quality images captured by security cameras.
Hence, the key components of our proposed project includes -

- **Anomaly Detection:** Utilizes deep learning to differentiate between normal and unusual events, enhancing threat detection.
- **Person Re-Identification:** Employs deep learning for tracking individuals across multiple cameras, ensuring continuous surveillance.
- **Alerts and Miscellaneous features:** In the event of an anomaly, users will receive timely alerts to ensure swift action. Moreover, users have the convenience of accessing live footage as well as saved clips showcasing detected anomalies, along with timestamps of all anomalies.

This system promises to elevate security in both public and private sectors, offering scalability and efficiency for widespread deployment. Automating anomaly detection and person re-identification facilitates quicker and more effective responses to security threats by personnel.

Contents

List of Abbreviations

AI - Artificial Intelligence
HMMs - Hidden Markov Models
AVAD - Autonomous Video Anomaly Detection
ROI - Region of Interest
BS - Background Subtraction
YOLOv5 - You Only Look Once Version 5
MoG - Mixture of Gaussian
PDF - Probability Density Function
CNN - Convolutional Neural Network
GNN - Graph Neural Network
DPGNN - Dual-Pooling Graph Neural Network
MLP - Multi-Layer Perceptron
RCRR - Reversion Correction and Regularized Random Walk Ranking
IRLS - Iteratively Reweighted Least Squares Algorithm
MAP - Maximum a Posteriori
HLF-Net - High Low Frequency Network
Re-ID - Re-Identification
CSV - Comma-Separated Values
OpenCV - Open Source Computer Vision
COCO - Common Objects in Context dataset
ACID - Atomicity, Consistency, Isolation, and Durability
IP -Internet Protocol
NMS -Non-maximum Suppression
ID -Identifier

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Chapter 1

Introduction

1.1 Background

Smart surveillance systems, integrating anomaly detection and person re-identification, have become pivotal in modern security and monitoring operations. With the integration of AI and deep learning, these systems have evolved to offer sophisticated functionalities. They not only provide real-time footage but also intelligently analyze it to detect unusual activities and consistently recognize individuals across various camera networks as shown in [Figure 1.1].

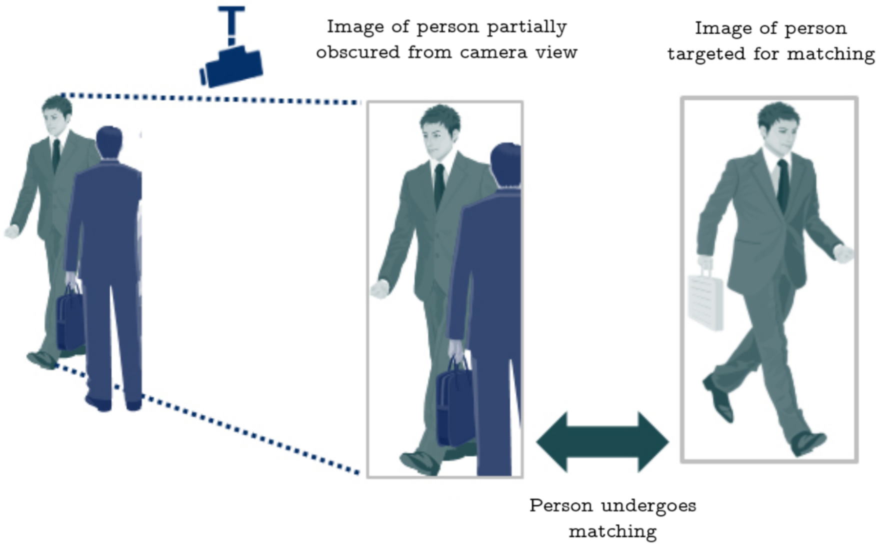

Figure 1.1: Illustration of Smart Surveillance technology in action.

Such systems are invaluable in enhancing the security and operational efficiency of public spaces, transportation systems, and commercial establishments by offering advanced surveillance capabilities.

1.2 Problem Definition

The problem addressed in the proposed project revolves around the challenges faced by traditional security camera systems, which have transitioned from analog to digital technology and integrated artificial intelligence (AI). The primary issues include the complexity and diversity of scenes, the labor-intensive and time-consuming nature of tasks, and the often suboptimal quality of images captured by security cameras

1.3 Scope and Motivation

1.3.1 Scope

The scope of smart surveillance technology extends beyond traditional monitoring, encompassing the broad spectrum of AI and computer vision. It includes the application of sophisticated algorithms for real-time anomaly detection and accurate person re-identification under various environmental conditions, such as variable lighting and diverse scenes.

1.3.2 Motivation

The motivation for advancing smart surveillance technology arises from the need to improve security measures in complex, dynamic environments. Traditional surveillance methods fall short in effectively processing the vast amount of data generated by camera networks. AI-driven anomaly detection and person re-identification promise enhanced accuracy and efficiency, leading to quicker response to security incidents and better public safety.

1.4 Objectives

1. **Efficient Anomaly Detection:** Develop algorithms to accurately detect unusual events, reducing the time to respond to potential security threats.

2. **Accurate Person Re-Identification:** Create robust systems capable of identifying and tracking individuals across multiple cameras, enhancing surveillance coverage.

3. **Integration with Existing Systems:** Ensure the technology seamlessly integrates with existing surveillance infrastructure, promoting widespread adoption.

4. **Handling Diverse Environmental Conditions:** Design algorithms that perform reliably under various conditions, including low-light and crowded scenes.

5. **Scalability and Flexibility:** Develop a system that is scalable to larger networks and flexible enough to adapt to different surveillance needs.

1.5 Challenges

1. **Resistance from the Public:** Public concerns about privacy or surveillance may lead to resistance or skepticism, requiring effective communication and transparency initiatives to address these issues.

2. **Technical Failure:** Technical failures or glitches in the system may temporarily disrupt surveillance operations.

3. **Maintenance:** Regular maintenance, including lens cleaning and system updates, is necessary to ensure optimal performance.

1.6 Assumptions

1. Cameras are able to provide usable footages in harsh weather conditions and poor lighting.

2. Unbiased dataset.

3. Uninterrupted processing

4. Stable and reliable network connection.

1.7 Societal / Industrial Relevance

The implementation of smart surveillance systems with advanced anomaly detection and person re-identification capabilities holds significant relevance in both social and industrial contexts. These systems are poised to revolutionize the way security and monitoring are conducted across various sectors.

Social Impact:

- **Enhanced Public Safety:** By promptly identifying potential threats and tracking individuals, these systems contribute to safer public spaces like malls, parks, and transportation hubs.

- **Crime Prevention:** The ability to detect anomalies and identify perpetrators quickly aids law enforcement in preventing and solving crimes, thereby contributing to societal well-being.

- **Community Confidence:** The presence of efficient surveillance systems can bolster public confidence in safety measures, creating a more secure living environment.

Industrial Significance:

- **Workplace Security:** In industrial settings, these systems ensure the safety of assets and personnel, particularly in areas prone to unauthorized access or hazardous conditions.

- **Operational Efficiency:** By automating surveillance and security tasks, industries can optimize their operations, reduce costs, and focus human resources on more critical tasks.

- **Data-Driven Insights:** Smart surveillance systems provide valuable data that can be analyzed for insights into operational improvements, customer behaviors, and other business intelligence.

In summary, the social and industrial relevance of these advanced surveillance systems is extensive, offering tangible benefits in security, safety, and operational efficiency. Their adoption not only protects assets and individuals but also paves the way for a more data-informed approach to security and business operations.

1.8 Organization of the Report

The report is organized as follows to provide a comprehensive understanding of smart surveillance technology:

- Chapter 1: Introduction to smart surveillance, its scope, motivation, and objectives.
- Chapter 2: A detailed literature survey on existing systems and the proposed system.
- Chapter 3: Explains the hardware and software requirements of the project along with functional requirements.
- Chapter 4: Design of the smart surveillance system, including architecture diagram and module descriptions.
- Chapter 5: System Implementation presenting the methodologies used.
- Chapter 6: Results and its analysis
- Chapter 7: Conclusion and future scope of the project.

1.9 Conclusion

The introduction chapter outlines the evolution of smart surveillance systems, emphasizing the integration of anomaly detection and person re-identification. It discusses the enhanced capabilities these systems bring to security and surveillance, addressing the need for advanced monitoring solutions in complex environments. The chapter sets the stage for in-depth discussions on implementation challenges,assumptions and the broader impact of these technologies in the society

Chapter 2

Literature Survey

2.1 A Review of Anomaly Detection in Automated Surveillance [1]

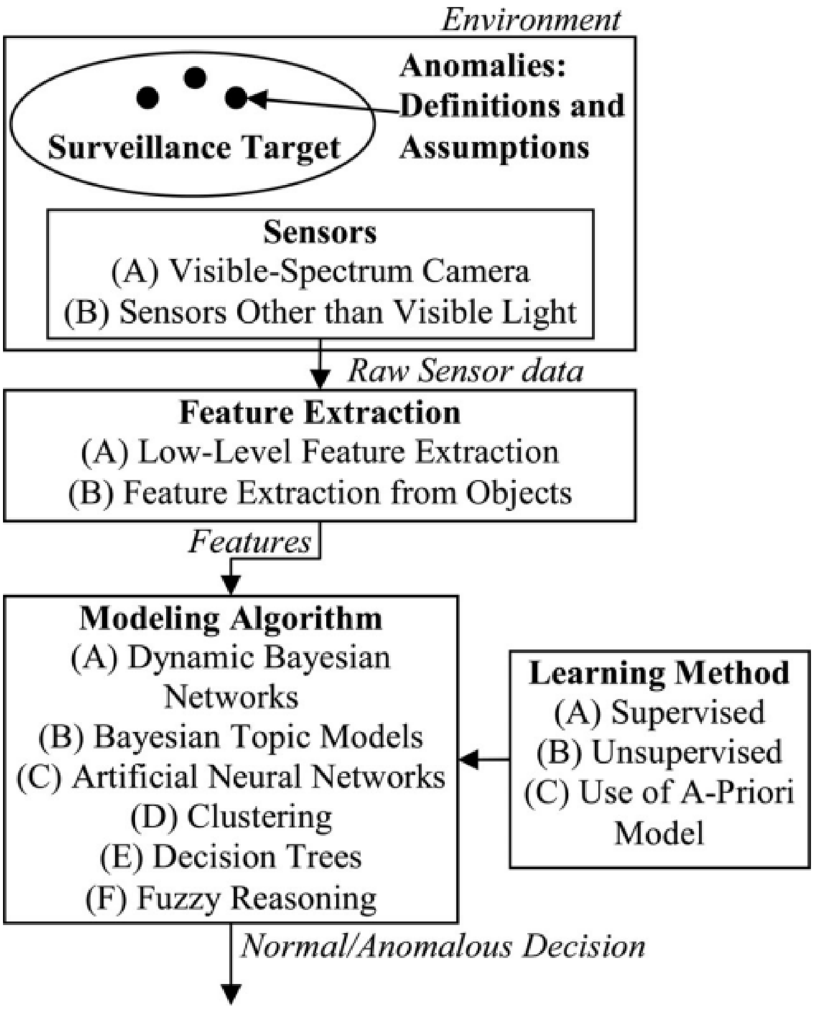

Figure 2.1: Diagram of the flow from environment to anomaly detection, illustrating the organization of this paper.

The paper provides a detailed examination of various aspects of anomaly detection in the field of automated surveillance. The content of the paper is structured into several key sections, each addressing a specific aspect of anomaly detection as shown in [Figure 2.1].

2.1.1 Surveillance Target

This section discusses the entities or targets upon which surveillance operates, like individuals, crowds, automobile traffic, and inanimate objects. It explains how different targets require different methods of anomaly detection and highlights the distinction between individual and crowd surveillance, emphasizing that methods suitable for one may not be effective for the other.

2.1.2 Anomaly Definitions and Assumptions

The authors outline various definitions and assumptions underpinning anomaly detection. They categorize anomalies based on their frequency of occurrence, distinct characteristics from normal events, and specific meaningful actions or occurrences. This section underscores the complexity in defining what constitutes an anomaly.

2.1.3 Sensors and Feature Extraction

Here, the focus is on the types of sensors used in surveillance and the corresponding feature extraction processes. The paper discusses the advantages and limitations of different sensors, like visible-spectrum cameras and audio sensors. It also delves into methods of feature extraction, including low-level and object-based methods, and how these are influenced by the type of sensor and surveillance target.

2.1.4 Learning Method

This section reviews various learning methods applied to behavior modeling and anomaly detection, broadly categorizing them into supervised learning, unsupervised learning, and application of a priori knowledge. The paper discusses each category in detail, highlighting their relevance to anomaly detection and the associated methods.

2.1.5 Modeling and Classification Algorithms

The final section provides an overview of different modeling and classification algorithms used in anomaly detection. It focuses on dynamic Bayesian networks, especially Hidden Markov Models (HMMs), and their applications in anomaly detection. The paper discusses the challenges in using HMMs, such as overfitting and determining the appropriate number of hidden states.

Overall, the paper provides a comprehensive overview of the state of research in anomaly detection within automated surveillance. It covers a wide range of topics, from the types of surveillance targets and anomaly definitions to the specifics of sensor technology, learning methods, and modeling algorithms, offering valuable insights into the complexities and challenges of this field.

2.2 Autonomous video anomaly detection (AVAD) [2]

The AVAD method trains an end-to-end model comprised of a spatial feature extractor and a temporal autoencoder that learn the spatio-temporal patterns of the frame sequence together. Some spatio-temporal patterns are:
Spatial patterns :
- Cubicles in an office.
- Benches arranged in a classroom.

Temporal patterns :
- Sunrise and sunset
- Change in seasons.

Autoencoders are divided to three parts [Figure 2.2] : Encoder, Bottleneck and Decoder.
- The encoder performs operations on the input , in this case convolution operation.
- The bottleneck contains the Code or the latent space representation obtained after encoding.
- The decoder recreates the input from the code and this is taken as the output.

Recreation error : The difference between the output and the input. If the recreation error is greater than a given threshold then, anomaly detected.
- Variables :

X: Input spatiotemporal data

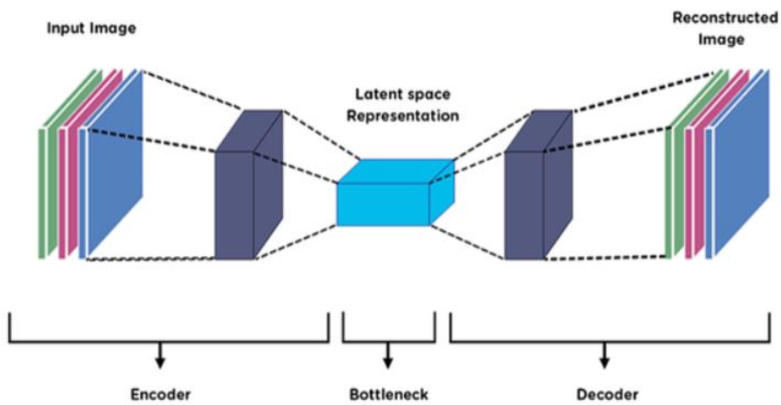

Figure 2.2: Autoencoder

Z: Latent space representation

E_s: Spatial encoding function

E_t: Temporal encoding function

D_s: Temporal decoding function

D_t: Spatial decoding function

$X_h$at: Reconstructed spatiotemporal data

- Encoder :

Temporal encoding : $Z_t = E_t$(X)

Spatial encoding : $Z_s = E_s$(X)

Z = $Z_t + Z_s$ (Combining the temporal and spatial encodings)

- Decoder :

Temporal decoding : $Z'_t = D_t$(Z)

Spatial decoding : $Z'_s = D_s$(X)

$X_h$at = $Z'_t + Z'_s$ (Combining the temporal and spatial decodings)

The reconstruction of raw frames for training the usual Spatio-temporal pattern at decoder output is computationally demanding. Furthermore, spatially redundant pixels in frame sequences are less informative, and the raw frame reconstruction carried the burden of recreating the redundant information. To circumvent these restrictions, implementing a strong BS can assist in determining the ROI and proceeding solely with the significant pixels as precisely as possible. BS is used to generate a foreground mask by subtracting the current frame from a background model that contains the static portion of the frame. Dynamic scene changes, repetitive motions, light reflectance etc make reliable and swift object detection challenging. As a result, AVAD's baseline object detection model is the fast one-stage method of YOLOv5.

The proposed system begins by dividing surveillance videos into a fixed number of segments which then undergo four key steps as graphically illustrated in [Figure 2.3]

The four key steps are :

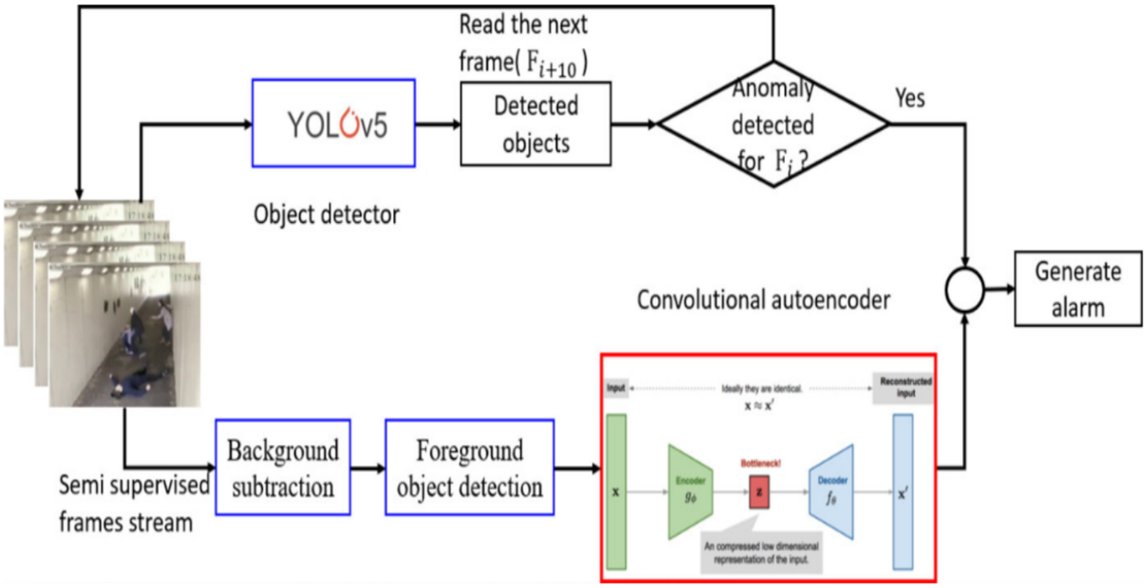

Figure 2.3: Architecture of AVAD

- Background subtraction and foreground object detection
- Convolution autoencoders
- Object detection
- Alarm generation

2.2.1 Background Subtraction :

Discarding the background to focus solely on the foreground items is a common preprocessing step in computer vision. AVAD uses MoG coupled with a convolutional autoencoder in a semi-supervised method to reduce the effort required to prepare the training set by training the model with a small quantity of labelled data.

Initially model is trained using two inputs, an original frame and a background model.

The model learns the spatio temporal patterns using these input. During testing phase, the probability density function (PDF) of each pixel is calculated. The model compare the previously learned patterns with the PDF of each pixels to differentiate the background and foreground of the frame. This approach is very efficient to localize the ROI before performing anomaly detection.

