
Palestine Polytechnic University

College of Information Technology and Computer Engineering Department of Computer System Engineering

# Escalator Safety System using Computer Vision and Deep Learning

**Project Team**
Hala Salhab, Mohammad Salhab and Amjad Khatib

**Supervisor**

Dr. Hashem Tamimi

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# Abstract

Escalators are essential components of modern infrastructure, facilitating vertical transportation in public spaces. However, escalator-related accidents pose a persistent safety challenge. This project introduces an escalator safety system that utilizes computer vision and deep learning to enhance hazard detection and response mechanisms.

The proposed system, built on an ESP32 and Raspberry Pi, employs a pre-trained deep learning action recognition mode, namely the LRCN to analyze video footage for identifying risks, such as people falling on the escalator or becoming jammed at key points.

The results showed that the system has high accuracy of nearly 94.99%. The results also showed that the LRCN model required high computational time. Although the simulation on a Personal computer was done in real time, we did not reach a real time response on the Raspberry Pi microcontroller.

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# Chapter 1: Introduction

## 1.1 Overview

Escalators are vital in public spaces, but rising accidents highlight the need for improved safety solutions. Traditional systems often fail in crowded areas. This project seeks to develop an intelligent system that uses computer vision and deep learning to monitor escalators in real time, detecting hazards and triggering interventions.

## 1.2 Objectives

The following objectives will be realized in this project:

1. **Autonomous monitoring:** Design and implement a stand alone escalator monitoring system that does not need human involvement during its operation but rather utilizes computer vision and deep learning to intelligently monitor escalator operations.
2. **Danger status detection:** The escalator safety system will identify and classify different dangerous scenarios. Although many scenarios may exist. We will realize the following ones within the scope of this project:
    1. Predicting falling down in the direction of the escalator.
    2. Person jammed on the escalator first or last steps.
    3. Having people located outside the escalator lane.
3. **Real-time incident response:** We take the responsive mechanism that triggers immediate interventions to reduce escalator-related risks into consideration, preventing accidents and enhancing overall passenger safety.

4. **Adaptability and continuous enhancement:** By relying on deep learning, our system will be capable of adapting to evolving patterns. The deep learning model and learning from new data, ensuring the scalability and effectiveness in dynamic and changing environments. This will be implemented by continuous development of new versions of the deep learning model
5. **Integration with Existing Infrastructure:** Ensure seamless integration of the proposed safety system with existing escalator infrastructure, minimizing disruptions and facilitating widespread adoption in diverse public spaces.

## 1.3 Project Requirements

### 1.3.1 Functional Requirements

1. **Action Recognition:** The system must be able to distinguish between normal and abnormal activities. It should classify detected actions accurately and reliably to trigger appropriate safety measures.
2. **Real-Time Analysis:** The system should analyze video frames in real-time to ensure immediate response to detected incidents. This includes processing video data and generating predictions without significant delay. We will study the system response time on a personal computer and on the microcontroller.
3. **Safety Mechanism Activation:** Upon detecting an abnormal activity, the system must activate safety mechanisms such as turning on a red LED, ringing a bell, and slowing down the escalator.
4. **Integration with Hardware Components:** The system must interface seamlessly with hardware components, including the ESP32 for controlling the LED and bell, and the stepper motor for adjusting the escalator speed.
5. **User Alerts:** The system should provide visual and auditory alerts to notify nearby individuals and operators of potential safety issues.

### 1.3.2 Non-functional Requirements

1. **Performance:** The system must operate efficiently with minimal latency, ensuring real-time response to detected incidents. The performance metrics include prediction speed and accuracy.
2. **Reliability:** The system should be highly reliable, with consistent performance across different scenarios and environments. It must handle varying lighting conditions and background noise effectively.
3. **Scalability:** The system should be scalable to accommodate future upgrades or extensions, such as adding more sensors or expanding the monitoring area.
4. **Power Consumption:** The system should be designed to minimize power consumption, especially when deployed in environments with limited power resources.
5. **Compliance:** The system should comply with relevant safety and regulatory standards to ensure its suitability for deployment in public areas.

## 1.4 Project Limitations/Constraints

Despite the successful implementation and testing of the escalator safety and intelligence system, several limitations and constraints impacted the project:

1. **Computational Limitations**

- Processing Power: The Raspberry Pi, while effective for basic tasks, has limited computational power compared to more advanced processors. This constraint affected the model's performance, particularly in terms of prediction speed and real-time processing.
- Model Complexity: The ConvLSTM model, though suitable for action recognition, is computationally intensive. Larger models or longer sequence lengths may further strain the Raspberry Pi's resources, potentially impacting performance.

2. **Hardware Constraints**

- Sensor Accuracy: The accuracy and reliability of the sensors used in the system are critical. Any limitations in sensor performance could affect the system’s ability to detect and respond to incidents accurately.

- Hardware Integration: Integrating various hardware components, such as the ESP32, stepper motor, and motor driver, required careful calibration and testing. Any discrepancies in hardware integration could impact the system's overall effectiveness.

3. **Environmental Factors**

- Lighting Conditions: The performance of the video-based action recognition model can be affected by varying lighting conditions. The system may struggle to detect incidents in low-light or high-glare environments.
- Background Interference: The presence of background objects or motion could potentially interfere with the model's ability to accurately detect and classify incidents, especially in crowded or dynamic environments.

4. **Data and Training Limitations**

- Dataset Size and Diversity: The model's performance is highly dependent on the quality and diversity of the training dataset. Limited data or lack of variety in the dataset could affect the model's accuracy and generalization ability.
- Training Duration: The time required to train the model on available hardware was a limiting factor. Extensive training times could impact project timelines and resource allocation.

Addressing these challenges will be crucial for improving the system's reliability and effectiveness in real-world applications.

### 1.5 Report outline

This report is structured to provide a comprehensive understanding of the project. Chapter 1 sets the stage by offering an overview of the project, detailing its objectives, and specifying both functional and non-functional requirements. This chapter also addresses project limitations and constraints, which highlight potential challenges and areas for improvement. Additionally, it includes a report outline that guides readers through the subsequent sections of the document.

Chapter 2 delves into the foundational aspects of the project. It includes an overview of the relevant literature, exploring existing solutions and providing a theoretical background. This

chapter covers critical areas such as computer vision, machine learning, and deep learning, with a specific focus on deep learning applications in computer vision, object detection, and action and activity recognition. It also discusses design options for hardware components like the Raspberry Pi, PIR motion sensor, and ESP32, as well as the system software components, software tools, deep learning models, programming languages used, and communication protocols.

Chapter 3 presents a detailed account of the project's system design. It includes an overview and brief description of the system, supplemented by visual aids such as block and schematic diagrams. This chapter elaborates on both hardware and software implementation, covering aspects such as training action recognition models, dataset preparation, dataset partitioning, and training options. It further discusses the training process for both CNN and LSTM models, coding practices, and essential functions related to the ESP32 setup, interrupt service routines, action recognition, and the main loop function.

Chapter 4 focuses on the practical aspects of implementing the system. It describes the hardware and software implementation processes in detail, including the training of action recognition models. The chapter covers dataset preparation and partitioning, training options, and the execution of the training process. It provides insights into the coding required for the project, including libraries installation and the development of key functions.

Chapter 5 provides validation and results details. The overview highlights the validation process for the escalator safety and intelligence system, evaluating the performance of each component and the overall system against project requirements. This chapter includes sections on hardware testing, software testing and evaluation, training results for CNN and LSTM models, experimental analysis, and system testing. It concludes with an assessment of system integration and performance, including findings from testing on the Raspberry Pi and other hardware components.

Chapter 6 consolidating the main findings and achievements. It also outlines potential future work, suggesting areas for further development and improvement

# Chapter 2: Background

## 2.1 Overview

This chapter introduces the theoretical background and the literature review, a short description of the parts used in the system and why they are chosen.