Once the background model is defined, the next step is to identify foreground pixels by comparing the current frame to the background model and then binarizing the difference. the difference is called a segmentation result which is obtained by comparing each pixel value to a threshold value. This is a segmentation technique called thresholding. If the subtracted pixel value is larger than the threshold value, the white colour will be assigned the maximum value (255), otherwise the black colour will be assigned (0). In practice, several threshold values corresponding to 0.7, 1, and 2 were investigated but the best results were at 0.7.

At the end, the segmented image gives the moving target in white with a black background. The entire process is shown in [Figure 2.4].

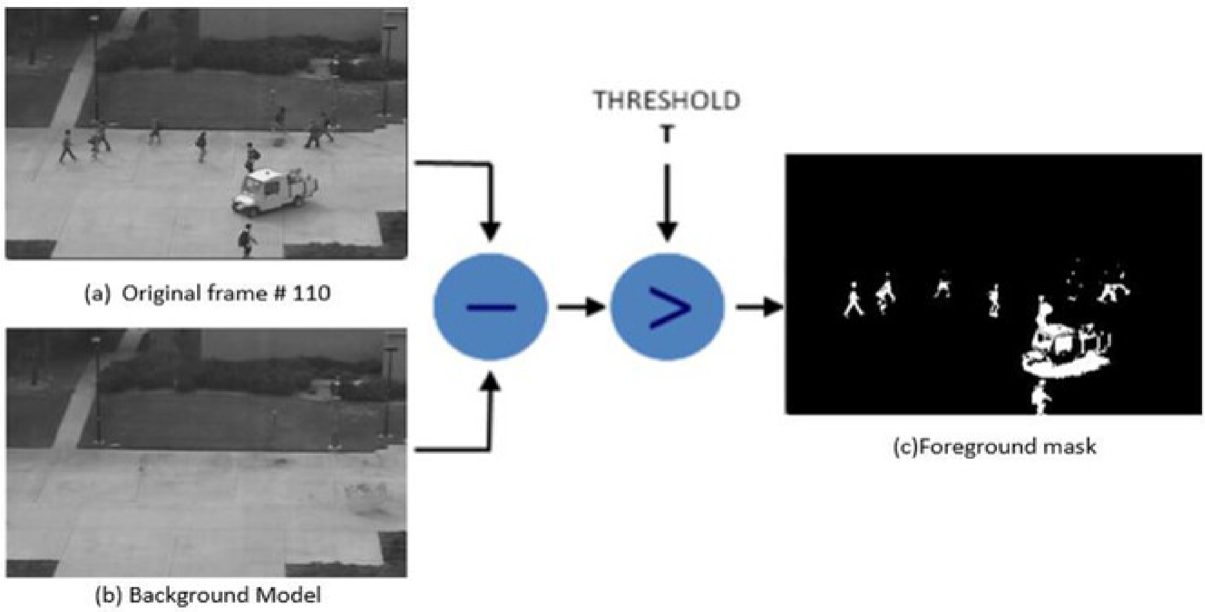

Figure 2.4: Background subtraction and foreground object detection

2.2.2 Convolution Autoencoders :

The model has only been trained for a standard pattern of spatiotemporal feature segments. The autoencoder's output is a rebuilt representation of the input frames. For anomalous events, the filters built during training cause large reconstruction errors. If the error exceeds a particular level, the video segment is considered an anomaly. Traditional autoencoders are unable to keep spatial characteristics. As a result, we employ convolutional autoencoders like spatio-temporal autoencoders.

By applying square filters, spatial convolution preserves the spatial correlation between image portions. These filters are employed in convolution processes that produce dot products with local regions of a particular frame. The most significant challenge is limiting the number of filters as they take more processing time and memory. Three convolutional layers and two pooling layers are used on the encoder side, while three deconvolutional layers and two un-pooling layers are used on the decoder side, as in [Figure 2.5].

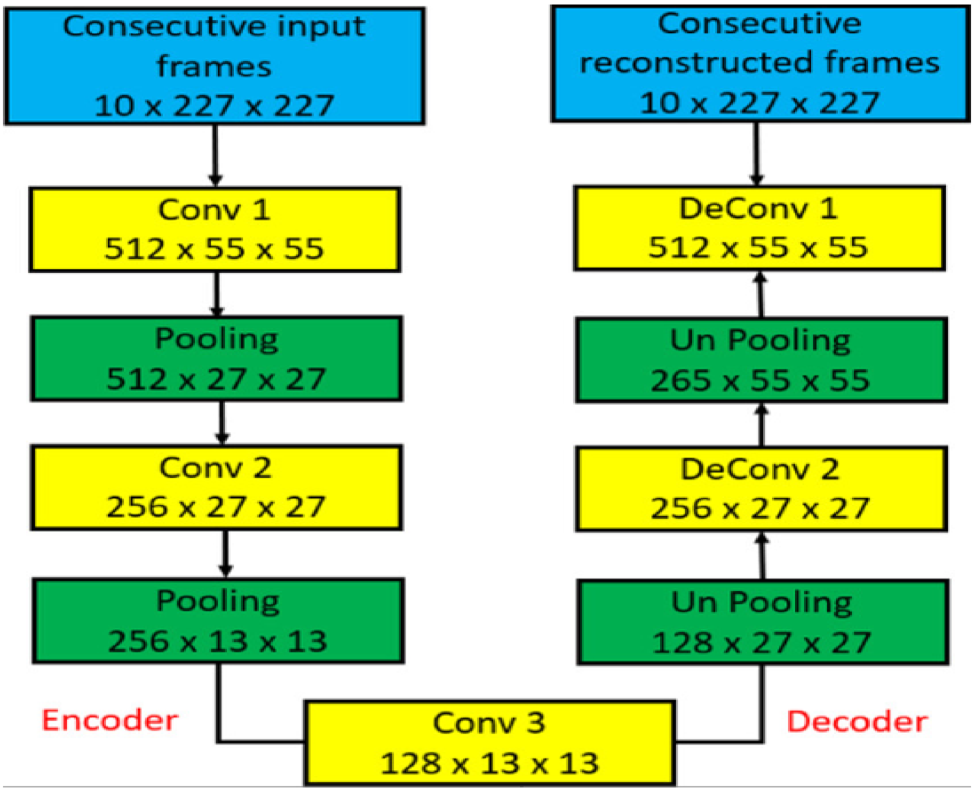

Figure 2.5: Background subtraction and foreground object detection

2.2.3 Object Detection :

YOLOv5 is used for object detection in the model. In YOLO, a frame is represented in a grid format (General grid size- 19x19). The objects in the frame is identified using CNN or regression. Localization is done by placing bounding box around the object. Bounded output, Y = [Pc, bx, by, bh, bw, c1, c2]. Classification is done by finding the maximum probability of the specified object.Applying object detection on every single frame causes a lot of redundant computation and processing time. So the model was trained with different intervals of input frames like 5, 10, and 15. The detection performance shows stability for intervals of both 5 and 10 frames as in [Figure 2.6].

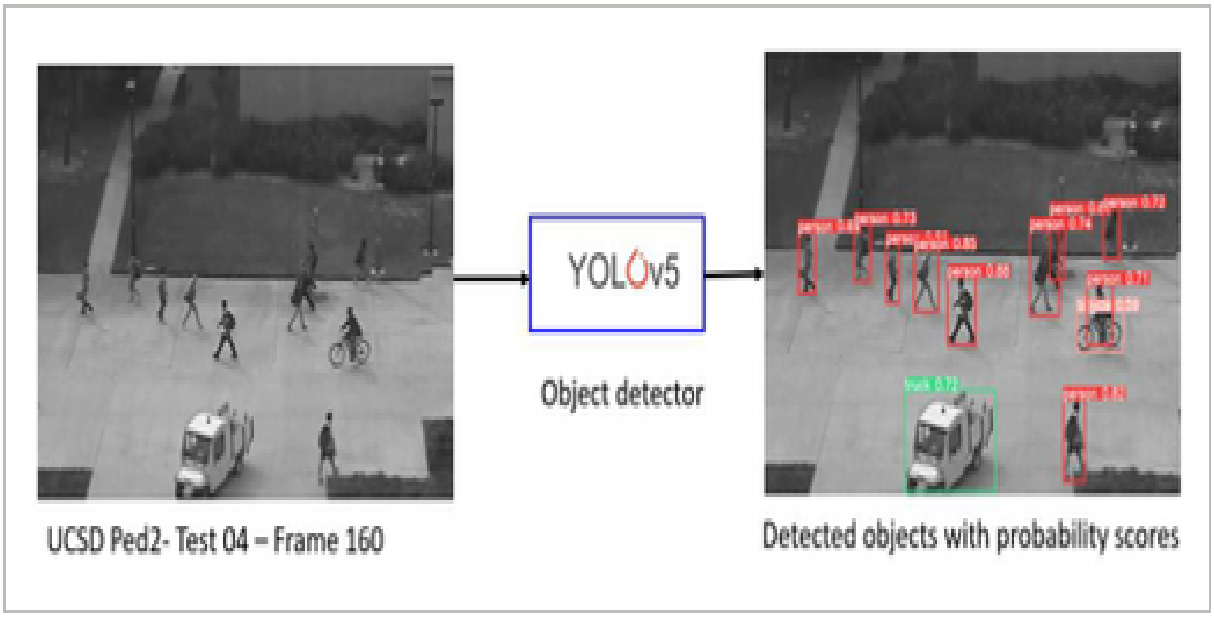

Figure 2.6: YOLO Process

2.3 Learning Dual-Pooling Graph Neural Networks for Few-shot Video Classification [3]

The proposed method of Dual-Pooling Graph Neural Networks for Few-shot Video Classification leverages intra-video and inter-video relations to improve the discriminative ability for accurately selecting representative video content and refining video relations. As shown in [Figure 2.7] the method involves a multistage GNN that considers the relations of intra-video and inter-video domains jointly. The framework is divided into an embedding layer, intra-video graph, and inter-video graph. The intra-video graph chooses the most representative node to extract robust video-level features with a node pooling module. The inter-video graph eliminates the negative relations of edges by designing an edge pooling module.

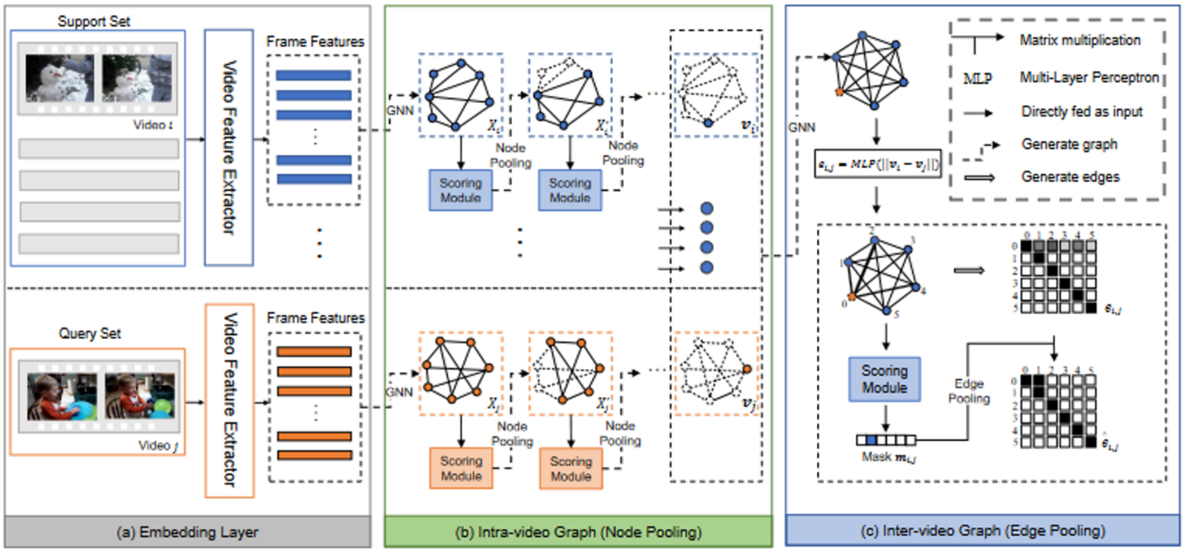

Figure 2.7: Proposed DPGNN Method

2.3.1 Intra-Video Graph

The intra-video graph is constructed to select the most representative frames in a video and extract robust video level features. Here each frame is made into a node and connect adjacent frames with edges The operations are made as several blocks and each contains a node pooling layer followed by a GNN layer. Node pooling layer is used to select the most representative nodes in the intra-video graph.

The graph G consists of(A_i, X_i) where A is adjacency matrix and X be the feature matrix with n row vectors for each node. The adjacency matrix is computed using cosine similarities of pairwise features with values in the range [0,1] where 1 indicates frames are similar and 0 when dissimilar. Average Node Pooling is then used to select the most important features, then the scores obtained are sorted by size and the the indices obtained are used to generate a new graph and sigmoid value of the pooling score of the index is used as feature representation for the next graph.

2.3.2 Inter-Video Graph

The inter-video graph is an undirected connection graph that captures the relations between different videos. The relations between two nodes in the inter-video graph are calculated using the edge attention score. To retain the most important edges, the paper proposes a refining mask that selects the top-k candidate nodes for further processing.

The edge pooling module is used to adaptively eliminate the negative relations in the inter-video graph. The graph G is a fully connected Graph G composed of nodes V and set of edges E, where node vi corresponds to the video-level feature of video. Here MLP (Multi-Layer Perceptron) to calculate the edge weights in the intra-video graph. Specifically, they use the Euclidean distance between the feature vectors of two nodes vi and vj as input to the MLP. For edge pooling scoring module is used to rank the videos for classification. To retain the most important edges a refining mask is used and it predicts the edge label for each graph.

2.4 Object Motion Deblurring [4]

The proposed method aims to automatically separate the moving object from the background and estimate the blur kernel for each region separately. The method utilizes an automatic GrabCut segmentation algorithm combined with guided filtering to achieve this goal. The proposed method also incorporates an optimized maximum a posterior deblurring framework and an unsharp masking algorithm to enhance the restoration effect and preserve edge details in the deblurred image. The proposed method is evaluated on a variety of datasets and compared with existing state of-the-art methods to demonstrate its effectiveness. The motivation behind this work is to address the limitations of existing methods for motion deblurring in single images under static background. These methods often rely on assumptions about the blur kernel or require multiple images to estimate the motion, which may not be feasible or effective in certain scenarios. The proposed method aims to overcome these limitations by using an automatic segmentation algorithm to separate the moving object from the background and estimate the blur kernel for each region separately. This approach allows for more accurate estimation of the blur kernel and better restoration of the image. The proposed method also incorporates an unsharp masking algorithm to enhance the clarity of the deblurred image and preserve edge details.

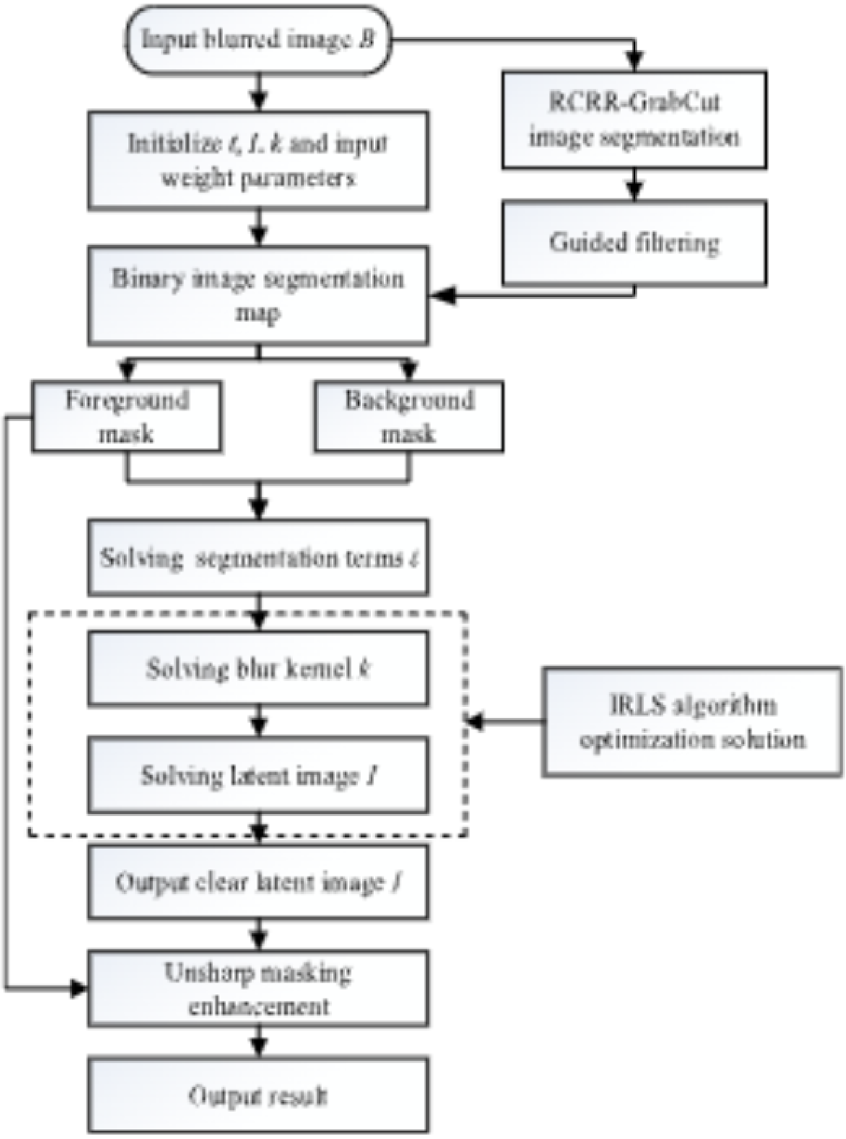

Figure 2.8: . Flow-chart of the algorithm.

[Figure 2.8] depicts the flowchart of the algorithm proposed in the study. The detailed steps and components of the algorithm are as follows:

The variables initialized in the flowchart are as follows:

- B: Blurred image
- I: Clear image
- k: Blur kernel
- RCRR: Algorithm or method used for the segmentation process.
- IRLS: Iteratively Reweighted Least Squares algorithm used to optimize the model solu-

tion for motion blur elimination in different regions.
- U: Region term in the energy function formula used in the GrabCut algorithm, which means that a pixel belongs to the negative logarithm of the target background probability.
- V: Boundary energy term in the energy function formula used in the GrabCut algorithm, representing the Euclidean distance between the colors of two adjacent pixels.
- Z_I: Normalization term for the sparsity image gradient prior.
- Z_k: Normalization term for the Laplacian prior.

Step 1: RCRR-GrabCut Segmentation Algorithm
GrabCut Segmentation Algorithm: The GrabCut algorithm is a method used for image segmentation, which automatically separates the foreground and background in an image based on user input or predefined markers.
Step 2: Guided Filtering
Guided Filtering: This is a specific image processing technique used to perform segmentation processing on the input blurred image and the segmented image obtained in Step 1. Guided filtering is a method for edge-preserving smoothing and detail enhancement.
Step 3: Maximum a Posteriori Deblurring Framework
Maximum a Posteriori (MAP) Deblurring Framework: This framework is a probabilistic approach used for image deblurring, aiming to estimate the most likely sharp image given the observed blurred image and prior knowledge about the blur.
Step 4: Unsharp Masking Algorithm
Unsharp Masking Algorithm: Unsharp masking is an image sharpening technique that enhances the edges and fine details in an image, typically by creating a blurred version of the original image and then subtracting it from the original to enhance edges.

The flowchart outlines the integration of the RCRR-GrabCut segmentation algorithm, guided filtering, maximum a posteriori deblurring framework, and unsharp masking algorithm to address the challenges of motion blur caused by moving objects in single images.

2.5 HLF-Net [5]

HLFNet (High Low Frequency Network), emerges as a cutting-edge solution in the realm of person re-identification (Re-ID) technologies. This model is purposefully crafted to overcome inherent challenges prevalent in real-world scenarios, where factors such as varying lighting conditions, diverse poses, and occlusions often impede the accurate identification of individuals. HLFNet introduces a novel paradigm by strategically amalgamating information from both high and low frequencies within the original input images(as shown in figure 3.1), aiming to significantly enhance the precision and robustness of person re-ID algorithms.

At its core, HLFNet seeks to provide an effective means of feature extraction by integrating both detailed and coarse-grained information from input images as shown in [Figure 2.9]. By harnessing the power of high-level features through a global branch and low-frequency features via a local branch, the model endeavors to create a holistic understanding of individual appearances. This innovative approach sets HLFNet apart, positioning it as a promising solution to the challenges posed by the dynamic and complex nature of person re-identification tasks in various practical scenarios.

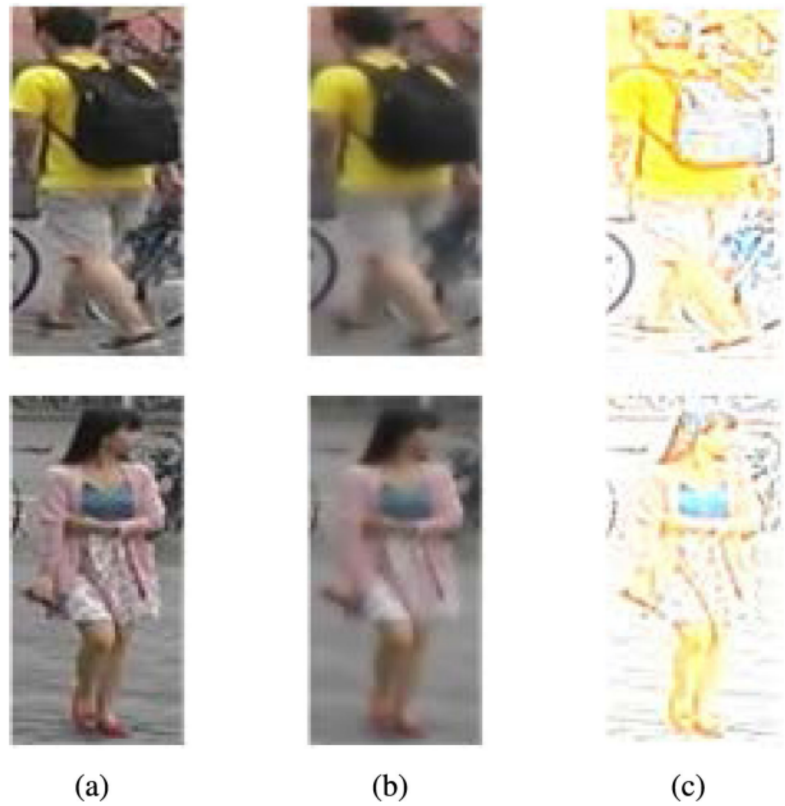

Figure 2.9: Examples of (a) original image, (b) smoothed low-frequency image and (c) high-frequency image.

2.5.1 Model Architecture

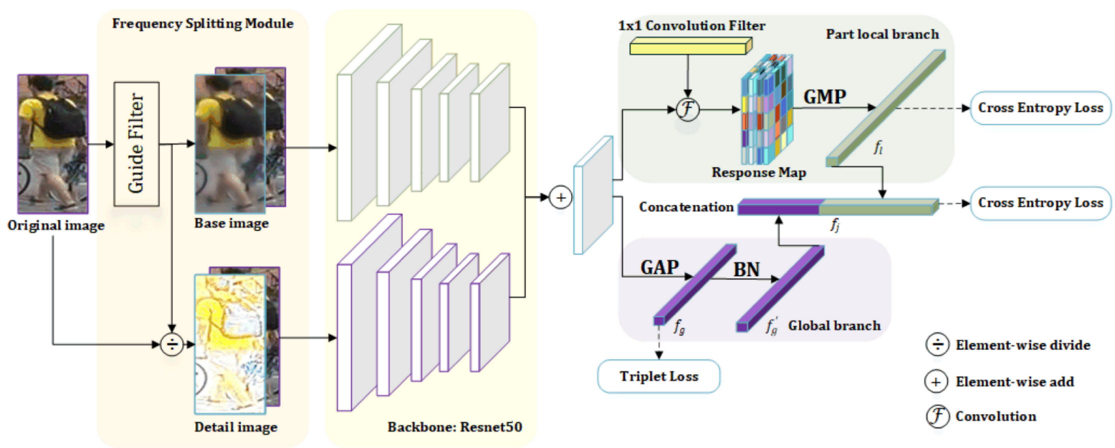

Figure 2.10: Architecture Diagram for HLFNet

The architecture of the HLFNet model [Figure 2.10] consists of two primary components: the global branch and the local branch. The global branch is responsible for learning high-level features from the input image, while the local branch focuses on learning low-frequency features. These two branches are guided by a local branch guide, which facilitates the integration of high- and low-frequency information to improve the overall performance of the model. This architecture enables the HLFNet model to effectively capture and leverage both high- and low-frequency details from the input images, contributing to its enhanced re-identification capabilities.

2.5.2 Training Process

The training process of the HLFNet model involves two distinct stages: the global branch training and the local branch training. During the global branch training stage, the model learns high-level features from the input image using a standard backpropagation procedure. Subsequently, in the local branch training stage, the model focuses on learning low-frequency features from the input image, facilitated by the innovative local branch guide. This training process is fundamental to the model's ability to effectively extract and integrate high- and low-frequency information, ultimately contributing to its superior performance in re-identifying individuals across different datasets and scenarios

2.6 Summary and Gaps Identified

2.6.1 Summary

Paper	**Advantages**	**Disadvantages**
A Review of Anomaly Detection in Automated Surveillance	• Rich resource for understanding the current state of research in this field. • Optimize the model for accuracy and speed.	• Implementation of real-time detection algorithms. • Limitation in the current scope of research and target range.
Autonomous video anomaly detection (AVAD)	• Semi-supervised learning approach allows to detect anomalies using weakly labeled or unlabeled data. • YOLOv5 object detection provides anomalous objects along with its confidence score.	• Difficulty in real time implementation of spatial extraction. • Integration of required models.
Dual-Pooling Graph Neural Networks	• Uses Few Shot learning to handle unseen cases. • The dual-pooling strategy captures comprehensive intra-video and inter-video relations.	• Require significant computational resources due to the use of GNNs and the dual-pooling strategy. • Large amount of training data required to achieve optimal performance.

Paper	Advantages	Disadvantages
Object Motion Deblurring	• Develop classification models for different anomaly types. • Optimize the model for accuracy and speed.	• Design and train models for re-identification purposes. • Ensure the re-ID system is robust across various scenarios.
HLF-Net	• Enhanced feature discrimination from high and low frequency images. • Robustness to noise and variations in image quality.	• Higher computational complexity due to splitting of image. • Potential of overfitting if dataset is not diverse enough.

Table 2.1: Paper Comparison

2.6.2 Gaps Identified

1. Further Research is required for the integration of various anomaly detection systems with surveillance feeds for effective responses in dynamic environments.
2. Using Graph Neural Networks along with Dual-Pooling is complex and optimization is required to reduce computational demands.
3. There is a risk of overfitting during Person Re-Identification if dataset used is not diverse enough.
4. Optimization of Motion Deblurring and Object Segmentation can help preserve edge details in images more effectively

2.6.3 Conclusion

In the literature survey, the first paper focused on anomaly detection in automated surveillance, providing a an overview of various aspects and highlighted the complexity of defining anomalies and the challenges associated with processing vast amounts of surveillance data. The second paper introduced an autonomous video anomaly detection (AVAD) method, which utilized end-to-end models with spatial feature extractors and temporal autoencoders. The approach incorporated background subtraction, convolutional autoencoders, and object detection to identify anomalies in surveillance videos. The third paper delved into few-shot video classification using Dual-Pooling Graph Neural Networks. The proposed method leveraged intra-video and inter-video relations, integrating a multistage GNN with node and edge pooling modules. The fourth paper focused on object motion deblurring, introducing a method that automatically separated moving objects from the background and estimated blur kernels for each region separately. The fifth paper, HLFNet, presented a cutting-edge solution for person re-identification. HLFNet introduced a unique approach by integrating information from both high and low frequencies in input images, aiming to enhance precision and robustness in real-world scenarios. In summarizing the findings, each paper had its strengths and limitations. The identified gaps include the need for real-time anomaly detection, integration of detection systems with surveillance feeds, potential computational complexity in few-shot video classification, and the challenge of overfitting in person re-identification when datasets are not diverse enough.

Chapter 3

Requirements

3.1 Hardware and Software Requirements

3.1.1 Hardware Specifications

- **Camera:** 3MP with IR Flash and 15-25m Coverage
- **Chips & Network:**
  - CPU (INTEL Core i5 10th GEN or higher)
  - GPU (NVIDIA GTX 16s and higher)
  - 4G/Optical Fiber Communication (OFC)
- **Storage:** Local Storage

3.1.2 Software Specifications

- **Operating System:** Windows 8 / Ubuntu 18.04
- **Platforms:** Google Colab (T4 GPU) & Visual Studio Code
- **Libraries & Data Sources:** Tensorflow, Pytorch, OpenCV, Roboflow, GIT & Kaggle

3.2 Functional Requirements

1. **Real-time Video Streaming:** The system shall be capable of streaming video in real-time from surveillance cameras. This includes maintaining a stable connection and ensuring minimal latency in video transmission.

2. **Anomaly Detection:** The system shall automatically detect anomalies in the surveillance footage. This includes identifying unusual activities or behaviors based on predefined criteria such as unexpected motion, forbidden area intrusions, or other suspicious activities.

3. **Person Re-identification:** The system shall re-identify individuals across different cameras within the surveillance network. It should accurately match individuals' appearances across diverse camera views and conditions.

4. **Alert Generation:** Upon detecting an anomaly or re-identifying a person of interest, the system shall generate and send alerts to the designated security personnel or system administrators.

5. **Data Storage and Retrieval:** The system shall store surveillance footage in a secure, organized manner, allowing for easy retrieval of specific video segments based on time, location, or detected events.

6. **User Interface for Monitoring:** The system shall provide a user-friendly interface for security personnel to monitor live footage, receive alerts, and access historical data.

7. **System Integration:** The system shall integrate with existing security infrastructures, including other surveillance cameras and security systems, without significant modifications to the current setup.

8. **Scalability:** The system shall be scalable to accommodate additional surveillance cameras or enhanced functionalities, such as improved anomaly detection algorithms or expanded database capacities.

9. **Maintenance and Support:** The system shall offer ease of maintenance and support, including regular updates for software components and timely technical assistance.

Chapter 4

System Architecture

The following chapter outlines the intricacies of the proposed system architecture designed to enhance surveillance capabilities. This architecture leverages machine learning and image processing techniques to detect and classify anomalies in real-time, which is pivotal for ensuring safety and security in various settings.

4.1 System Overview

The surveillance system operates continuously, monitoring the environment for potential anomalies. Upon the detection of an anomaly, the system initiates a classification process to identify the nature of the anomaly. If an anomaly is classified as a brawl or a fire, person re-identification process is invoked. This comprehensive mechanism ensures a robust response to incidents, enhancing the overall security measures.

The architecture begins with a continuous surveillance stage where a camera feeds live footage to the system. This system is equipped with advanced algorithms capable of detecting irregularities in the stream. If it identifies an event that deviates from the norm, it triggers the anomaly detection module.

Once an anomaly is detected, the system poses a query: "Anomaly Detected?". If the answer is no, the system persists in its surveillance state, attentively scanning the environment. Conversely, if an anomaly is indeed detected, the process transitions to the anomaly classification phase.

In the anomaly classification phase, the system distinguishes between the types of anomalies.This classification is crucial as it dictates the subsequent steps of the response. The architecture includes a person re-identification (Re-ID) module. This module is sophisticated in its ability to recognize and track individuals across different camera feeds or time intervals. This capability is vital in situations like a brawl, where perpetrators need to be swiftly and accurately identified for security interventions.

4.2 Architectural Design

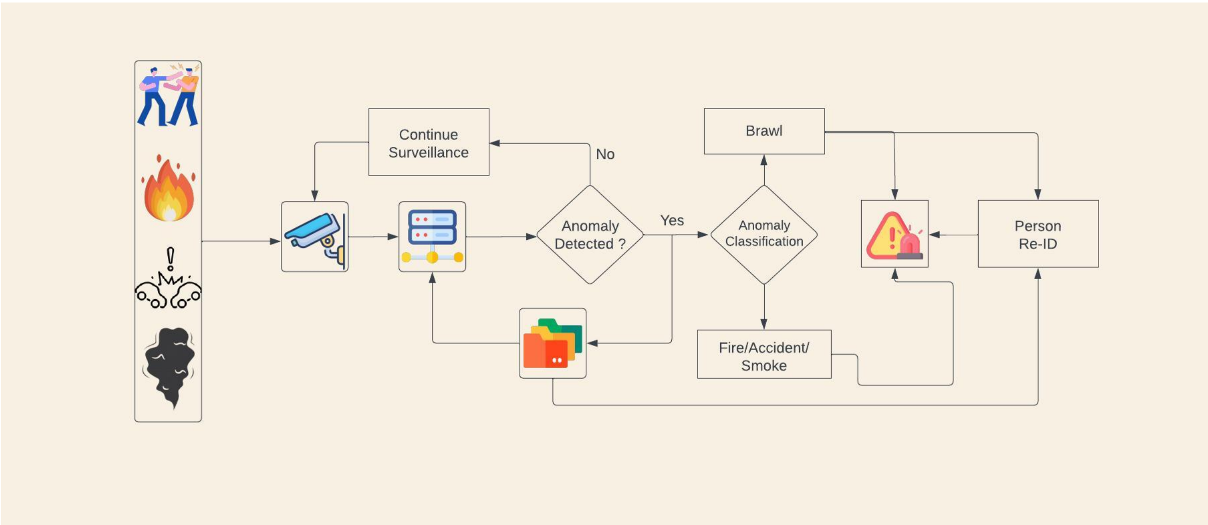

Figure 4.1: Architecture Diagram of the Proposed System

4.3 Sequence Diagram

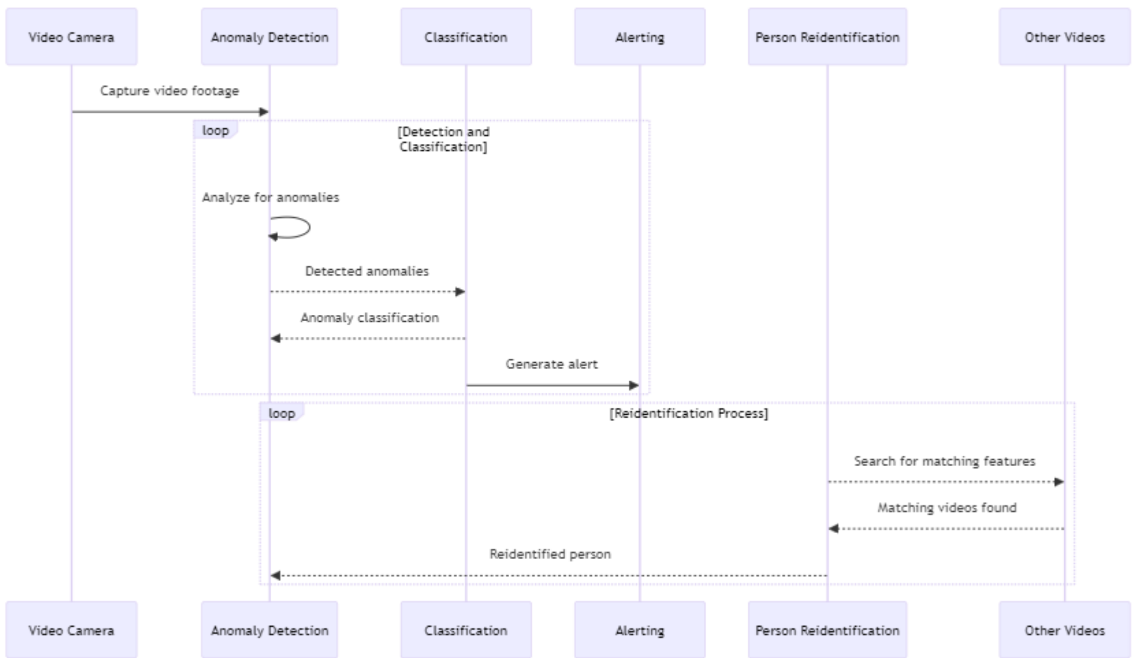

Figure 4.2: Sequence Diagram for Real-Time Anomaly Detection and Classification

4.4 Module Division

The project is divided into two key modules: Anomaly Detection and Person Re-Identification.

4.4.1 Anomaly Detection

The developed anomaly detection system employs the latest YOLOv8 object detection technology to discern various irregular events within live camera streams. These events include accidents, fights, fires, and instances of smoke. The system operates in real-time, swiftly identifying anomalies and alerting the users through intuitive pop-up notifications. Simultaneously, it logs these occurrences alongside their respective timestamps in a CSV file for visualising the timestamps of each anomalies.
Additionally, the system captures frames containing anomalies, compiling them into short video files for documentation and subsequent analysis. With multi-threading capabilities, the system manages the monitoring of multiple camera feeds, ensuring comprehensive surveillance across diverse environments. OpenCV is used for efficient video processing and Torch for robust deep learning-based object detection, the system seamlessly integrates these technologies to provide a reliable solution for heightened security monitoring and anomaly detection.

4.4.2 Person re-ID

The person re-identification module commences with the utilization of a pre-trained ResNet-50 model for feature extraction, followed by the loading of a YOLO (You Only Look Once) model for object detection.
Images are preprocessed using transformations, and their features are extracted using the ResNet-50 model. Meanwhile, the YOLO model, coupled with the COCO class labels, is employed to detect and localize persons within the video frames. Detected persons are subjected to non-maximum suppression to refine the bounding boxes and eliminate redundant detections.
The system employs cosine similarity to match persons detected in subsequent video frames with those in a set of reference frames. Bounding boxes are drawn around detected persons with high similarity scores, aiding in visualizing the matched individuals. Additionally, the system utilizes the face recognition library to identify and mark facial

regions within the frames.

The code dynamically processes input videos, matching detected persons across frames and augmenting the output frames with visual annotations. Finally, the processed frames are aggregated into an output video file, encapsulating the detection and matching results for further analysis and review.

Module	**Assigned to**	**Responsibilities**
Anomaly Detection	Nevil Biju	• Implemented alerts. • Developed YOLOv8 model.
Anomaly Detection	Shreepad Sumesh P	• Developed YOLOv8 model. • Dataset generation.
Person Re-Id	Romain Robert	• Person and face detection for person re-id. • User Interface
Person Re-ID	Rayyan Fadi	• Feature extraction for person re-id. • User interface.

Table 4.1: Work Breakdown Structure with Assigned Responsibilities

4.5 Work Schedule - Gantt Chart

The project is structured into a series of milestones, each with a designated timeframe for completion. The schedule commences in December 2023 and progresses through May 2024, as visualized in the accompanying Gantt chart (Figure 4.3).