## 2.2 Literature Review

The groundwork for our project was laid with the aid of the following research and studies, serving as a foundational source of inspiration and guidance for the development of our project idea.

1. **Intelligent escalator passenger safety management [1]**

   **Year:** 2022

   **Summary:** The proposed approach integrates advanced information processing through machine learning and recurrent neural networks, utilizing video, audio, and sensors. This novel system aims to enhance escalator safety with a focus on artificial intelligence methods and cloud/fog computing. Existing studies highlight challenges in processing heterogeneous information. The proposed system draws inspiration from complex control systems, offering a comprehensive safety solution for escalators.

2. **Research on Pedestrian Fall Action Recognition from Escalators [2]**

   **Year:** 2017

   **Summary:** This solution utilizes intelligent video surveillance. Leveraging computer vision and deep learning, the system focuses on fall recognition problems, offering an advanced approach to public safety. This paper proposes a method using Temporal Segment Networks (TSN) as a backbone, enhancing efficiency and effectiveness. By incorporating related temporal and spatial networks, the proposed algorithm improves the accuracy of pedestrian fall action recognition, mitigating false alarms and increasing overall effectiveness.

Our escalator safety project aligns closely with prior initiatives that leverage computer vision and deep learning for enhanced safety measures. Similar to these projects, our approach emphasizes the utilization of advanced technologies to address safety concerns on escalators. While some existing efforts may incorporate different elements, our project distinguishes itself by focusing specifically on the power of computer vision and deep learning techniques. This singular reliance on computer vision and deep learning signifies our commitment to developing a cutting-edge solution that harnesses the potential of these technologies to ensure passenger safety on escalators.

**2.3 Existing Solutions**

To address safety concerns associated with escalator usage, traditional methods rely on manual monitoring by operators and basic technical systems. These approaches have limitations like high costs, inaccuracies, and slow responses. While adding tools like video cameras and facial recognition helps, it still doesn't provide a comprehensive solution.

The proposed Escalator Safety System leverages Computer Vision and Deep Learning to offer a more advanced and effective approach. It processes data from video cameras and sensors using machine learning algorithms to analyze passenger behavior in real-time. This system proactively identifies potential safety risks and responds quickly, unlike conventional methods that depend on manual observation, which can be error-prone and slow.

The system's ability to issue warnings, manage passenger flow, and provide timely recommendations makes it dynamic and adaptive. By integrating machine learning and neural networks, it surpasses existing solutions, offering a nuanced understanding of safety threats.

In summary, the intelligent Escalator Safety System significantly enhances accuracy, efficiency, and responsiveness, reducing reliance on manual monitoring and ensuring passenger safety with a modern, technology-driven approach.

## 2.4 Theoretical Background

This section provides some information about some technologies and algorithms that will be used in our project.

### 2.4.1 Computer Vision

Computer vision [3] leverages artificial intelligence (AI) to allow computers to obtain meaningful data from visual inputs such as photos and videos. The insights gained from computer vision are then used to take automated actions. Just like AI gives computers the ability to ‘think’, computer vision allows them to ‘see’.

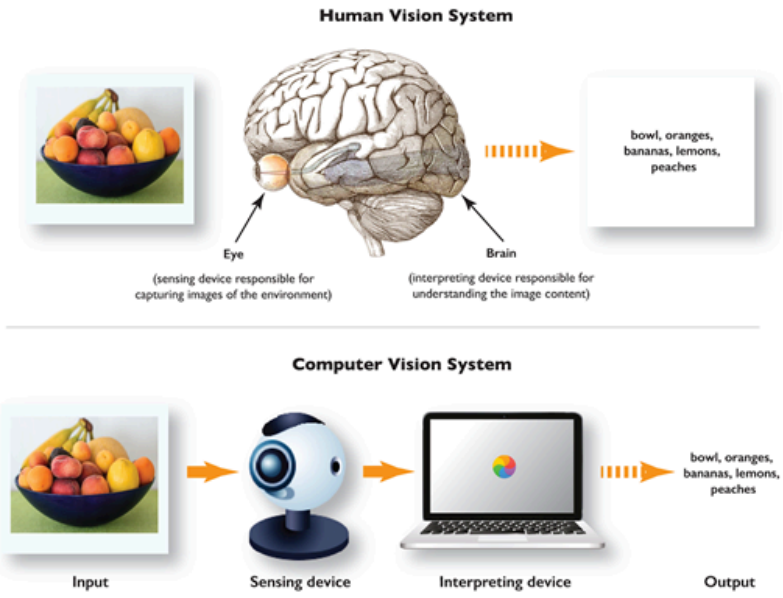



Figure 2.1: Human Vision vs. Computer Vision: source [4]

A typical process of Computer vision [4] is illustrated in the above image. It mainly performs

three steps, which are:

1. **Capturing an Image**

A computer vision software or application always includes a digital camera or CCTV to capture the image. So, firstly it captures the image and puts it as a digital file that consists of Zero and one's.

2. **Processing the image**

In the next step, different CV algorithms are used to process the digital data stored in a file. These algorithms determine the basic geometric elements and generate the image using the stored digital data.

3. **Analyzing and taking required action**

Finally, the CV analyzes the data, and according to this analysis, the system takes the required action for which it is designed.

Computer vision [5] was mainly based with image processing algorithms and methods. The main process of computer vision was extracting the features of the image. Detecting the color, edges, corners and objects were the first step to do when performing a computer vision task. These features are human engineered and accuracy and the reliability of the models directly depend on the extracted features and on the methods used for feature extraction.

The difficulty with this approach of feature extraction in image classification is that you have to choose which features to look for in each given image. When the number of classes of the classification goes high or the image clarity goes down it’s really hard to cope up with traditional computer vision algorithms.

The accuracy and the speed of processing and identifying images captured from cameras has developed through decades. Being the well-known boy in town, **deep learning** is playing a

major role as a computer vision tool. See Figure 2.2

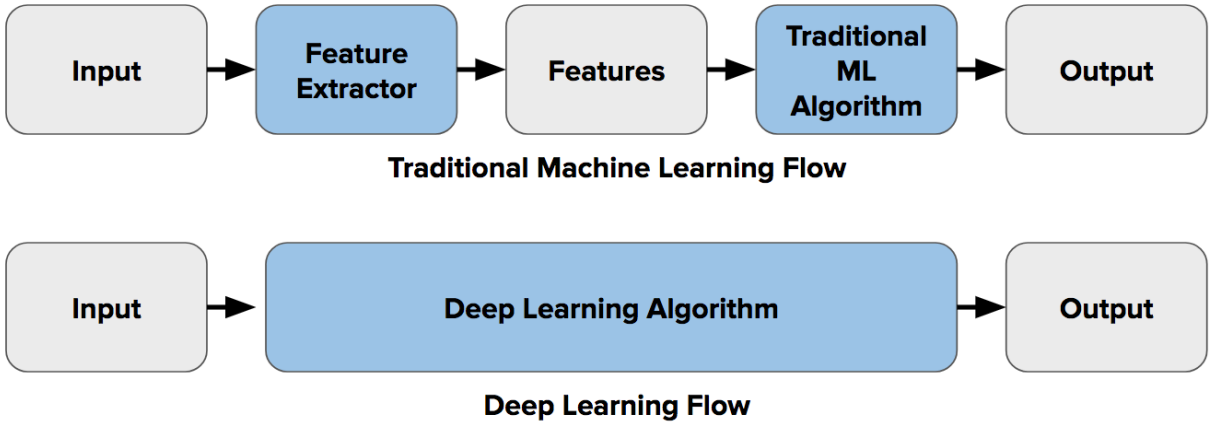



Figure 2.2: Traditional ML flow vs DL flow[5]

### 2.4.2 Machine Learning and Deep Learning

Machine learning is a branch of AI that mimics the workings of the human brain in processing data for use in many areas such as detecting objects, recognizing speech, translating languages, and making decisions. Deep learning[6] is a branch of machine learning that extracts picture features without the need for human interference. Over the last years deep learning [7] methods have been shown to outperform previous state-of-the-art machine learning techniques in several fields, with computer vision being one of the most prominent cases.

Deep Learning introduced the concept of end-to-end learning where the machine is just given a dataset of images which have been annotated with what classes of object are present in each image. Thereby a Deep Learning model is ‘trained’ on the given data, where neural networks discover the underlying patterns in classes of images and automatically works out the most descriptive and salient features with respect to each specific class of object for each object.

### 2.4.3 Action and Activity Recognition

Human action and activity recognition is a research issue that has received a lot of attention from researchers [8]. Many works on human activity recognition based on deep learning techniques have been proposed in the literature in the last few years. Deep learning was used for complex event detection and recognition in video sequences: first, saliency maps were used for detecting and localizing events, and then deep learning was applied to the pretrained features for identifying the most important frames that correspond to the underlying event.

#### 2.4.3.1 CNN

CNN (Convolutional Neural Network) is a category of machine learning model, namely a type of deep learning algorithm well suited to analyzing visual data [10]. CNNs use principles from linear algebra, particularly convolution operations, to extract features and identify patterns within images. Although CNNs are predominantly used to process images, they can also be adapted to work with audio and other signal data.

Unlike CNNs, former forms of neural networks often needed to process visual data in a piecemeal manner, using segmented or lower-resolution input images. CNN's comprehensive approach to image recognition lets it outperform a traditional neural network on a range of image-related tasks and, to a lesser extent, speech and audio processing.

**How do CNNs work?**

CNNs use a series of layers, (see Figure 2.5) each of which detects different features of an input image. Depending on the complexity of its intended purpose, a CNN can contain dozens, hundreds or even thousands of layers, each building on the outputs of previous layers to recognize detailed patterns.

The process starts by sliding a filter designed to detect certain features over the input image, a process known as the convolution operation (hence the name "convolutional neural network"). The result of this process is a feature map that highlights the presence of the detected features in the image. This feature map then serves as input for the next layer, enabling a CNN to gradually

build a hierarchical representation of the image.

Initial filters usually detect basic features, such as lines or simple textures. Subsequent layers' filters are more complex, combining the basic features identified earlier on to recognize more complex patterns. For example, after an initial layer detects the presence of edges, a deeper layer could use that information to start identifying shapes.

Between these layers, the network takes steps to reduce the spatial dimensions of the feature maps to improve efficiency and accuracy. In the final layers of a CNN, the model makes a final decision. For example, classifying an object in an image -- based on the output from the previous layers.

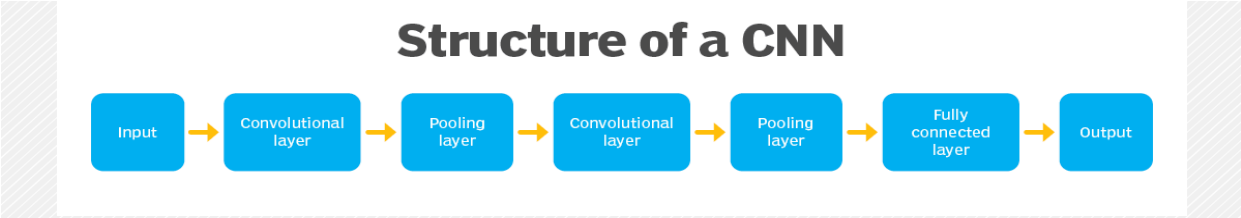



Figure 2.3: CNN Structure [10]

#### 2.4.3.2 Long Short Term Memory Networks

Long Short Term Memory networks are a special kind of RNN[9] that are capable of learning long-term dependencies. They were introduced by Hochreiter & Schmidhuber (1997), and were refined and popularized by many people in the following work. They work tremendously well on a large variety of problems, and are now widely used. LSTMs are able to process and analyze sequential data, such as time series, text, and speech. They use a memory cell and gates to control the flow of information, allowing them to selectively retain or discard information as needed and thus avoid the vanishing gradient problem that plagues traditional RNNs. LSTMs are widely used in various applications such as natural language processing, speech recognition, and time series forecasting.

As shown in Figure (2.7), the architecture of the LSTM network consists of multiple layers designed to process sequential data efficiently.

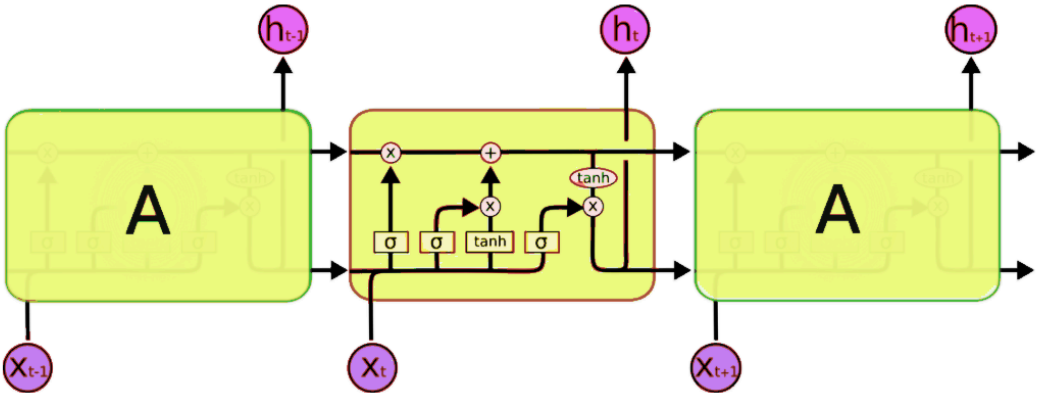



Figure 2.4: Architecture of LSTM [10]

**How do Long short Term Memory networks work?**

The structure of an LSTM network consists of a series of LSTM cells, each of which has a set of gates (input, output, and forget gates) that control the flow of information into and out of the cell. The gates are used to selectively forget or retain information from the previous time steps, allowing the LSTM to maintain long-term dependencies in the input data.

The LSTM cell also has a memory cell that stores information from previous time steps and uses it to influence the output of the cell at the current time step. The output of each LSTM cell is passed to the next cell in the network, allowing the LSTM to process and analyze sequential data over multiple time steps.

With the recent breakthroughs that have been happening in data science, it is found that for almost all of these sequence prediction problems, Long Short Term Memory networks, a.k.a LSTMs, have been observed as the most effective solution.

LSTMs have an edge over conventional feed-forward neural networks and RNN in many ways. This is because of their property of selectively remembering patterns for long durations of time.

**Integration of CNN and LSTM Layers in Action Recognition**

In the field of action recognition, the combination of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks plays a crucial role in capturing both spatial and temporal information from video data. CNNs are designed to effectively extract spatial features from individual frames by detecting patterns such as edges, textures, and shapes. These features are fundamental building blocks for understanding the visual content of each frame. LSTMs, on the other hand, are specialized for handling sequential data and are capable of modeling temporal dependencies over time. This makes them ideal for understanding the progression of actions across multiple frames.

## 2.5 Design options for hardware components

This section describes the main hardware components needed to construct our project and illustrates each component's function

### 2.5.1 Raspberry Pi

The Raspberry Pi 4 Model B (shown in Figure 2.8) . This product’s key features include a high-performance 64-bit quad-core processor, a dual-display asset at resolutions up to 4K via a pair of micro-HDMI ports, hardware tape decodes at up to 4Kp60, up to 4GB of RAM, dual-band 2.4/5.0 GHz wireless LAN, Bluetooth 5.0, Gigabit Ethernet, USB 3.0.

Figure 2.5: Raspberry Pi [11]

Table 2.1 provides a comprehensive comparison between Arduino Mega and Raspberry Pi microcontrollers. It highlights the key differences and features of both components.