- **Initiation Phase:** Starting 20th November, the project kicks off with preliminary research and planning, slated to conclude by the end of November.
- **Development Phase I:** This phase begins on December, focusing on the development of YOLOv5, and also creating a dataset with 2 classes (fire and accident).
- **Development Phase II:** Following phase 1, the second development phase involves refining the dataset and creating the user portal,lasting until mid-January.
- **Development Phase III:** Starting on 17th January, this phase upgrades to a newer YOLOv8 model with a more refined dataset consisting of 4 classes (Fire, Smoke, Accident and Fight)
- **Development Phase IV:** From 28th February, development of Person reidentification begins along with alerts and other miscellaneous features.
- **Integration Testing:** Starting on 21st March, this phase involves the integration of modules and their testing, which lasts till 3rd April.
- **Final Presentation:** The final presentation preparation begins on 4th April and is completed by first of May, marking the project's culmination.

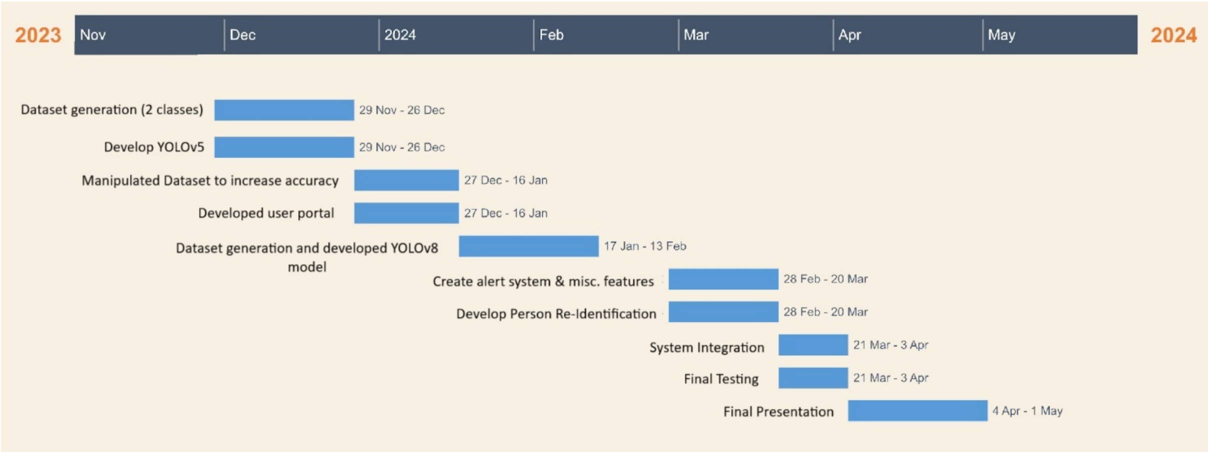

Figure 4.3: Gantt Chart reflecting the Project Milestones & Schedule

This schedule outlines a clear path from the project's inception to its final deployment, ensuring systematic progress through each critical stage.

This chapter has systematically outlined the system architecture for a next-generation surveillance platform. It encompasses a suite of sophisticated yet intuitive modules, each designed to ensure comprehensive monitoring and safety in dynamic environments. The architecture's intelligent anomaly detection and classification capabilities, paired with person re-identification techniques, signify a leap in surveillance technology. The integration of these modules demonstrates the system's potential to not only identify and react to immediate threats but also to adapt and learn, providing a secure atmosphere.

Chapter 5

System Implementation

The System Implementation section presents a detailed account of the methodologies, algorithms, and design considerations employed in the development of the anomaly detection and person re-identification system. It begins by introducing the datasets identified for training and evaluation purposes, followed by a discussion on the proposed methodologies and algorithms for anomaly detection and person re-identification tasks. The user interface design and database schema overview are also outlined to provide insights into the user interaction and data management aspects of the system. Additionally, implementation strategies, including video capture and custom model development, are elucidated to offer a comprehensive understanding of the technical approaches adopted in building and testing the system

5.1 Datasets Identified

The dataset comprises 7958 annotated images, meticulously labeled across four distinct classes: fight, fire, smoke, and accident. Among these, the fight class encompasses 4495 images, representing instances of physical altercations or violent behavior. Additionally, there are 2188 images labeled for the fire class, denoting scenes depicting flames or fire-related incidents, 1906 images of the smoke class, signifying situations where smoke is observed, possibly indicating a fire hazard or other environmental concerns. Lastly, the accident class contains 1731 images, depicting various types of accidents, such as car collisions and flips. Overall, the dataset offers a diverse collection of annotated images, totaling 10320 annotations, providing a rich resource for training and evaluating models for anomaly detection.

5.2 Proposed Methodology/Algorithms

The algorithm for the proposed system is divided into two parts. The first part is for the anomaly detection phase and the second part is for the person re-identification phase.

5.2.1 Anomaly Detection Algorithm :

1. In the class Anomaly_Detection initialize variables, capture_source = capturing device msg_sent = False, to control the alert messages send. frames=[], list used to combine the frames to generate the anomaly video. no_detct = 0, to count the number of no detection's received after a detection.

2. Initially the real-time video captured through the capturing device is taken frame by frame using Computer Vision's (CV's) cv2.VideoCapture() function.

3. Each frame is then read into a variable 'im0' using CV's cap.read() function and 'im0' is passed to the predict() function.

4. In the predict() function, initialize list clss=[] to store the anomaly class type as integer when detection takes place.

5. Initialize variable 'results' which stores the detection's,
   results = self.model.predict(source=im0, conf=0.6),where prediction takes place using a custom trained YOLOv8 model on input 'im0'.

6. Initialize a list anomaly = ["Accident", "Fight", "Fire", "Smoke"], to map the class of the detected anomaly.

7. Repeat step 7.1 until 'r' in 'results' is empty,

   7.1 Store the classes found during detection as integers into 'clss' as,
   clss = r.boxes.cls.cpu().numpy().astype(int), where boxes.cls() is a function provided by the YOLOv8 library to obtain the class.

8. If the condition len(clss)¡=0 is satisfied,

   8.1 Then increment 'no_detct' by 1.

9. If the condition len(clss)¿0 is satisfied,

9.1 Set 'no_detct' as 0.

9.2 Append 'im0' into 'frames'.

9.3 Repeat step 9.3.1 until 'cl' in 'clss' is empty, If 'msg_sent' is False.

9.3.1 Call send_msg() function with parameter as 'anomaly[cl]'.

9.4 Set 'msg_sent' as True.

10. Else, set 'msg_sent' as False.

11. If conditions no_detct¿10 and len(frames)¿0 is satisfied,

11.1 Calculate current date and time.

11.2 Set output path for the video to be saved with the date and time as 'out_path'.

11.3 Call frames_to_video() function for saving the detected video.

12. In the send_msg() function the anomaly identified from predict() function stored in 'anomaly[cl]' can be delivered to a destination or managed as per the user preference.

13. In the frames_to_video() the frames detected frames are combined to form a video with desired frame rate and size using CV's cv2.VideoWriter() function and saved into the 'out_path'.

5.2.2 Person Re-Identification Algorithm :

1. Utilize pre-trained deep learning models:

1.1 ResNet-50: A convolutional neural network (CNN) architecture renowned for its effectiveness in image feature extraction.

1.2 YOLO (You Only Look Once): YOLO is renowned for its speed and accuracy, making it suitable for real-time applications like person detection in videos.

2. Establish preprocessing transformations, including resizing and normalization, to prepare input images for feature extraction by ResNet-50.

3. Define essential functions for feature extraction using ResNet-50, cosine similarity calculation for feature comparison, and bounding box visualization for result interpretation.

4. Extract a set of reference frames from the first video, ensuring diverse representation of scenes and persons.

5. Utilize the YOLO model to detect persons within each reference frame.

6. Extract features from each detected person using the ResNet-50 model.

7. Assign a unique identifier (ID) to each detected person based on their extracted features enabling tracking and matching of the persons across different videos.

8. Iterate through frames from the second video to identify and match persons.

9. Utilize the YOLO model to detect persons in each frame of the second video.

10. Extract features from each detected person using ResNet-50 and compare these features with those extracted from reference frames in Video 1.

11. Assign IDs to detected persons in Video 2 based on feature similarity with persons in Video 1.

    11.1 A match results in assigning the same ID, while no match leads to assigning a new ID.

12. Visualize detected persons by drawing bounding boxes around them in each frame of both videos. Labeling:

13. Label each bounding box with its corresponding ID for easy identification and tracking of persons across frames and videos.

14. Create processed videos with annotated bounding boxes and IDs for visualization and further analysis.

5.3 User Interface Design

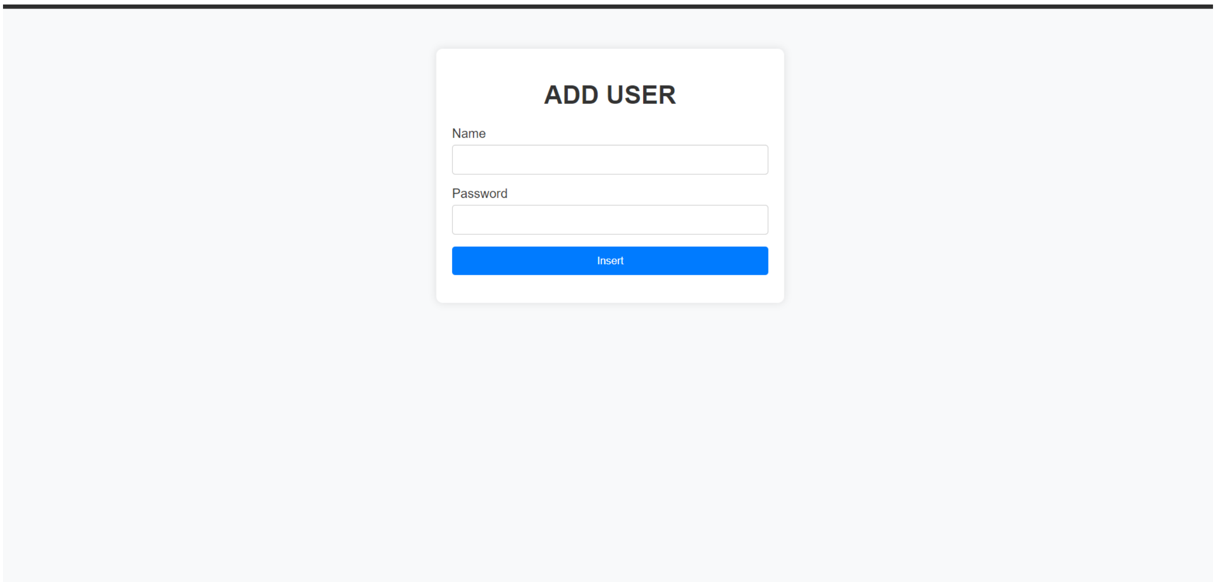

Figure 5.1: User registration page

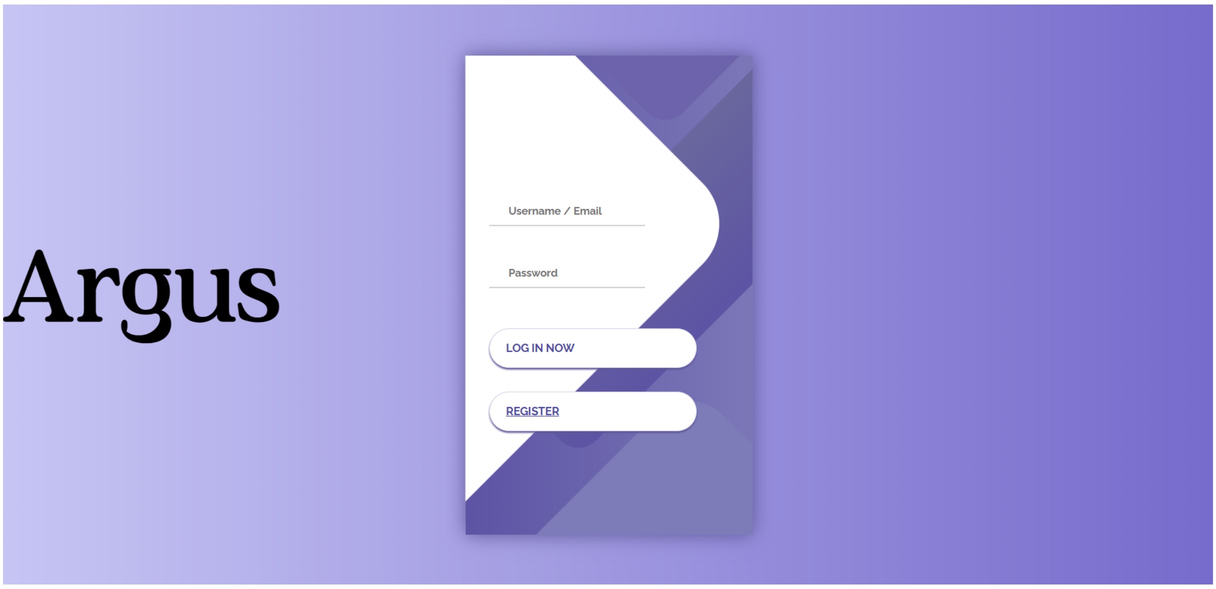

Figure 5.2: User login page

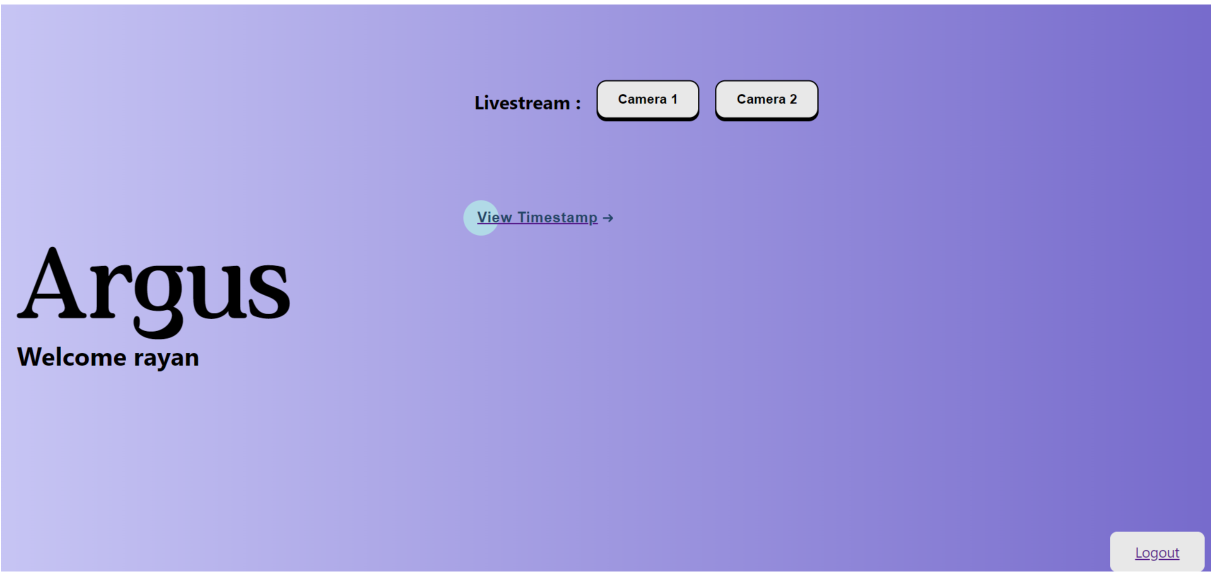

Figure 5.3: Admin portal after login

Camera 1	2024-04-0901-45-44	Fire
Camera 1	2024-04-0901-45-45	Fire
Camera 1	2024-04-0901-46-00	Smoke
Camera 2	2024-04-0901-46-00	Smoke
Camera 2	2024-04-0901-46-00	Smoke

Figure 5.4: Timestamps of anomalies detected.

5.4 Database Design

In this section, we present the database design along with its schema. The database utilized for this work is a relational database management system (RDBMS) due to its structured nature and suitability for handling login credential data efficiently.

5.4.1 Database Schema Overview

Figure 5.5: Schema of tb_users

The database schema comprises a single table, `tb_users`, designed to store login credentials securely. The table schema includes the following fields:

- `user_name`: A unique identifier for each user, serving as their login credential.
- `password`: The hashed representation of the user's password, ensuring confidentiality and security.

This minimalistic yet effective schema design prioritizes simplicity and security, focusing solely on the essential components required for user authentication.

5.4.2 Database Selection Justification

It's important to note that this database is stored locally and intended solely for demonstration purposes. By utilizing XAMPP, the database setup is convenient and accessible for local testing and development environments. However, for production deployment, a more robust and scalable infrastructure would be necessary.
The advantages of an SQL database are as follows -

- Relational Model Suitability
- ACID Compliance
- Scalability
- Query Flexibility

5.5 Description of Implementation Strategies

5.5.1 Video Capture :

The proposed method works with real-time videos from capturing devices. These devices are connected to the program using its IP address and threading as shown in Figure 5.6

```
# Instantiate anomaly detection for each camera
detector1 = AnomalyDetection(capture_source=0, camera_name='Camera 1')
detector2 = AnomalyDetection(capture_source='http://192.168.63.251:8080/video', camera_name='Camera 2')

# Start anomaly detection for each camera in separate threads
thread1 = threading.Thread(target=detector1._call_)
thread2 = threading.Thread(target=detector2._call_)

# Start both threads
thread1.start()
thread2.start()

# Wait for both threads to finish
thread1.join()
thread2.join()
```

Figure 5.6: Real time video capture using IP & Threading

The video captured is then taken frame by frame using methods from Computer Vision libraries like cv2.VideoCapture(), read(), set() etc as shown in Figure 5.7

```
cap = cv2.VideoCapture(self.capture_source)
assert cap.isOpened()
cap.set(cv2.CAP_PROP_FRAME_WIDTH, 640)
cap.set(cv2.CAP_PROP_FRAME_HEIGHT, 640)
while True:
    ret, im0 = cap.read()
    assert ret
```

Figure 5.7: Frame extraction using Computer Vision

5.5.2 Custom Models :

- **YOLOv8**

  The YOLOv8 model is used for anomaly detection and is trained using custom dataset. The training is done by referring the YOLOv8 docs and library.

```
Training

!yolo task=detect mode=train model=yolov8m.pt data='/content/Datast-8/data.yaml' imgsz=640 batch=3 epochs=100
```

Figure 5.8: YOLOv8 Training

In Figure 5.8 it shows that the pre-trained model used is yolov8m in 'train' mode for task 'detect' for 100 epochs.

the trained model is then integrated into the alert system code using YOLOv8 library functions like model.predict() and boxes.cls() as shown in Figure 5.9 and Figure 5.10

```
results = self.model.predict(source=im0, conf=0.6)
```

Figure 5.9: YOLOv8 Prediction

```
for r in results:
    clss = r.boxes.cls.cpu().numpy().astype(int)
```

Figure 5.10: Retrieving predicted class as integers

5.5.3 Person Reidentification

The proposed method starts with preprocessing the images before feeding them into the pre-trained ResNet-50 model (as shown in Figure 5.11). These transformations include resizing, converting to tensor and normalization. The output obtained is a feature embedding.

```
# Function to extract features using ResNet-50
def extract_features(image):
    if image is None:
        return None

    image = Image.fromarray(cv2.cvtColor(image, cv2.COLOR_BGR2RGB))
    image = preprocess(image)
    image = torch.unsqueeze(image, 0)
    with torch.no_grad():
        features = model(image)
    return features.squeeze().numpy()
```

Figure 5.11: Feature extraction using ResNet-50

The similarity between two feature embeddings is calculated with a cosine similarity functions as shown in Figure 5.12

```
def cosine_similarity(embedding1, embedding2):
    return np.dot(embedding1, embedding2) / (np.linalg.norm(embedding1) * np.linalg.norm(embedding2))
```

Figure 5.12: Cosine function measures how similar the features are.

Similarly, the image is preprocessed for a pretrained YOLO model and the individual detections are stored to outs (as shown in Figure 5.13)

```
net.setInput(blob)
outs = net.forward(output_layers)
```

Figure 5.13: Outs contain class confidence scores (here the only class is person)

If the confidence is high enough and the class is "person", the function extracts the bounding box coordinates for the detected person. The extracted bounding boxes might have overlaps. NMS is a technique used to filter out these overlapping bounding boxes. It keeps the box with the highest confidence score and removes others with significant overlap. The function uses cv2.dnn.NMSBoxes to perform NMS on the list of bounding boxes (boxes) with their corresponding confidence scores (confidences). It sets the parameters for NMS, including the threshold for the overlap ratio (0.4) and the threshold for filtering detections with low confidence scores (0.5).
After applying NMS, the function might still have a list containing both valid and empty bounding boxes. It iterates through the indexes obtained from NMS to filter out detections that were removed during NMS.

```
detected_boxes = []
if len(indexes) > 0:
  for i in indexes.flatten():
    detected_boxes.append(boxes[i])
```

Figure 5.14: Iterates through indexes obtained from NMS to filter.

Finally, the function returns the list of detected person bounding boxes (detected_boxes). This list can be used to draw bounding boxes around detected people in the frame

5.5.4 Evaluation :

- **YOLOv8**

  The YOLOv8 model is validated using the mode 'val' in task 'detect' referred from the YOLOv8 docs as shown in Figure 5.15 and Figure 5.16

Validate

```
[ ] !yolo task=detect mode=val model='/content/drive/MyDrive/modeltesting/best.pt' data='/content/drive/MyDrive/Datast.v5i.yolov8/data.yaml'
```

Figure 5.15: YOLOv8 Validation

```
Ultralytics YOLOv8.1.34 🚀 Python-3.10.12 torch-2.2.1+cu121 CUDA:0 (Tesla T4, 15102MiB)
Model summary (fused): 218 layers, 25842076 parameters, 0 gradients, 78.7 GFLOPs
Downloading https://ultralytics.com/assets/Arial.ttf to '/root/.config/Ultralytics/Arial.ttf'...
100% 755k/755k [00:00<00:00, 23.1MB/s]
val: Scanning /content/drive/.shortcut-targets-by-id/1YCMzKyHQczGoEHCqmta47ayJk-IcEB9a/Datast.v5i.yolov8/valid/labels.cache... 803 images, 6 backgrounds,
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100% 51/51 [00:38<00:00,  1.33it/s]
                   all        808       1047      0.469      0.478      0.389      0.191
              accident        808        286      0.641      0.874      0.837      0.499
                 fight        808        223      0.351      0.448      0.264     0.0667
                  fire        808        313      0.449       0.46      0.334      0.151
                 smoke        808        225      0.433      0.129      0.119     0.0471
Speed: 0.7ms preprocess, 20.0ms inference, 0.0ms loss, 1.9ms postprocess per image
Results saved to runs/detect/val
```

Figure 5.16: YOLOv8 Validation Result

The System Implementation section encapsulates the intricate process of developing and deploying the anomaly detection and person re-identification system. Through the identification and utilization of datasets, coupled with the implementation of robust methodologies and algorithms, the system achieves its objectives effectively. The discussion on user interface design and database schema provides effective user experience and data management aspects, ensuring seamless interaction and efficient storage of information. Furthermore, the elucidation of implementation strategies underscores the systematic approach adopted in building and evaluating the system components. In conclusion, the System Implementation section serves as a comprehensive guide to the technical intricacies involved in realizing the anomaly detection and person re-identification system, paving the way for enhanced security and surveillance capabilities.

Chapter 6

Results and Discussions

The Results and Discussions section provides a comprehensive analysis of the system's performance and outcomes. This section begins with an overview of the testing procedures conducted to evaluate the system's efficacy. Subsequently, quantitative results are presented, shedding light on the system's performance metrics such as accuracy, precision and recall. Additionally, graphical analysis techniques are employed to visually represent the system's performance trends and comparative analysis across different scenarios or datasets. Finally, the section delves into detailed discussions, offering insights into the observed results, potential limitations, and avenues for future improvements.

6.1 Overview

The anomaly detection system has demonstrated remarkable proficiency in identifying a range of anomalies within video streams.The system has exhibited proficient accuracy in detecting various anomalous events, including fire outbreaks, violent altercations, instances of smoke, and car accidents. The quantitative analysis underscores the program's high precision and recall rates across these diverse anomaly categories, ensuring minimal false positives and false negatives. Timely alerts are seamlessly generated and dispatched to users upon the detection of any of these anomalies. Furthermore, the integration with local storage allows storing video frames for subsequent analysis and person re-identification.

In the person re-identification phase, a systematic algorithm is employed to accurately match individuals across different video frames:

In the reference frame selection phase, a set of diverse reference frames is captured from the first video. These frames serve as a basis for identifying and matching individuals across videos.

Next, a YOLO model is used to detect individuals within each reference frame. This is followed by features being extracted from each detected individual using the ResNet-50 model. ResNet-50's deep architecture enables the extraction of rich and discriminative features from person images. Once features are extracted, a matching process is initiated in the subsequent video frames. Persons detected in these frames are compared with the reference frames' features to determine matches. If a match is found, the individual is assigned the same identifier (ID); otherwise, a new ID is assigned.
Finally, bounding boxes are visualized around detected persons in each frame, and IDs are labeled for easy tracking across frames and videos. The processed videos with annotated bounding boxes and IDs serve as valuable output for evaluating the algorithm's performance in person re-identification.

6.2 Testing

- Testing the YOLOv8 model generate result as shown in Figure 6.1

Figure 6.1: Fire Detection on test video.

- Testing the anomaly detection system in real time generates results as shown in Figure 6.2 to Figure 6.6

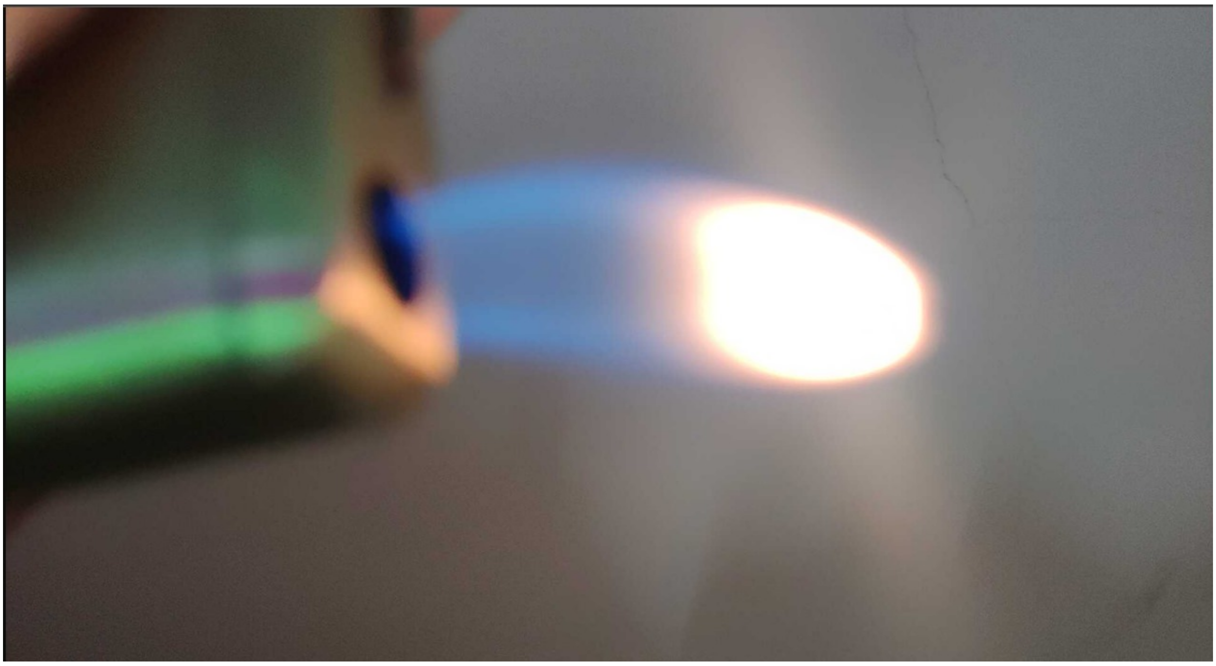

Figure 6.2: Real time camera feed.

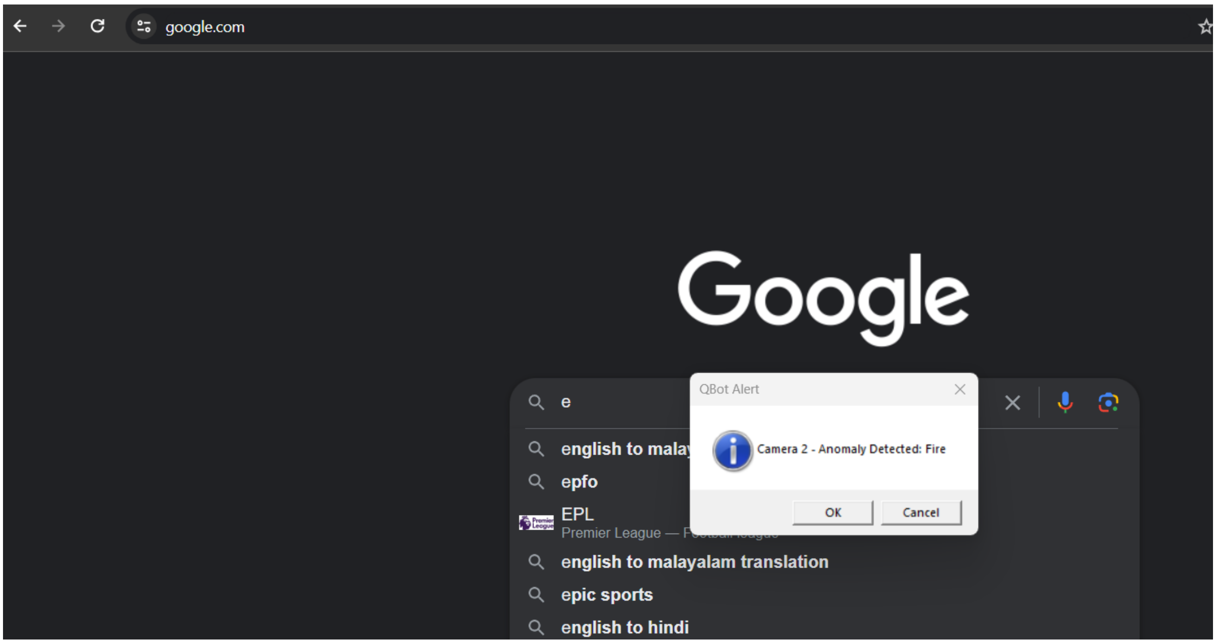

Figure 6.3: The popup generated on the user system when anomaly detected .

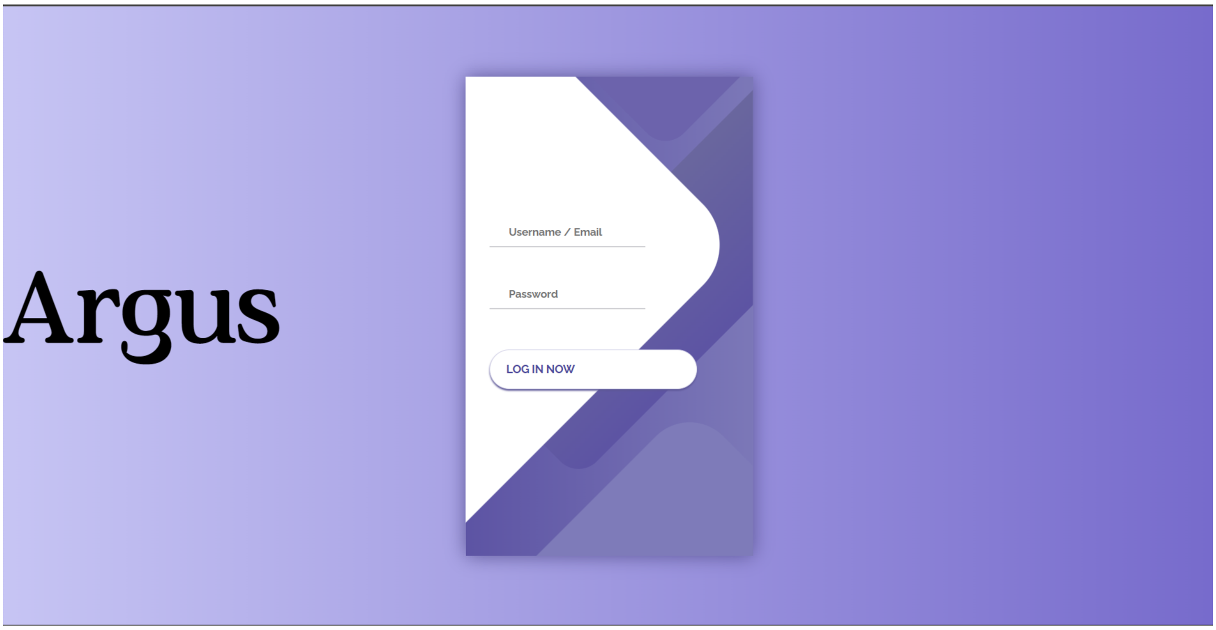

Figure 6.4: The login page when ”OK” is selected.

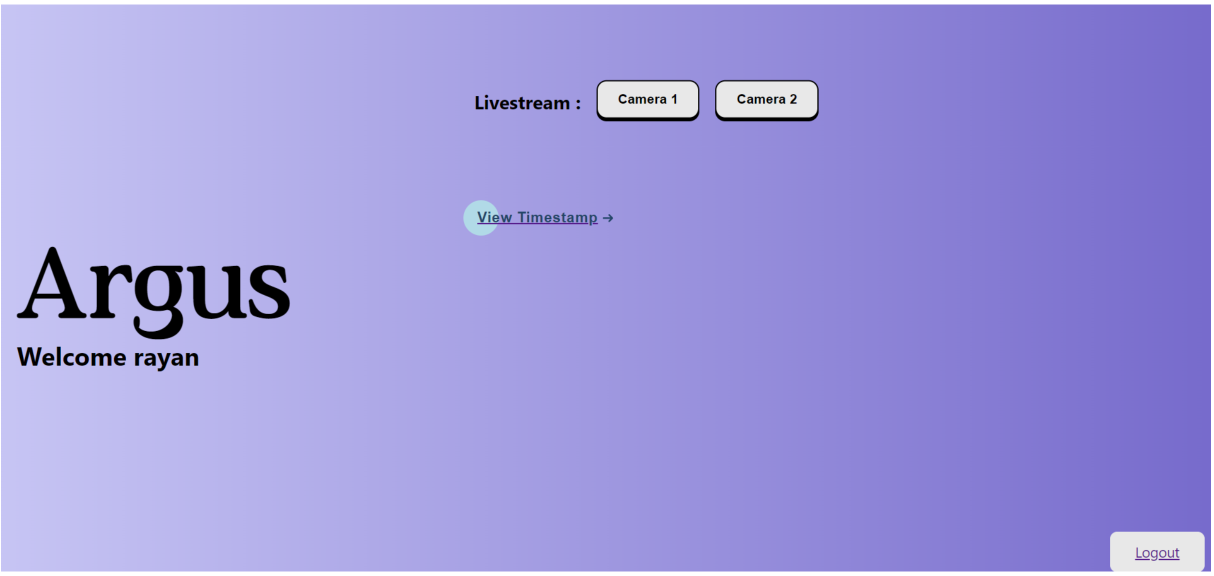

Figure 6.5: Admin portal after login

Camera 1	2024-04-0901-45-44	Fire
Camera 1	2024-04-0901-45-45	Fire
Camera 1	2024-04-0901-46-00	Smoke
Camera 2	2024-04-0901-46-00	Smoke
Camera 2	2024-04-0901-46-00	Smoke

Figure 6.6: Timestamps of anomalies detected.

- In the Person Re-identification phase, a set of frames are selected so that they contain both facial and feature information.

Figure 6.7: Input frame of a fight where face of culprit is visible.

- The algorithm then processes other input feeds like provided below

Figure 6.8: Input frame from a live camera containing a person of interest.

Figure 6.9: Similar input frame containing another person of interest from the anomaly.

- The output is as follows:

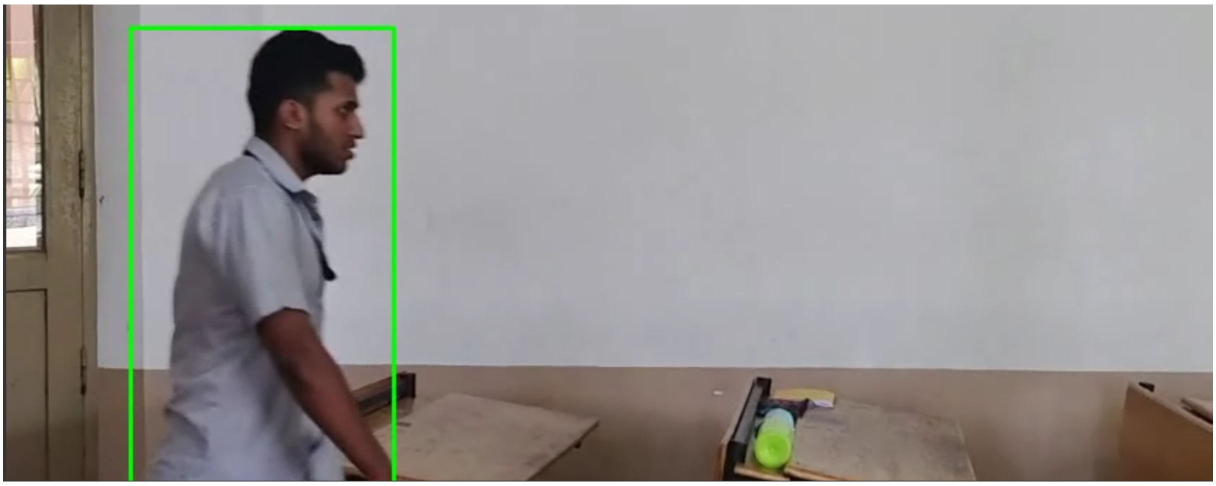

Figure 6.10: Output with only feature identification bounding box.