Table 2.1: A comprehensive comparison between Arduino Mega and Raspberry Pi microcontrollers

| SBC | Raspberry Pi 4B | Arduino Mega 2560 |
|---|---|---|
| **CPU** | Quad-core ARM Cortex-A72 64-bit @ 1.5 GHz | Atmega2560 |
| **GPU** | Broadcom VideoCore VI (32-bit) | - |
| **Networking** | Gigabit Ethernet / Wifi 802.11ac | Serial communication / Ethernet |
| **USB** | 2x USB 3.0, 2x USB 2.0 | 1x USB 2.0 |
| **Video Encoder** | H264(1080p30) | - |
| **Video Decoder** | H.265(4Kp60) H.264(1080p60) | - |
| **GPIO** | 40-pin GPIO | 16-pin GPIO |
| **Price** | $35 | 30$ |

Raspberry Pi 4 Model B is much more powerful than the Arduino Mega 2560, making it a better choice for our system that requires significant computational resources. More powerful microcontrollers that exist are beyond our budget and time limitation.

### 2.5.2 Passive Infrared Motion Sensor

PIR (Passive Infrared) sensors detect movement by sensing changes in infrared radiation within their field of view. Made of a pyroelectric sensor, they passively receive infrared energy emitted by humans and animals without emitting any themselves. These sensors are commonly used in security systems, producing electrical signals to trigger alarms or notifications when motion is detected.

PIR sensors are valued for their simplicity, cost-effectiveness, and reliability. They detect

infrared radiation from living beings, concentrated in the 8-12 µm wavelength range. To extend their detection range, optical systems, such as plastic Fresnel lenses (see Figure 2.9), are often used to focus the infrared radiation onto the sensor, enhancing its effectiveness in motion detection [12].

Usually, plastic optical reflection systems or plastic Fresnel lenses are used as a focusing system for infrared radiation.

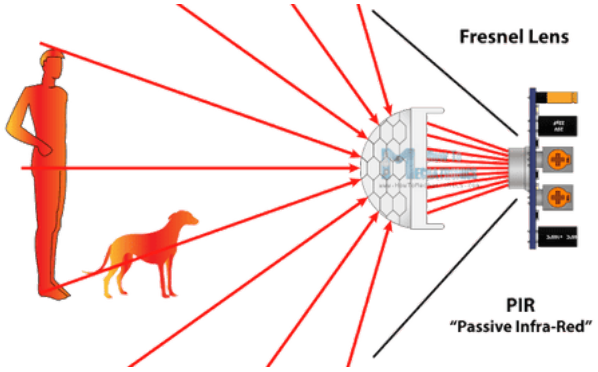



Figure 2.6: PIR Sensor working principle [12]

The project utilizes the PIR sensor to cover areas not covered by the camera. In addition to its relatively wide range, which provides us with a broader coverage area, especially for covering the staircase, Figure 2.10 presents the main pins of the PIRsensor.


Figure 2.7: PIR Motion Sensor

### 2.5.3 ESP 32

The ESP32 is a highly versatile and widely used microcontroller module developed by Espressif Systems. Combining a dual-core processor, built-in Wi-Fi, and Bluetooth connectivity, the ESP32 is designed for a broad range of applications in the Internet of Things (IoT) and embedded systems. Its dual-core Tensilica LX6 microprocessors operate at speeds up to 240 MHz, while integrated wireless capabilities enable seamless communication over Wi-Fi and Bluetooth, facilitating the creation of interconnected devices. The ESP32 offers a variety of input/output interfaces, including GPIO pins, UART, SPI, and I2C, making it adaptable to different sensor and peripheral requirements. With support for low-power modes, diverse programming environments such as Arduino IDE and Espressif IDF, and an active community, the ESP32 has become a popular choice for developers and enthusiasts seeking a cost-effective and powerful solution for IoT projects, home automation, robotics, and more.

Figure 2.11 presents the pins of the ESP32.

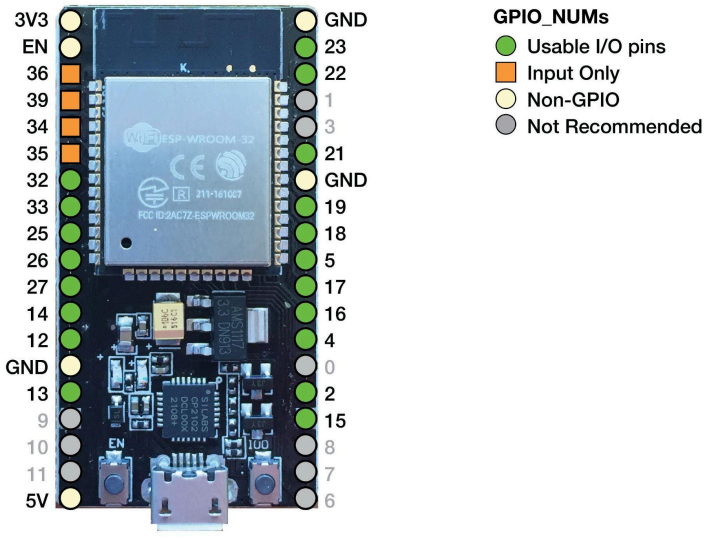



Figure 2.8: ESP32 pins[13]

We decided to use the ESP32 due to its built-in Wi-Fi and Bluetooth connectivity and the high Clock Speed of ESP32 which is important for real time applications.

### 2.5.4 L298N Motor Driver Module

This L298N Motor Driver Module as shown in figure 2.12 is a high power motor driver module for driving DC and Stepper Motors. This module consists of an L298 motor driver IC and a 78M05 5V regulator. L298N Module can control up to 4 DC motors, or 2 DC motors with directional and speed control.

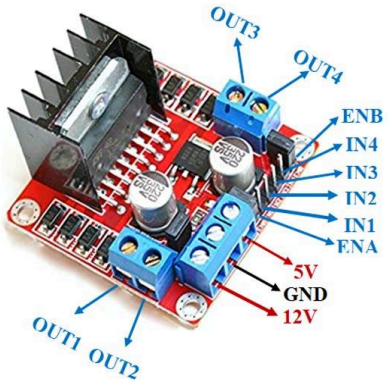



Figure 2.9: L298N-Module-Pinout

The L298N Motor Driver module consists of an L298 Motor Driver IC, 78M05 Voltage Regulator, resistors, capacitor, Power LED, 5V jumper in an integrated circuit.[14]

The 8M05 Voltage regulator will be enabled only when the jumper is placed. When the power supply is less than or equal to 12V, then the internal circuitry will be powered by the voltage regulator and the 5V pin can be used as an output pin to power the microcontroller. The jumper should not be placed when the power supply is greater than 12V and separate 5V should be given through a 5V terminal to power the internal circuitry.

ENA & ENB pins are speed control pins for Motor A and Motor B while IN1& IN2 and IN3 & IN4 are direction control pins for Motor A and Motor B.

Internal circuit diagram of L298N Motor Driver module is given in figure 2.13:

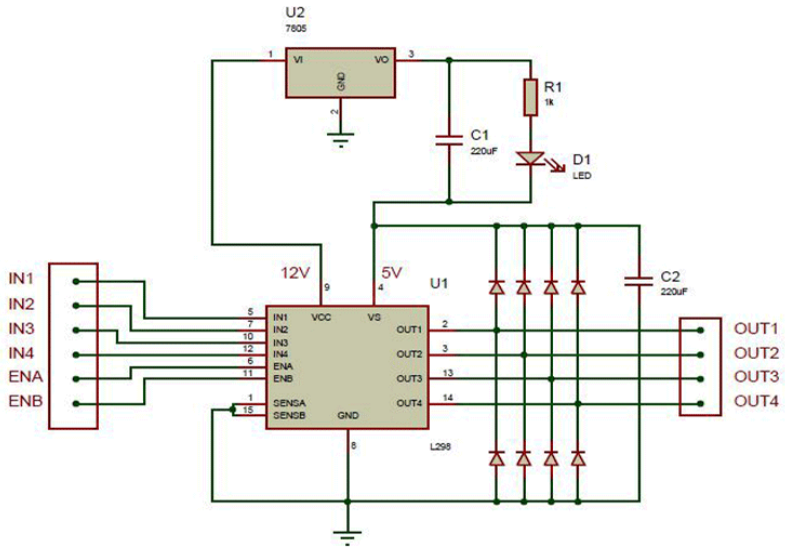



Figure 2.10 :Internal circuit diagram of L298N[14]

### 2.5.5 DC Motor

A DC (Direct Current) as shown in figure 2.14 motor is an electrical machine that converts direct electrical energy into mechanical energy. It operates on the principle that when a current-carrying conductor is placed in a magnetic field, it experiences a mechanical force. DC motors are widely used in various applications due to their simple control mechanism, ease of speed variation, and cost-effectiveness

Figure 2.11 : DC Motor

In our project, the DC motor is used to represent the operation of the escalator. By controlling the speed and direction of the DC motor, we simulate the escalator's movement, adjusting its speed based on real-time hazard detection. This allows the system to react dynamically, slowing down or stopping the "escalator" in response to motion or incidents detected by sensors and the machine learning model. The motor's versatility in speed control makes it ideal for this application.[16]

The use of a DC motor for this simulation provides a scalable and efficient way to model how a real escalator would respond to safety triggers, such as unexpected motion or incidents.

## 2.6 System Software Components

### 2.6.1 Software Tools

**Raspberry Pi Raspbian**: An operating system is the set of basic programs And utilities that make your Raspberry Pi run.

Python IDE: It's the code editor that is used to write the python code that processes and classifies mail.

**Google CoLab**: A cloud-based platform used for training the machine learning models. Google Colab provides access to high-performance GPUs and a convenient environment for developing and training models, allowing for efficient experimentation and model optimization. It integrates seamlessly with Google Drive for data storage and sharing.

### 2.6.2 Deep Learning Models

Our choice for action recognition will be LRCN networks, considering the advantages previously outlined in our project scope.

### 2.6.4 Used Programming Languages

We use Python as the main programming language because it is simple and easy to handle

complex algorithms in machine learning and deep learning.
Python has a wide variety of libraries and frameworks, it's well-structured and well-tested, and it will reduce development and testing time, for example (Keras, TensorFlow, and Scikit-learn).
We will use better protocols that achieve real time applications.

## 2.7 Communication Protocols

- **MQTT**

Message Queuing Telemetry Transport, is a lightweight and efficient messaging protocol designed for reliable communication in constrained or remote environments. Originally developed by IBM in the late 1990s, MQTT has gained widespread adoption, particularly in the realm of the Internet of Things (IoT). Its simplicity and low overhead make it well-suited for scenarios where devices may have limited processing power, bandwidth, or connectivity. MQTT operates on a publish-subscribe model, allowing devices to publish messages to specific "topics" and subscribe to topics of interest. This decoupled architecture enables communication between devices without the need for direct point-to-point connections, promoting scalability and flexibility. Additionally, MQTT supports Quality of Service (QoS) levels, ensuring different levels of message delivery assurance, and it can use a broker-based system where a central server (broker) manages message distribution among connected devices.

In practical terms, MQTT is used for real-time data exchange between devices, making it an ideal choice for applications like home automation, industrial monitoring, and telemetry systems. Its efficiency, low latency, and ability to operate over unreliable networks contribute to its widespread use in diverse IoT deployments. MQTT's open nature and support in various programming languages further contribute to its popularity, making it a key player in the communication protocols landscape.

When a device wants to publish information as shown in figure 2.15, it sends an MQTT "publish" message to the broker, specifying the topic and the payload. Subscribed devices

receive these messages through the broker. The broker, acting as a message distributor, efficiently manages the flow of information. Additionally, MQTT supports last will and testament messages, allowing devices to specify a message that the broker will broadcast in case the device unexpectedly disconnects. This feature enhances the reliability and robustness of the communication. The simplicity of the MQTT protocol, combined with its ability to handle varying levels of quality of service and reliability, makes it a versatile and widely adopted solution for distributed systems.[17]

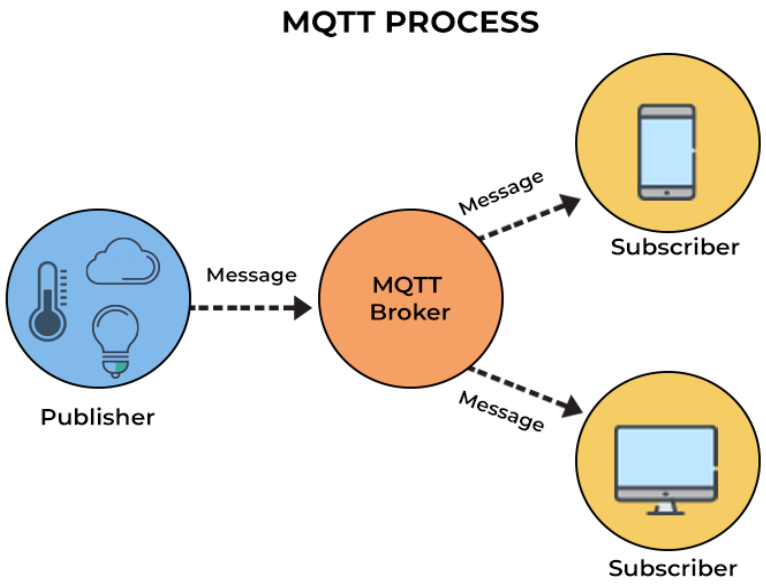



Figure 2.12: MQTT process [17]

- **Data Distribution Service**

Stands as a robust middleware standard designed to facilitate real-time and high-performance data distribution across distributed systems. It operates on a publish-subscribe model, allowing various applications or devices to publish data and subscribe to information of interest.

Developed by the Object Management Group (OMG), DDS addresses the unique challenges of real-time systems where low-latency communication, reliability, and scalability are paramount. Unlike traditional message-oriented middleware, DDS focuses on efficient and direct data-centric communication, making it an ideal choice for applications with stringent requirements such as industrial automation, healthcare, and defense.[18]

At the core of DDS is its commitment to real-time communication, ensuring that data exchange occurs with minimal latency and in a deterministic manner. The middleware standard offers a rich set of Quality of Service (QoS) policies, allowing developers to tailor communication characteristics to match the specific needs of their applications.

# Chapter 3: System Design

## 3.1 Overview

This chapter discusses the overall design of the system and the way its components are integrated, showing the schematic diagram, block diagram, pseudocode, hardware setup, and the flowchart for the system.

## 3.2 Brief Description of the System

The system is an intelligent Escalator Safety System that leverages cutting-edge technologies, including computer vision and deep learning. This advanced system is designed to monitor escalator operations in real-time, analyze visual data, and promptly detect anomalies or potential safety hazards. By incorporating a diverse dataset for training the deep learning model, the system becomes adept at identifying various scenarios such as overcrowding, irregular movements, and object obstructions.

Upon detection of anomalies, the system initiates immediate interventions to prevent escalator-related accidents, contributing to enhanced overall passenger safety. The adaptability of the system allows it to learn from evolving patterns, ensuring continuous improvement in anomaly detection accuracy.

The system's architecture includes hardware components such as cameras for capturing escalator operations, a processing unit for real-time analysis, and connectivity components for seamless integration with existing escalator infrastructure. The software component encompasses a development environment for implementing computer vision and deep learning algorithms, a user-friendly interface for monitoring, and integration capabilities with existing escalator control systems.

With a focus on performance, scalability, reliability, and usability, the intelligent Escalator Safety System aims to provide a comprehensive solution for creating safer public spaces by preventing escalator-related accidents through proactive monitoring and immediate response mechanisms.

### 3.3 Block Diagram

The block diagram in Figure 3.1 depicts the interconnection and interaction of system components as distinct blocks, illustrating the relationships and interactions between them.