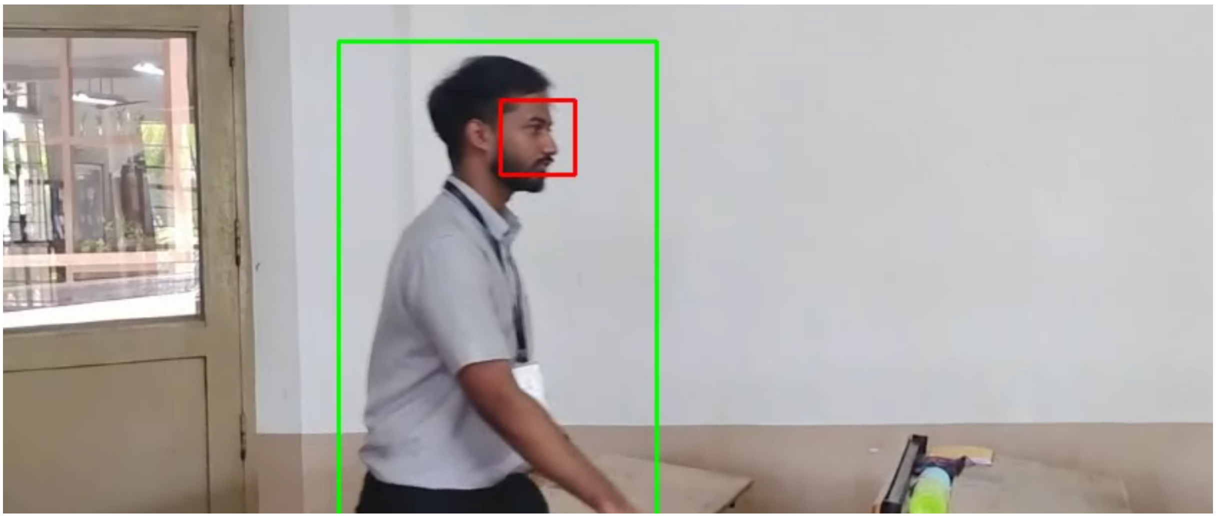

Figure 6.11: Output with bounding box for face and feature identification.

6.3 Quantitative Results

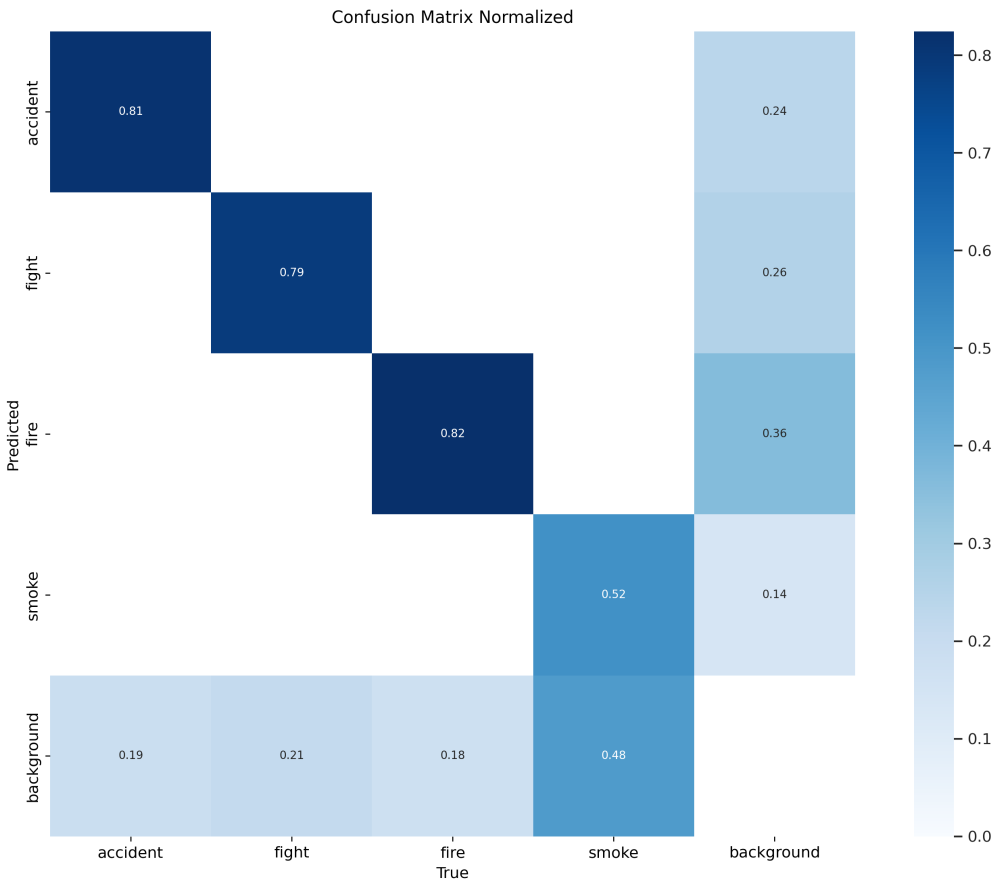

Figure 6.12: Confusion matrix specifying the accuracy of different classes

Class	Images	Instances	Box(P	R	mAP50	mAP50-95): 100% 96/96 [00:42<00:00, 2.25it/s]
all	1523	1818	0.779	0.656	0.702	0.42
accident	1523	326	0.729	0.752	0.744	0.395
fight	1523	889	0.881	0.783	0.843	0.561
fire	1523	433	0.77	0.762	0.819	0.525
smoke	1523	170	0.735	0.327	0.402	0.197

Figure 6.13: Validation results showing the precision,recall and mean average precision of each class

6.4 Graphical Analysis

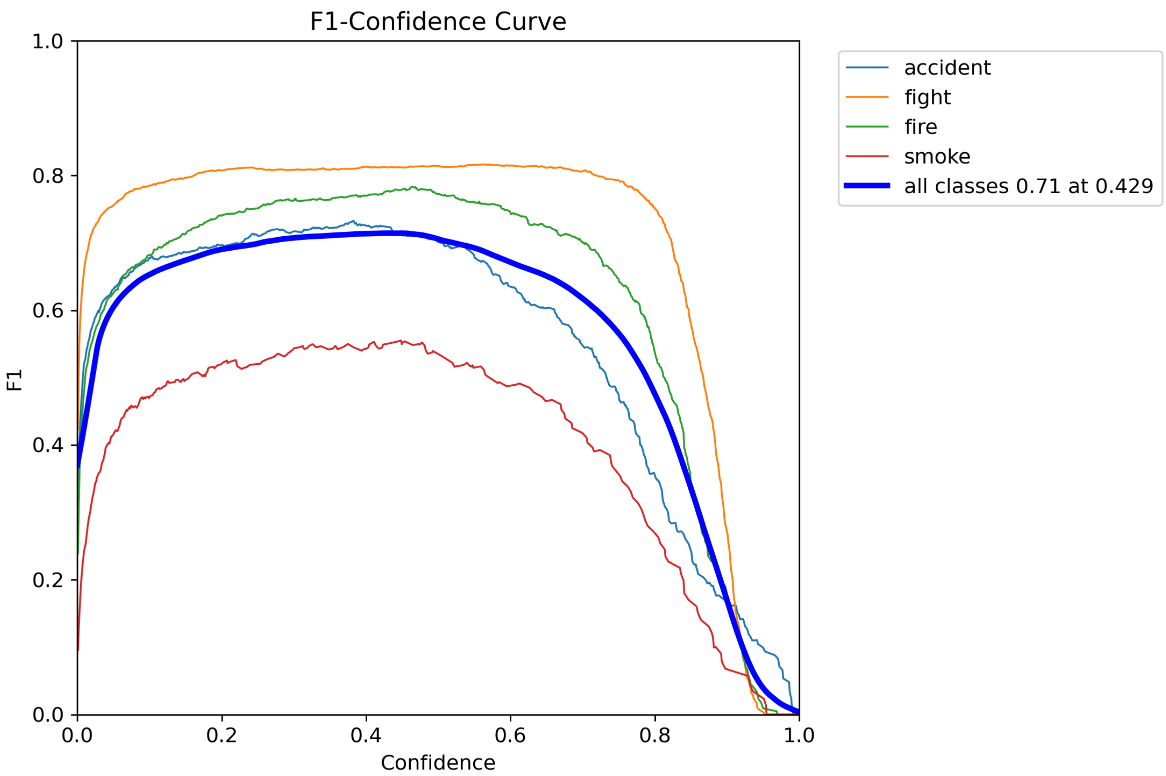

Figure 6.14: F1-Confidence Curve plots the F1 score of a model at different confidence thresholds

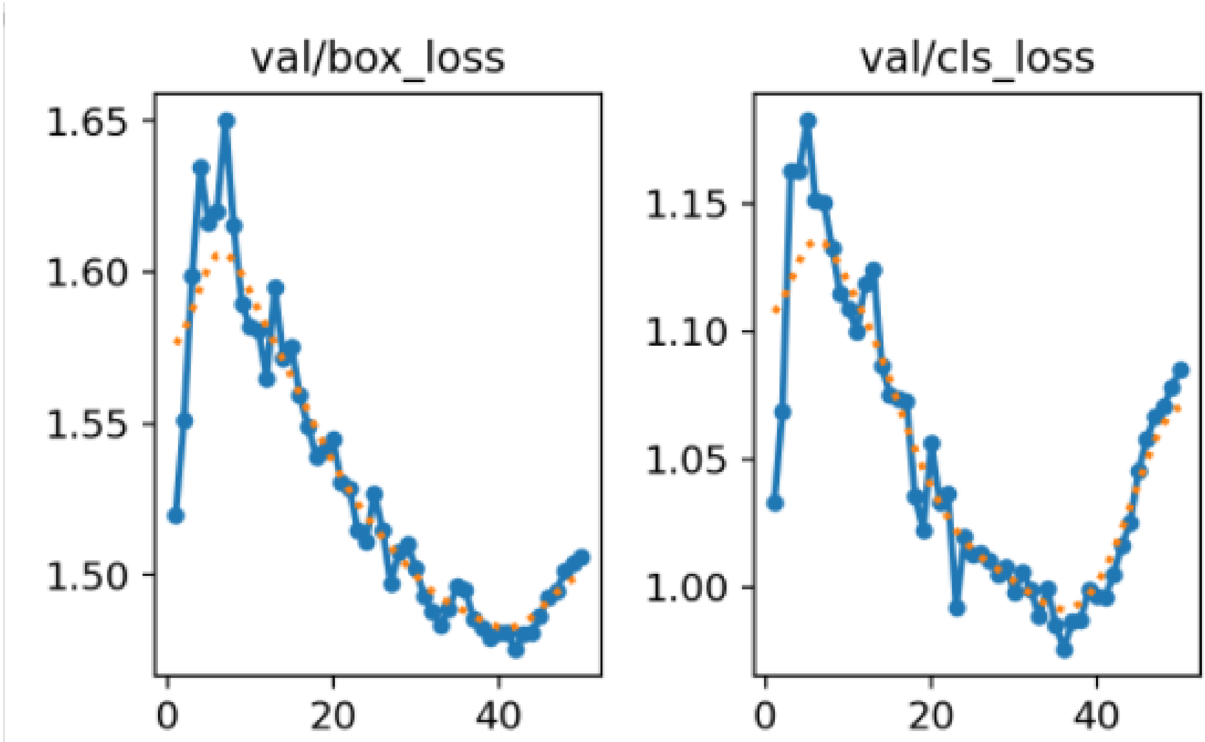

Figure 6.15: Curve plots the losses during validation test

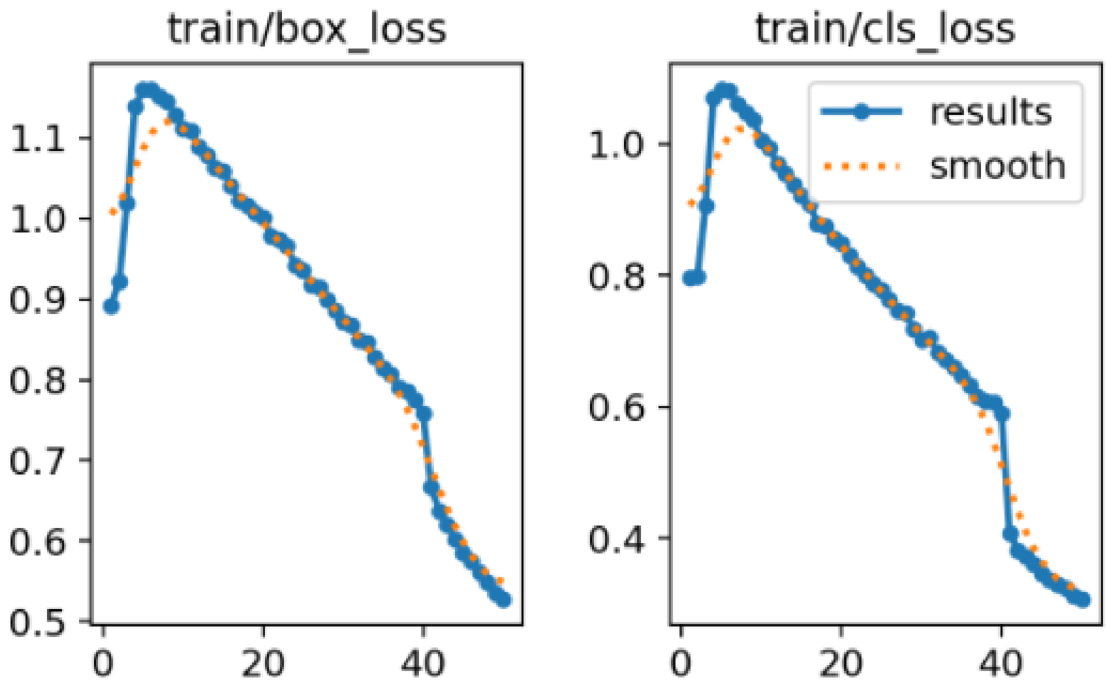

Figure 6.16: Curve plots the losses during training

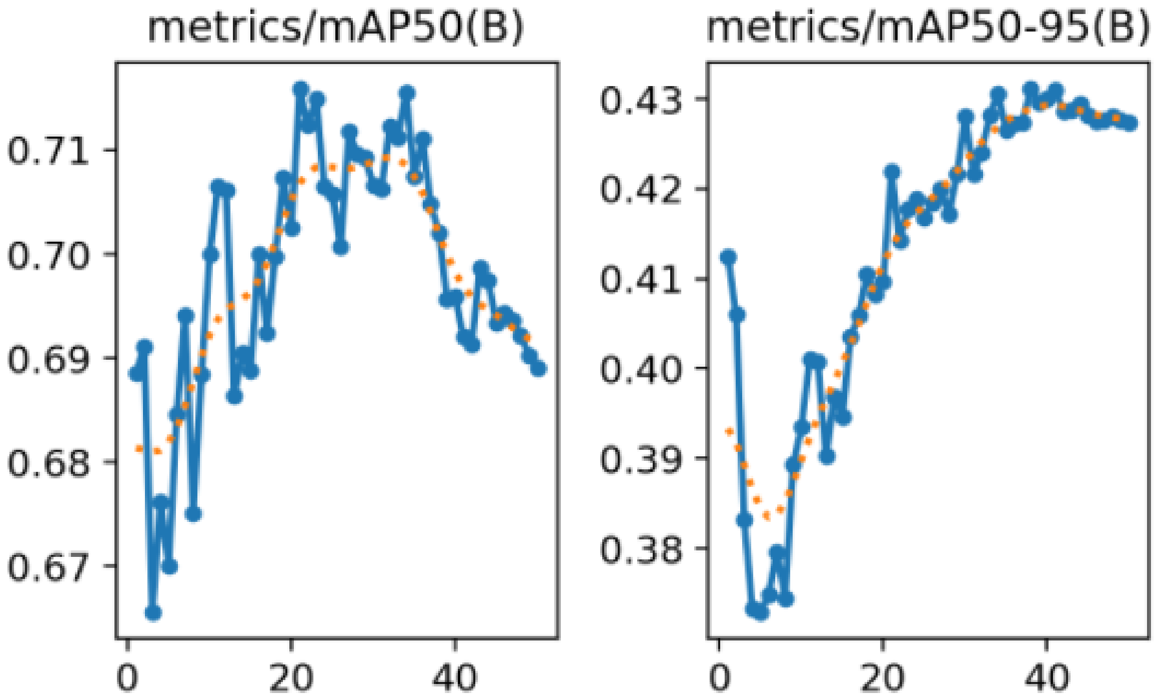

Figure 6.17: Mean Average Precisions

6.5 Discussion

The Confusion matrix highlights a notable trend: the accident, fight, and fire classes exhibit higher accuracy in accurately predicting objects within video frames compared to the smoke class. This disparity could stem from the inherent complexity of smoke detection, which often leads to false positives due to variations in lighting conditions or image blurriness.

The overall system demonstrates commendable performance, boasting an average mean average precision of 70.2% across all classes. Notably, the F1-confidence curve scores the system's efficacy in correctly predicting classes, with an average score of 0.71 achieved at a confidence value of 0.429.

During validation, results indicate a consistent decline in losses up to epoch 40, beyond which they begin to escalate once more. Conversely, during training, an initial uptick in losses gives way to a steady decline, commencing around epoch 10 and persisting throughout subsequent epochs.

The person reidentification module demonstrates remarkable performance by extracting both facial and feature information. This dual approach significantly enhances the algorithm's ability to accurately identify individuals across different frames or videos. By utilizing both feature and facial data, the system shows in its output whether it matched based on features or also includes facial recognition, thereby increasing accuracy and user-friendliness. This integrated functionality ensures a greater reliability and usability of the program in diverse scenarios.

This section provides a comprehensive evaluation of the anomaly detection and person re-identification system. Through rigorous testing and analysis, key insights into the system's performance metrics, quantitative results, and graphical representations have been elucidated. The testing phase has revealed notable trends in the system's accuracy across different classes, with specific challenges identified in smoke detection due to environmental factors. Quantitative assessments, including mean average precision and F1-confidence curves, highlight the system's overall effectiveness in class prediction. Graphical analyses further enhance our understanding of performance dynamics, showcasing trends in loss functions and validation results over epochs

Chapter 7

Conclusions & Future Scope

7.1 Conclusion

The research endeavors to address significant challenges in anomaly detection and person re-identification. Beginning with an insightful literature survey that elucidates existing methodologies and identifies gaps within, the report then systematically progresses through the identification of requirements, formulation of system architecture, and meticulous implementation strategies.

The testing phase, followed by quantitative results and graphical analysis, provides a thorough evaluation of the system's performance, offering valuable insights into its efficacy and limitations. Through rigorous testing and analysis, key findings regarding the accuracy, precision, and robustness of the system are uncovered.

Furthermore, the discussion section delves deeper into the implications of these findings, addressing challenges such as smoke detection complexity and proposing avenues for future improvement. The report concludes by highlighting the societal and industrial relevance of the research, emphasizing its potential impact on security and surveillance applications.

7.2 Future Scope

1. **Integration with Emerging Technologies**: Explore the integration of the current system with emerging technologies like artificial intelligence, edge computing, and Internet of Things (IoT) to enhance real-time processing and decision-making capabilities.

2. **Scalability and Adaptability**: Focus on enhancing the scalability of the system to handle larger networks of cameras and sensors, and adaptability to different

environments and scenarios, including challenging weather conditions and diverse lighting.

3. **Advanced Analytics and Predictive Capabilities**: Develop advanced analytics features, leveraging machine learning and data analytics for predictive surveillance, which can anticipate potential security breaches or anomalies before they occur.

4. **Enhanced Privacy Protection**: Implement advanced privacy protection features, ensuring the system adheres to evolving data privacy laws and ethical standards, particularly in the context of increasing concerns about surveillance and personal data security.

5. **Cross-Platform Integration and User Accessibility**: Work towards seamless integration with various platforms and systems, improving user accessibility and control, ensuring the system is user-friendly and accessible to people with different levels of technical expertise.

This future scope aims to address the evolving demands in surveillance technology, focusing on integration, scalability, advanced analytics, privacy, and user accessibility.

References

[1] A. A. Sodemann, M. P. Ross, and B. J. Borghetti, "A review of anomaly detection in automated surveillance," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 2012.