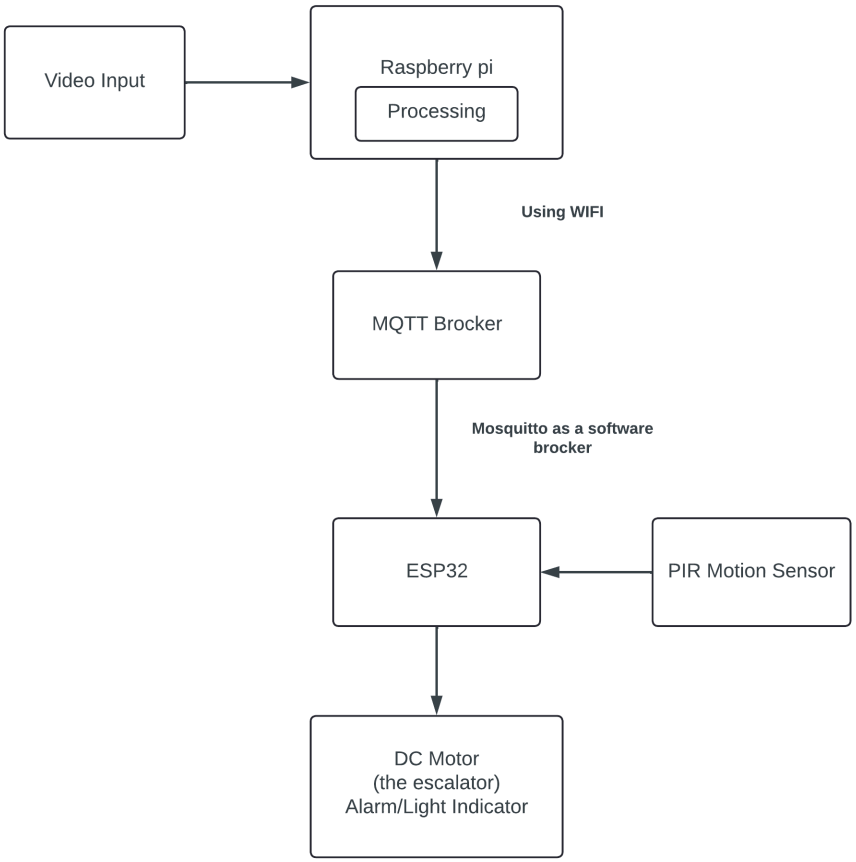



Figure 3.1: System block diagram

### 3.4 Schematic Diagram

The following schematic diagram shown in figure 3.2 illustrates the hardware setup for the escalator safety and intelligence project. This diagram shows the connections between the ESP32

microcontroller, Raspberry Pi,camera, stepper motor, sensors, and other components such as the lights and the bell. Each component is connected to specific GPIO pins on the ESP32, as indicated in the diagram. Additionally, the ESP32 communicates wirelessly with the Raspberry Pi via Wi-Fi:

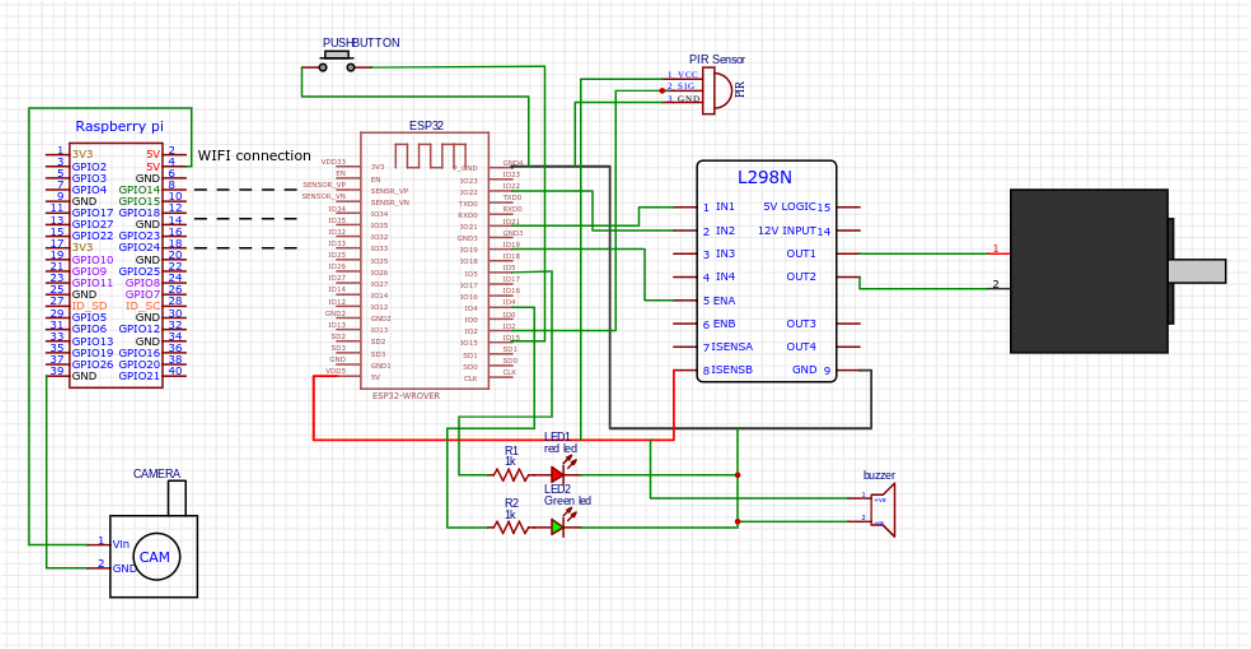



Figure 3.2: schematic diagram

The following is the connection between raspberry pi and ESP 32 , through WIFI connection, with using of MQTT protocol:

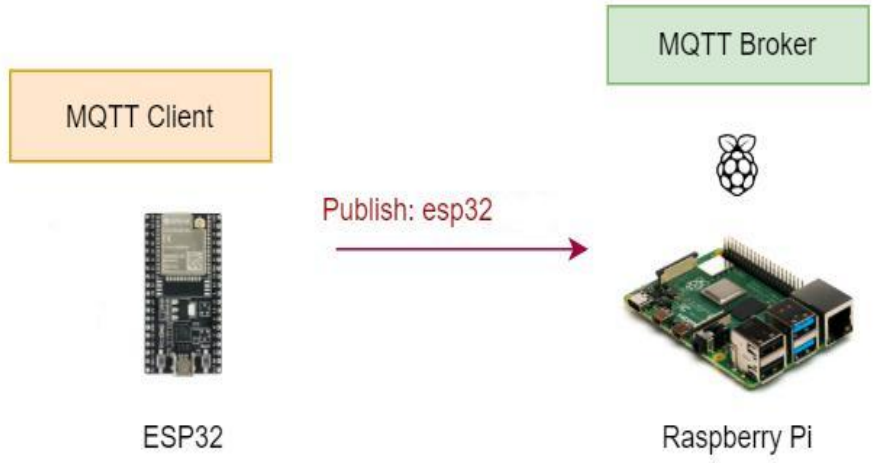



Figure 3.3: Connection between raspberry pi and ESP 32

### 3.5 Software design

The system is designed to detect both abnormal activity and normal activity on an escalator. **The abnormal activities include:**

- Falling in the direction of the escalator.
- Person jammed on the first or last steps of the escalator.
- Persons outside the escalator lane.

**For normal activity,** the system will monitor regular escalator use with no incidents.

#### 3.5.1 Design Options for Classification

We considered two approaches for classifying activities detected by the system:

1. **Multiple Abnormal Models:**

   As shown in Figure 3.4, we considered an approach where multiple models are used to classify specific abnormal activities individually:

   - Model 1 detects Fall vs. Normal activity.
   - Model 2 detects Stuck Body Parts vs. Normal activity.
   - Model 3 detects Outside Lane activity vs. Normal activity.

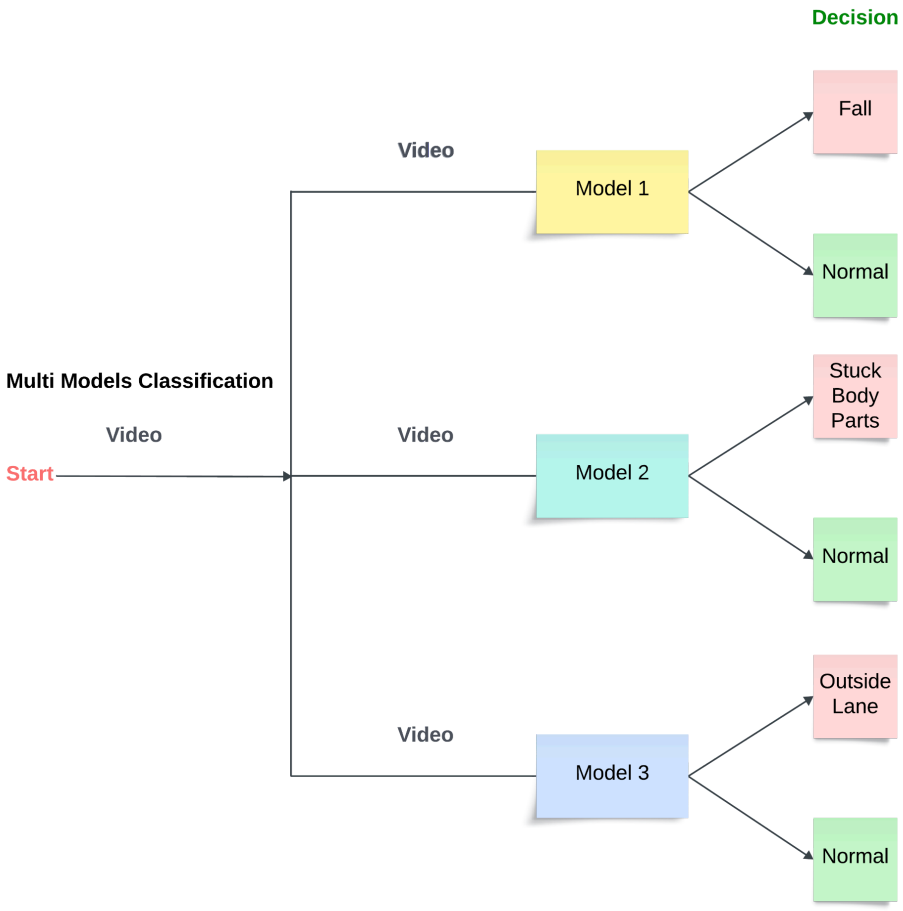



Figure 3.4: Multiple Abnormal Models

This design enables the system to classify different types of incidents separately, providing detailed information about the exact nature of the abnormal event detected in real-time. Each model operates independently, receiving the same video input and outputting a decision based on its specialized task.

2. **Binary Classification (Chosen Approach):**

In this approach, see figure 3.5 the system is simplified into two classes only:

- Abnormal Class: Covers all types of abnormal activities, including falling, getting jammed, or being outside the escalator lane.
- Normal Class: Represents normal escalator operation without any incidents.

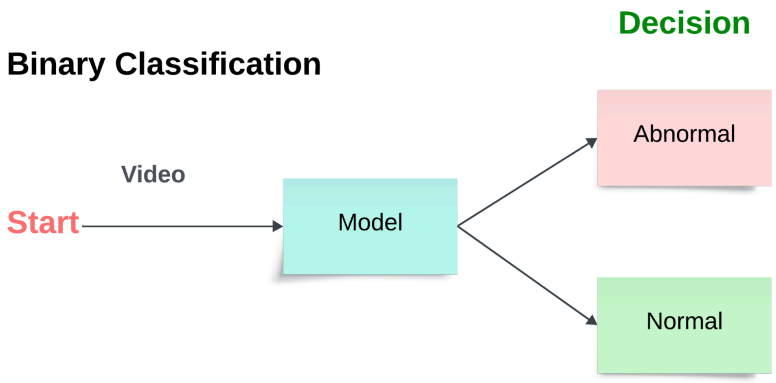



Figure 3.5: Binary Classification

We chose this approach for its simplicity and efficiency in real-time applications. By focusing on a binary classification of "abnormal" vs. "normal," the system can quickly and accurately detect incidents without the need for more granular classification.

### 3.5.2 Action Recognition:

In the software design for this project, the primary goal is to detect abnormal activities on an escalator through video sequences using deep learning techniques. The system implements advanced models such as ConvLSTM and LRCN (Long-term Recurrent Convolutional Network) to capture both spatial and temporal features, enabling accurate real-time action recognition.

**1. ConvLSTM Approach**

The first approach explored in the design is based on ConvLSTM cells, which integrate convolutional operations with Long Short-Term Memory (LSTM) networks. This architecture is ideal for handling video data as it simultaneously captures spatial information from each frame and models temporal relationships across consecutive frames.

Unlike standard LSTM models, which can only process 1-dimensional inputs, ConvLSTM is designed for 3-dimensional input (width, height, and number of channels). This feature makes ConvLSTM highly effective for spatiotemporal data, where both spatial (within-frame) and temporal (between-frame) information is crucial.

**Key elements of the ConvLSTM architecture include:**

- **ConvLSTM2D layers:** Extract spatial features while preserving temporal dependencies between frames.
- **MaxPooling3D layers:** Reduce the dimensionality of the input, thus optimizing computational efficiency.
- **Dropout layers:** Prevent overfitting by regularizing the model during training.

The result is a model with fewer trainable parameters, optimized for handling small datasets while effectively capturing the complex dynamics in escalator video sequences.

**2. LRCN Approach**

Another key design choice for action recognition is the LRCN model, which combines CNN and LSTM layers to perform end-to-end spatiotemporal learning. Instead of training CNN and LSTM models separately (with CNN extracting spatial features and LSTM handling temporal sequences), the LRCN approach merges these functionalities into a unified architecture.

- **Convolutional layers:** These layers extract spatial features from the individual frames of video.
- **LSTM layers:** The extracted spatial features are fed into LSTM layers, which process temporal dependencies between frames to model ongoing activities.

To ensure consistent processing of video sequences, the LRCN design incorporates a TimeDistributed wrapper, which applies the same convolutional operation to each frame of the video sequence independently. This allows the model to handle video data effectively while retaining the temporal integrity of the frame sequence.

The overall LRCN architecture consists of:

- **TimeDistributed Conv2D layers:** Responsible for spatial feature extraction.
- **MaxPooling2D and Dropout layers:** Reduce the dimensionality and prevent overfitting.
- **Flatten layers:** Prepare the extracted features for processing by the LSTM layers.
- **LSTM layers:** Model the temporal relationships across the sequence of frames.
- **Dense layers with softmax activation:** Output the probability of each action category (abnormal vs. normal).

Both the ConvLSTM and LRCN approaches were evaluated for their ability to capture the complexities of escalator-related actions, with the LRCN approach providing a powerful solution for real-time spatiotemporal learning.

**System Workflow**

The LRCN model was selected for final implementation due to its ability to process sequences of video frames in real-time. The workflow for this action recognition system is as follows:

1. **General Workflow**
- Camera Monitoring: A camera will be installed to monitor the entire escalator, providing video input in real-time.
- The video frames will be captured continuously and processed frame by frame.
2. **Frame Preprocessing:**
   Each captured frame will be preprocessed to fit the input requirements of the LRCN model (e.g., resizing and normalization).
3. **Frame Sequence Creation:**
   A sequence of 50 frames (or another specified sequence length) will be collected before making a prediction. These frames will be stored in a buffer for sequential analysis by the LRCN model.

4. **Abnormal Activity Prediction:**

   Once the required number of frames has been collected, the sequence will be fed into the LRCN model. The LRCN model will then analyze the sequence and output a prediction indicating whether any abnormal activity (e.g., falling, getting jammed) has occurred.