[2] M. M. Ali, "Real-time video anomaly detection for smart surveillance," *IET Image Processing*, 2023.

[3] Y. Hu, J. Gao, and C. Xu, "Learning dual-pooling graph neural networks for few-shot video classification," *IEEE Transactions on Multimedia*, 2021.

[4] W. Zuo, D. Ren, D. Zhang, S. Gu, and L. Zhang, "Object motion deblurring in single image under static background," *IEEE Trans. Image Process.*, 2016.

[5] C. Liu, L. Guo, and R. Zhang, "Hlfnet: High-low frequency network for person re-identification," *IEEE Signal Processing Letters*, 2021.

Appendix A: Presentation

Project Phase-II Presentation

Smart Surveillance System with Anomaly Detection & Person Re-Id

Group-14
Rayyan Fadi (U2003164)
Shreepad Sumesh (U2003199)
Nevil Biju (U2003150)
Romain Robert (U2003173)

Guide- Dr.Renu Mary Daniel
Assistant Professor
Dept. of CSE

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Problem Definition

- Current surveillance systems grapple with issues such as crime detection, poor image quality, data overload, etc.
- These challenges hinder their ability to ensure public safety and security effectively.
- Addressing these issues and introducing new features such as person reidentification (re-id), smart alerts will improve performance of surveillance systems.

Project Objectives

- Anomaly Detection

  Accurately detect different anomalies

- Person Re-Identification

  Track individuals across multiple cameras.

- Alert Systems

  Provide reliable custom alerts to users.

Novelty of Idea:

The novelty in our project lies in the integration of anomaly detection with an accurate person reidentification model. Additionally -

- Increased Accuracy :
  - Continuous 24/7 monitoring exceeds human capabilities.
  - Can detect anomalies that may go unnoticed by human eye.
- Increased Efficiency :
  - Person re-id significantly reduces manual labour of authorities.
  - Custom and smart alerts improve response times.
- Potential uses :
  - Can recognize trends and collect data for other applications.

Scope of Implementation

The program could be used by both public and private sectors due to its -

1. Cost-savings : It can be retrofitted to existing surveillance system.
   Less personnel required.
2. Quality : Less susceptible to human error/bribery.
3. Adaptability : Can be trained to detect specific anomalies.

Literature Survey

Automatic video classification: A survey of the literature

- The paper provides a comprehensive survey of the existing literature on automatic video classification.
- The authors review various methods and techniques proposed in the literature for automatic video classification. They discuss approaches such as feature extraction, machine learning algorithms, and content-based analysis.
  The paper highlights the challenges and opportunities in this field, including issues related to scalability, accuracy, and real-time processing.

Literature Survey

Real-time video anomaly detection for smart surveillance.

- The system being discussed uses spatio-temporal autoencoders (STAE),which utilizes deep neural networks to learn both spatial and temporal patterns by performing convolution operation.
- The decoder recreates the input from the code created and this is taken as the output. If the recreation error is greater than a given threshold then, anomaly detected.
- Using STAE alone in anomaly detection does not provide promising results. As spatial redundant pixels in the frame sequences are less informative. These limitations can be handled by using - Background subtraction (BS) and YOLOv5 (You only Look Once)

Literature Survey

Learning Dual-Pooling Graph Neural Networks for Few-Shot VideoClassification

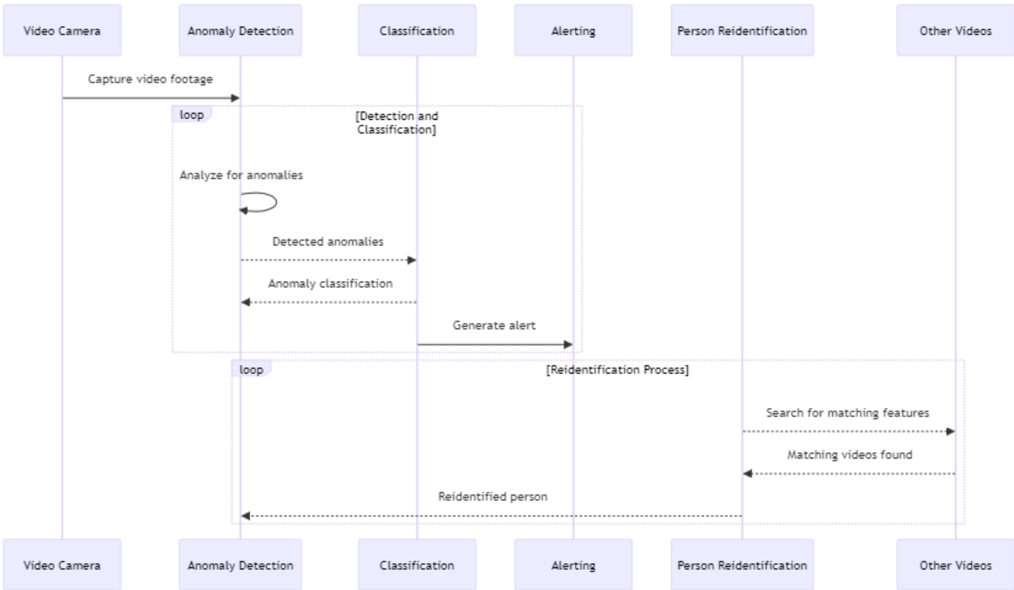
- In the first stage, an intra-video graph is constructed for each video to capture the local relations among frames.
- In the second stage, an inter-video graph is constructed to capture the global relations among videos. Edge pooling operation is then done to update the edges and drive inter-video graphs into a structure that is easier to classify.
- Finally, a simple weighted voting method to classify each node based on the support set labels and edge-label prediction results.

Literature Survey

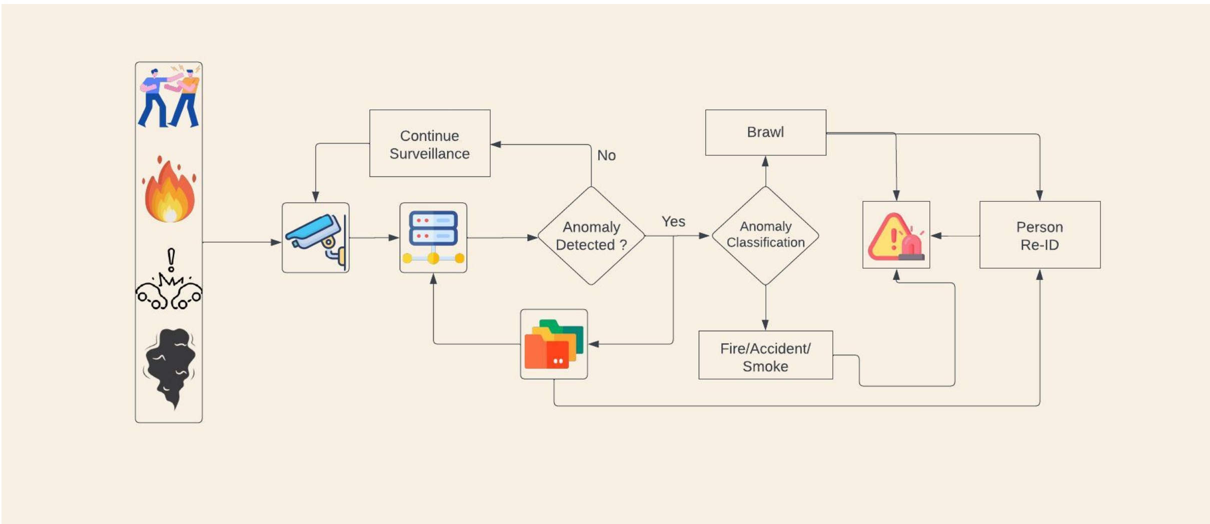
High Low Frequency Network for Person Reidentification

- In the proposed method, called HLFNet, we use the image information of different frequencies and focus on the information between them.
- High frequency and low frequency information are initially extracted from the original image.
- Two backbones are applied to extract the features from two information branches.
- Different frequencies of image information complement each other.

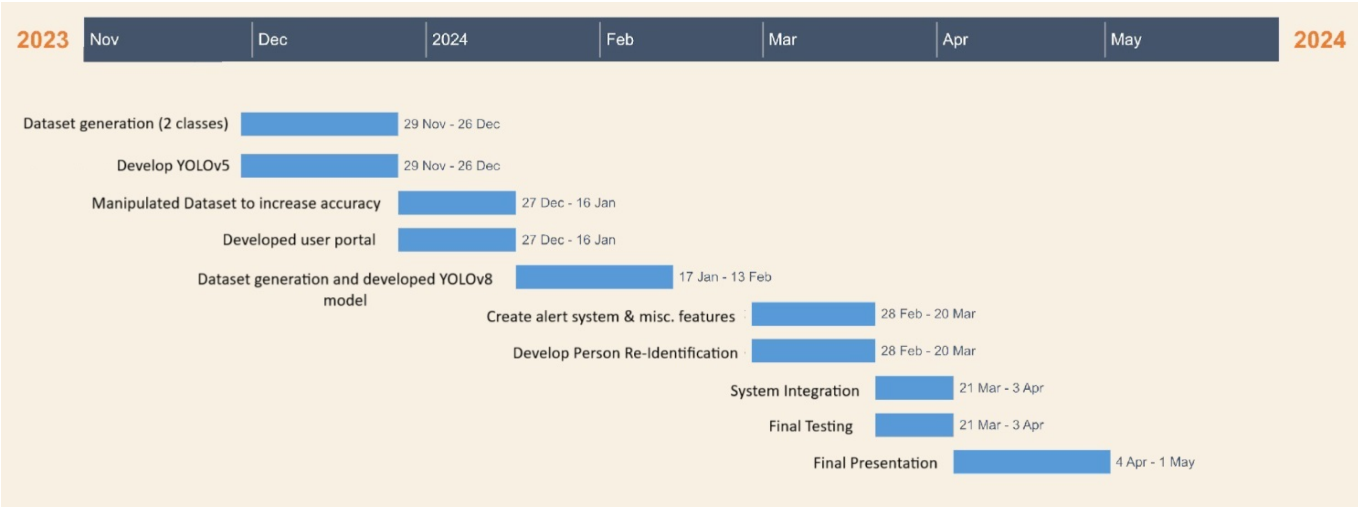
Sequence Diagram



Architecture Diagram



Gantt Chart



30% Work Done

1. Develop a dataset to include classes such as vehicular accidents and fire
2. Train Yolov5 model for object detection based on the defined classes
3. Deploy a background subtraction technique for region of interest identification
4. Develop an autoencoder based system for anomaly detection trained using video data

30% Output

Class	Images	Instances	P	R	mAP50	mAP50-95:
all	31	94	0.512	0.621	0.53	0.258
Fire	31	67	0.355	0.493	0.342	0.101
Crash	31	27	0.669	0.749	0.717	0.415

60% Work Done

1. Develop a dataset to include classes such as fights, vehicular accidents, fire and smoke
2. Train an updated YOLOv8 model for real time anomaly detection
3. Generate alerts on YOLOv8's detection results, implementing a real time monitoring system for anomaly detection

60% Output

```
Model summary (fused): 168 layers, 3006428 parameters, 0 gradients, 8.1 GFLOPs
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95):
                   all        808       1047      0.582      0.579      0.548       0.23
              accident        808        286       0.67      0.752      0.759      0.354
                 fight        808        223      0.606      0.641      0.606      0.256
                  fire        808        313      0.491      0.457      0.403      0.146
                 smoke        808        225      0.561      0.467      0.424      0.164
```


100% Work Done

1. Expand the dataset to encompass wider instances of anomalies, notably including instances of violent behavior involving weapons
2. Refining the YOLOv8 model to improve its accuracy in detecting anomalies within video footage.
3. Develop and a robust system for accurately re-identifying individuals across different video segments, improving overall surveillance efficacy.

100% Output

Class	Images	Instances	Box(P	R	mAP50	mAP50-95): 100% 96/96 [00:42<00:00, 2.25it/s]
all	1523	1818	0.779	0.656	0.702	0.42
accident	1523	326	0.729	0.752	0.744	0.395
fight	1523	889	0.881	0.783	0.843	0.561
fire	1523	433	0.77	0.762	0.819	0.525
smoke	1523	170	0.735	0.327	0.402	0.197

Final Results

Figure: YOLOv8 detecting fire

Final Results

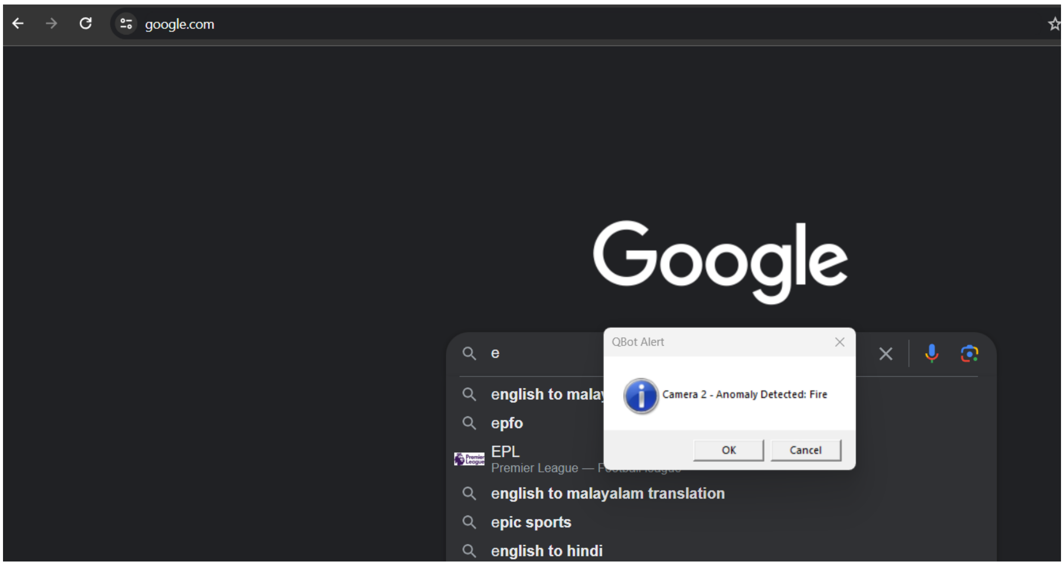


Figure: User receiving alert

Final Results

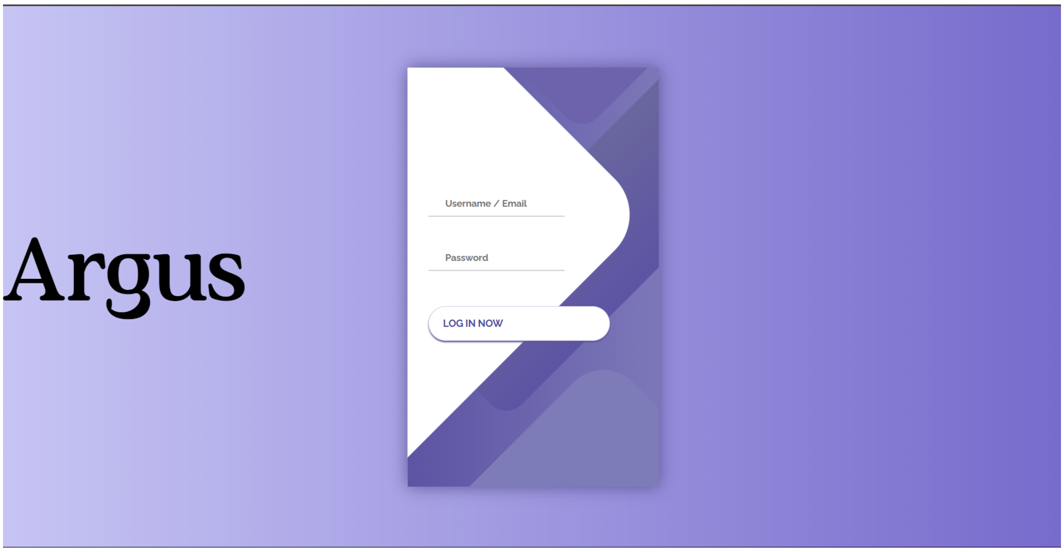


Figure: User redirected to login page

Final Results

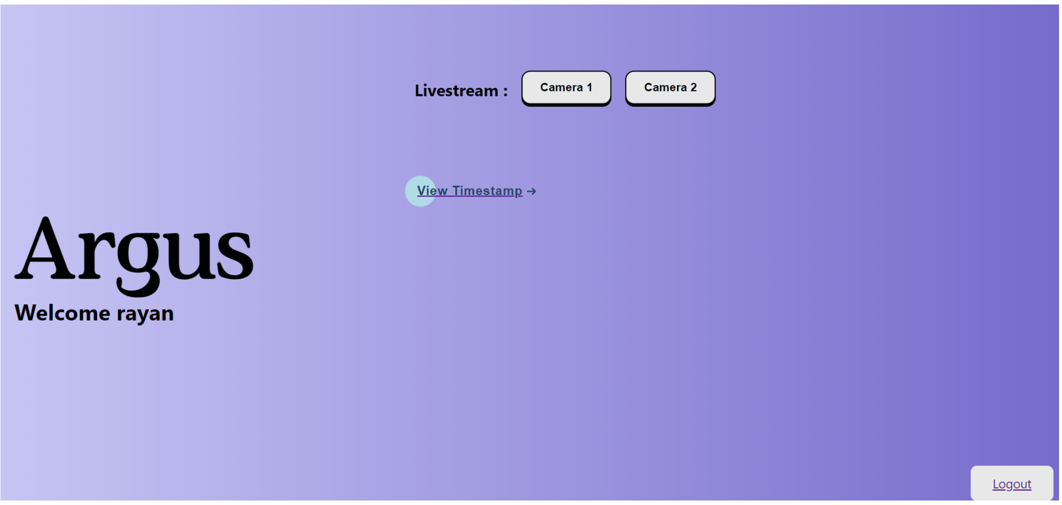


Figure: Admin Portal after login.

Final Results

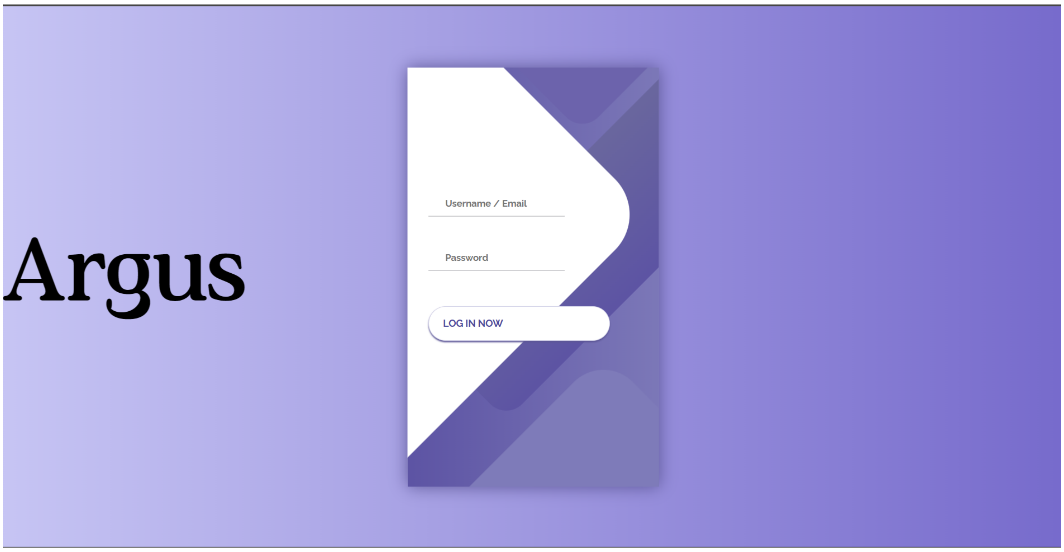


Figure: User redirected to login page

Final Results

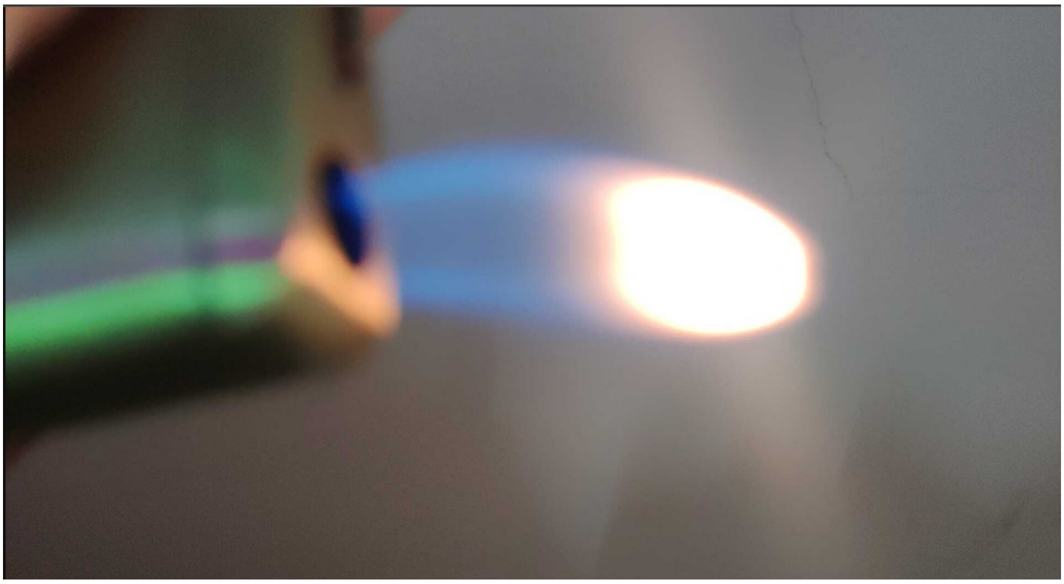


Figure: Live cctv footage displayed

Final Results

Camera 1	2024-04-0901-45-44	Fire
Camera 1	2024-04-0901-45-45	Fire
Camera 1	2024-04-0901-46-00	Smoke
Camera 2	2024-04-0901-46-00	Smoke
Camera 2	2024-04-0901-46-00	Smoke

Figure: Timestamps of anomalies detected.

Final Results

Figure: Input frame of a fight where face of culprit is visible.

Final Results

Figure: Input frame from a live camera containing a person of interest.

Final Results

Figure: Similar input frame containing another person of interest from the anomaly.

Final Results

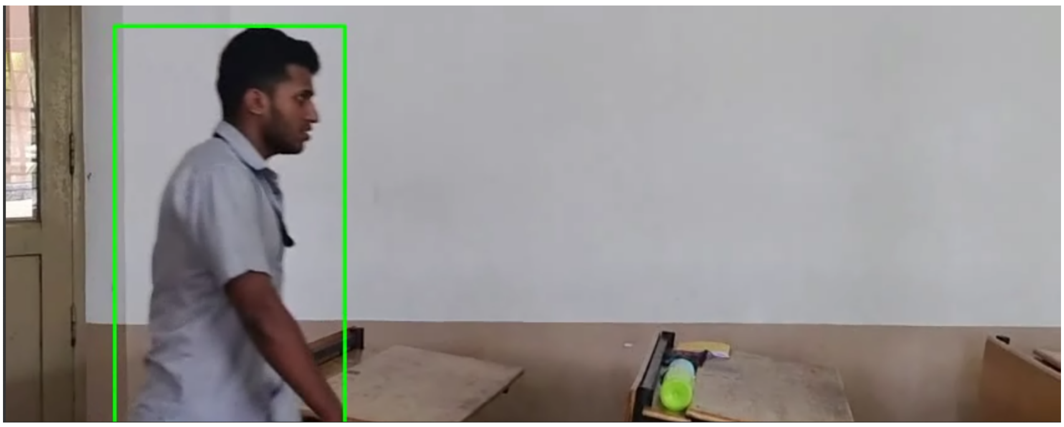


Figure: Output with only feature identification bounding box.

Final Results

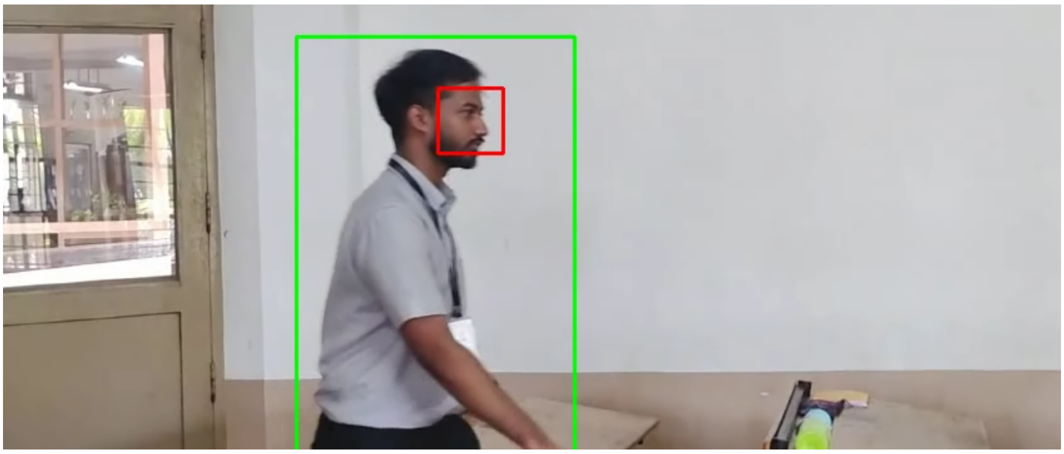


Figure: Output with bounding box for face and feature identification.

Future Scope

1. Develop human-in-the-loop systems where AI-driven detections are augmented by human operators for validation, decision-making, and intervention when necessary.
2. Explore applications of the technology beyond security and surveillance, such as in retail analytics, crowd management, traffic monitoring, or healthcare for patient monitoring.
3. Incorporate advanced algorithms for behavioral analysis, enabling the system to detect suspicious behaviors beyond simple anomalies, such as crowd disturbances, loitering, or erratic movements.

Task Distribution

Nevil Biju- Developing Alert generation system based on results obtained.
Develop YOLOv8 model for anomaly detection

Rayan Fadi- Feature extraction for enhanced Person Re-Identification.
User Interface.

Romain Robert- Person and face detection for Person Re-Identification.
User Interface.

Shreepad Sumesh- Develop YOLOv8 model for anomaly detection.
Dataset generation.

Conclusion

1. **HARNESS AI & COMPUTER VISION**- To meet the growing demands of security and surveillance in both public & private sector obtained.
2. **INTEGRATION OF TECHNOLOGIES**- Anomaly detection, classification and person re-id together ensures unparalleled protection.
3. **SEAMLESS INTEGRATION**- Eliminates the need for additional hardware costs, making advanced security more accessible and scalable

References

1 E. Saykol, U. Gudukbay, and O. Ulusoy, “Scenario-based query processing for video-surveillance archives,” Eng.Appl. Artif. Intell., vol. 23, no. 3, pp. 331–345, 2010.

2 D. Brezeale and D. J. Cook, “Automatic video classification: A survey of the literature,” IEEE Trans. Syst., Man,Cybern. C, Appl. Rev., vol. 38, no. 3, pp. 416–430, May 2008.

3 G. Lavee, E. Rivlin, and M. Rudzsky, “Understanding video events: A survey of methods for automatic interpretation of semantic occurrences in video,” IEEE Trans. Syst., Man, Cybern. C, Appl. Rev., vol. 39, no. 5,pp.489–504, Sep. 2009.

4 H. Buxton, “Learning and understanding dynamic scene activity: A review,” Image Vision Comput., vol. 21, no. 1,pp. 125–136, 2003.

5 Doshi, K., Yilmaz, Y.: Online anomaly detection in surveillance videos with asymptotic bound on false alarm rate.Pattern Recognit. 114, 107865 (2021).

References

6 Zaheer, M.Z., Mahmood, A., Khan, M.H., Astrid, M., Lee, S.-I.: An anomaly detection system via moving surveillance robots with human collaboration. In: 2021 IEEE/CVF International Conference on Computer Vision Workshops(ICCVW), pp. 2595–2601. Montreal, BC, Canada (2021).https://doi.org/10.1109/ICCVW54120.2021.00293

7 Duman, E., Erdem, A.: Anomaly detection in videos using optical flow and convolutional autoencoder. IEEE Access 7(99), 183914–183923 (2019)

8 B. Chen, W. Deng, and J. Hu,“Mixed high-order attention network for person re-identification,” in Proc. IEEE Int.Conf. Comput. Vis., 2019, pp. 371–381.

9 G. Chen, C. Lin, L. Ren, J. Lu, and J. Zhou, “Self-critical attention learning for person re-identification,” in Proc.IEEE Int. Conf. Comput. Vis., 2019, pp. 9637–9646.

10 X. Fan, W. Jiang,and M. Fei,Deep hypersphere manifold embedding for person re-identification,” J. Vis. Commun. Image Representation,pp. 51–58, 2019

Paper Status

1. Initial Draft has been created in IEEE format. We are considering our paper to be presented as a conference paper. We are looking into a conference event that could help us to showcase our paper.

Appendix B: Vision, Mission, Programme Outcomes and Course Outcomes

Vision, Mission, Programme Outcomes and Course Outcomes

Institute Vision

To evolve into a premier technological institution, moulding eminent professionals with creative minds, innovative ideas and sound practical skill, and to shape a future where technology works for the enrichment of mankind.

Institute Mission

To impart state-of-the-art knowledge to individuals in various technological disciplines and to inculcate in them a high degree of social consciousness and human values, thereby enabling them to face the challenges of life with courage and conviction.

Department Vision

To become a centre of excellence in Computer Science and Engineering, moulding professionals catering to the research and professional needs of national and international organizations.

Department Mission

To inspire and nurture students, with up-to-date knowledge in Computer Science and Engineering, ethics, team spirit, leadership abilities, innovation and creativity to come out with solutions meeting societal needs.

Programme Outcomes (PO)

Engineering Graduates will be able to:

1. Engineering Knowledge: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

2. Problem analysis: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

3. Design/development of solutions: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

4. Conduct investigations of complex problems: Use research-based knowledge including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

5. Modern Tool Usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

6. The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal, and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

7. Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

8. Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

9. Individual and Team work: Function effectively as an individual, and as a member or leader in teams, and in multidisciplinary settings.

10. Communication: Communicate effectively with the engineering community and with society at large. Be able to comprehend and write effective reports documentation. Make effective presentations, and give and receive clear instructions.

11. Project management and finance: Demonstrate knowledge and understanding of engineering and management principles and apply these to one's own work, as a member and leader in a team. Manage projects in multidisciplinary environments.

12. Life-long learning: Recognize the need for, and have the preparation and ability to engage in independent and lifelong learning in the broadest context of technological change.

Programme Specific Outcomes (PSO)

A graduate of the Computer Science and Engineering Program will demonstrate:

PSO1: Computer Science Specific Skills
The ability to identify, analyze and design solutions for complex engineering problems in multidisciplinary areas by understanding the core principles and concepts of computer science and thereby engage in national grand challenges.

PSO2: Programming and Software Development Skills
The ability to acquire programming efficiency by designing algorithms and applying standard practices in software project development to deliver quality software products meeting the demands of the industry.

PSO3: Professional Skills
The ability to apply the fundamentals of computer science in competitive research and to develop innovative products to meet the societal needs thereby evolving as an eminent researcher and entrepreneur.

Course Outcomes (CO)

Course Outcome 1: Model and solve real world problems by applying knowledge across domains (Cognitive knowledge level: Apply).

Course Outcome 2: Develop products, processes or technologies for sustainable and socially relevant applications (Cognitive knowledge level: Apply).

Course Outcome 3: Function effectively as an individual and as a leader in diverse teams and to comprehend and execute designated tasks (Cognitive knowledge level: Apply).

Course Outcome 4: Plan and execute tasks utilizing available resources within timelines, following ethical and professional norms (Cognitive knowledge level: Apply).

Course Outcome 5: Identify technology/research gaps and propose innovative/creative solutions (Cognitive knowledge level: Analyze).

Course Outcome 6: Organize and communicate technical and scientific findings effectively in written and oral forms (Cognitive knowledge level: Apply).

CO-PO AND CO-PSO MAPPING

	PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11	PO 12	PSO 1	PSO 2	PSO 3
CO 1	2	2	2	1	2	2	2	1	1	1	1	2	3		
CO 2	2	2	2		1	3	3	1	1		1	1		2	
CO 3									3	2	2	1			3
CO 4					2			3	2	2	3	2			3
CO 5	2	3	3	1	2							1	3		
CO 6					2			2	2	3	1	1			3

3/2/1: high/medium/low

JUSTIFICATIONS FOR CO-PO MAPPING

MAPPING	LOW/MEDIUM/ HIGH	JUSTIFICATION
100003/ CS722U.1-PO1	M	Knowledge in the area of technology for project development using various tools results in better modeling.
100003/ CS722U.1-PO2	M	Knowledge acquired in the selected area of project development can be used to identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions.

100003/ CS722U.1-PO3	M	Can use the acquired knowledge in designing solutions to complex problems.
100003/ CS722U.1-PO4	M	Can use the acquired knowledge in designing solutions to complex problems.
100003/ CS722U.1-PO5	H	Students are able to interpret, improve and redefine technical aspects for design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
100003/ CS722U.1-PO6	M	Students are able to interpret, improve and redefine technical aspects by applying contextual knowledge to assess societal, health and consequential responsibilities relevant to professional engineering practices.
100003/ CS722U.1-PO7	M	Project development based on societal and environmental context solution identification is the need for sustainable development.
100003/ CS722U.1-PO8	L	Project development should be based on professional ethics and responsibilities.
100003/ CS722U.1-PO9	L	Project development using a systematic approach based on well defined principles will result in teamwork.
100003/ CS722U.1-PO10	M	Project brings technological changes in society.

100003/ CS722U.1-PO11	H	Acquiring knowledge for project development gathers skills in design, analysis, development and implementation of algorithms.
100003/ CS722U.1-PO12	H	Knowledge for project development contributes engineering skills in computing & information gatherings.
100003/ CS722U.2-PO1	H	Knowledge acquired for project development will also include systematic planning, developing, testing and implementation in computer science solutions in various domains.
100003/ CS722U.2-PO2	H	Project design and development using a systematic approach brings knowledge in mathematics and engineering fundamentals.
100003/ CS722U.2-PO3	H	Identifying, formulating and analyzing the project results in a systematic approach.
100003/ CS722U.2-PO5	H	Systematic approach is the tip for solving complex problems in various domains.
100003/ CS722U.2-PO6	H	Systematic approach in the technical and design aspects provide valid conclusions.
100003/ CS722U.2-PO7	H	Systematic approach in the technical and design aspects demonstrate the knowledge of sustainable development.

100003/ CS722U.2-PO8	M	Identification and justification of technical aspects of project development demonstrates the need for sustainable development.
100003/ CS722U.2-PO9	H	Apply professional ethics and responsibilities in engineering practice of development.
100003/ CS722U.2-PO11	H	Systematic approach also includes effective reporting and documentation which gives clear instructions.
100003/ CS722U.2-PO12	M	Project development using a systematic approach based on well defined principles will result in better teamwork.
100003/ CS722U.3-PO9	H	Project development as a team brings the ability to engage in independent and lifelong learning.
100003/ CS722U.3-PO10	H	Identification, formulation and justification in technical aspects will be based on acquiring skills in design and development of algorithms.
100003/ CS722U.3-PO11	H	Identification, formulation and justification in technical aspects provides the betterment of life in various domains.
100003/ CS722U.3-PO12	H	Students are able to interpret, improve and redefine technical aspects with mathematics, science and engineering fundamentals for the solutions of complex problems.

100003/ CS722U.4-PO5	H	Students are able to interpret, improve and redefine technical aspects with identification formulation and analysis of complex problems.
100003/ CS722U.4-PO8	H	Students are able to interpret, improve and redefine technical aspects to meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.
100003/ CS722U.4-PO9	H	Students are able to interpret, improve and redefine technical aspects for design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
100003/ CS722U.4-PO10	H	Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools for better products.
100003/ CS722U.4-PO11	M	Students are able to interpret, improve and redefine technical aspects by applying contextual knowledge to assess societal, health and consequential responsibilities relevant to professional engineering practices.
100003/ CS722U.4-PO12	H	Students are able to interpret, improve and redefine technical aspects for demonstrating the knowledge of, and need for sustainable development.
100003/ CS722U.5-PO1	H	Students are able to interpret, improve and redefine technical aspects, apply ethical principles and commit to

		professional ethics and responsibilities and norms of the engineering practice.
100003/ CS722U.5-PO2	M	Students are able to interpret, improve and redefine technical aspects, communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.
100003/ CS722U.5-PO3	H	Students are able to interpret, improve and redefine technical aspects to demonstrate knowledge and understanding of the engineering and management principle in multidisciplinary environments.
100003/ CS722U.5-PO4	H	Students are able to interpret, improve and redefine technical aspects, recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.
100003/ CS722U.5-PO5	M	Students are able to interpret, improve and redefine technical aspects in acquiring skills to design, analyze and develop algorithms and implement those using high-level programming languages.
100003/ CS722U.5-PO12	M	Students are able to interpret, improve and redefine technical aspects and contribute their engineering skills in computing and information engineering domains like

		network design and administration, database design and knowledge engineering.
100003/ CS722U.6-PO5	M	Students are able to interpret, improve and redefine technical aspects and develop strong skills in systematic planning, developing, testing, implementing and providing IT solutions for different domains which helps in the betterment of life.
100003/ CS722U.6-PO8	H	Students will be able to associate with a team as an effective team player for the development of technical projects by applying the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.
100003/ CS722U.6-PO9	H	Students will be able to associate with a team as an effective team player to Identify, formulate, review research literature, and analyze complex engineering problems
100003/ CS722U.6-PO10	M	Students will be able to associate with a team as an effective team player for designing solutions to complex engineering problems and design system components.
100003/ CS722U.6-PO11	M	Students will be able to associate with a team as an effective team player, use research-based knowledge and research methods including design of experiments, analysis and interpretation of data.

100003/ CS722U.6-PO12	H	Students will be able to associate with a team as an effective team player, applying ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.
100003/ CS722U.1-PSO1	H	Students are able to develop Computer Science Specific Skills by modeling and solving problems.
100003/ CS722U.2-PSO2	M	Developing products, processes or technologies for sustainable and socially relevant applications can promote Programming and Software Development Skills.
100003/ CS722U.3-PSO3	H	Working in a team can result in the effective development of Professional Skills.
100003/ CS722U.4-PSO3	H	Planning and scheduling can result in the effective development of Professional Skills.
100003/ CS722U.5-PSO1	H	Students are able to develop Computer Science Specific Skills by creating innovative solutions to problems.
100003/ CS722U.6-PSO3	H	Organizing and communicating technical and scientific findings can help in the effective development of Professional Skills.