5. **Response Actions:**

   a. **Incident Detected (Abnormal Activity):**

      If the LRCN model predicts abnormal activity (falling, jamming, etc.), a signal will be sent via MQTT to the ESP32 microcontroller. The escalator can be slowed down or stopped, and alarms (such as lights or bells) can be triggered.

   b. **Normal Activity:**

      If no abnormal activity is detected, the system will continue to monitor without taking any action.

**Pseudocode:**

```
START
SETUP MQTT connection to the broker
    - Define broker address and topic
    - Connect to MQTT broker
LOAD pre-trained model from specified path

DEFINE function to preprocess a video frame
    - Resize frame to (200, 200)
    - Normalize the frame by dividing pixel values by 255.0

INITIALIZE video capture with a specified video file path
INITIALIZE an empty list to hold a sequence of frames
SET sequence_length to 50 (number of frames per sequence)

WHILE the video is open:
    READ a frame from the video
    IF frame is not successfully read:
        EXIT the loop
    PREPROCESS the frame using the preprocessing function
```

```
    ADD preprocessed frame to the sequence list
    IF sequence list contains 50 frames:
        CONVERT sequence to numpy array and add batch dimension
        START timer to measure prediction time
        MAKE a prediction using the loaded model
        STOP the timer and calculate time taken for prediction
        DISPLAY the time taken for prediction
        IF prediction indicates an incident (prediction score > 0.5):
            SEND "incident_detected" message via MQTT
            PRINT "Incident detected, message sent"

        REMOVE the oldest frame from the sequence list
    DISPLAY the current video frame

    IF 'q' key is pressed:
        BREAK the loop

RELEASE video capture and close any open windows
DISCONNECT from the MQTT broker
END
```

# Chapter 4:Implementation

## 4.1 Overview

This chapter covers the system's hardware setup, software development, and action recognition model training. Key coding functions are also highlighted, providing an overview of the system's implementation from setup to operation.

## 4.2 Hardware implementation

In the previous chapter, we detailed the integration of components within the escalator monitoring system. This section outlines the assembly and connections of these components with the ESP32.

As shown in Figure 4.1, the prototype consists of a DC motor representing the escalator, the PIR motion sensors placed at strategic positions to detect unauthorized presence, and an ESP32 microcontroller responsible for controlling the motor's and responding to incidents. The system also incorporates visual and auditory signals, including indicator lights and a bell, to alert users in case of motion detection or an emergency situation. This setup demonstrates how the components work together to ensure escalator safety and prevent accidents.

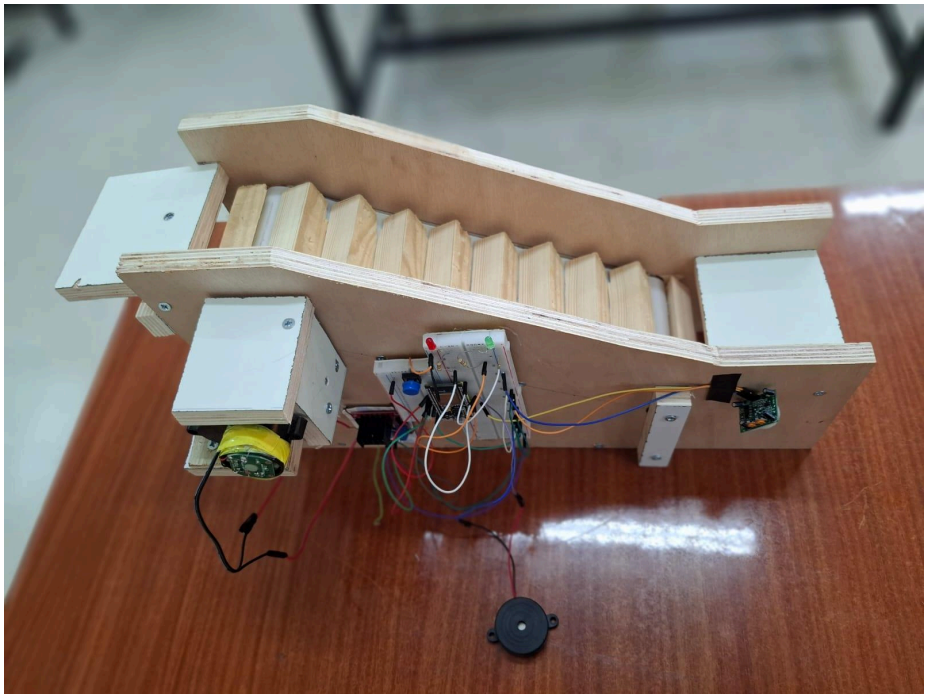


Figure 4.1 : Escalator Safety System Prototype

**Figure 4.1: Escalator System**

The hardware implementation of the escalator safety system primarily involves integrating the ESP32 microcontroller, a stepper motor, motor driver, PIR sensor, and several output components like LEDs and a bell. The ESP32 is chosen for its Wi-Fi capabilities, allowing it to communicate with the Raspberry Pi using the MQTT protocol. The PIR sensor is placed near the escalator to detect motion, and when triggered, it sends a signal to the ESP32, which initiates specific actions such as controlling the stepper motor and signaling alerts through the red LED and the bell. The stepper motor, connected via the L298N motor driver, controls the speed and movement of the escalator, ensuring it can slow down or stop in case of detected incidents.

The stepper motor is controlled using the stepper driver connected to the ESP32 through the STEP and DIR pins. The motor driver allows for precise control over the motor's speed and direction, which is essential for adjusting the escalator's speed based on sensor inputs or incident signals received from the Raspberry Pi. The system's safety measures are reinforced by

LEDsgreen and red lights are used to indicate the escalator's status. The green light remains on during normal operation, while the red light and bell are activated when an incident or motion is detected.

### 4.3 Software implementation

This section provides an in-depth account of the software components involved in the system implementation, along with a comprehensive overview of the various phases that were undertaken to realize the project.

#### 4.3.1 Training Action Recognition Models

For this project, we focused on developing models capable of recognizing human actions in video sequences by utilizing advanced deep learning techniques. The training process consisted of several phases to ensure that the models accurately captured both spatial and temporal relationships in the video data.

##### 4.3.1.1 Dataset

To train the models, we used a dataset consisting of annotated video sequences capturing various human actions. The dataset was selected based on its relevance to the project's objectives and its capacity to represent the diversity of actions. For our models, the dataset was divided into sequences of frames, each labeled with the corresponding action.

For this project, we collected a dataset comprising 78 videos categorized into two classes: 64 videos of abnormal activities and 14 of normal activities.

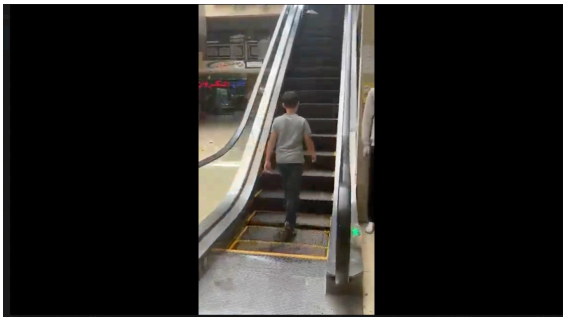
**Samples from the Dataset:**

1. Abnormal Activity Samples:

   The following are snapshots/frames of videos of people with Abnormal activities


2. Normal Activity Samples:

   The following are snapshots/frames of videos of people using the escalator normally without any abnormal activities



The dataset preparation process involved several key steps:

**1. Visualization**

Initially, we visualized the videos and their labels to understand the dataset's content and distribution.

**2. Preprocessing**

We resized the frames of the videos to a fixed width and height to reduce computational load and normalized pixel values to the range [0-1] by dividing by 255. This normalization step helps accelerate convergence during training.

**3. Frame Extraction**

We developed a function, frames_extraction(), to process each video file by reading and resizing frames, then normalizing them. The function selects an evenly distributed sequence of frames from each video to ensure consistency in the dataset.

**4. Dataset Creation**

Another function, create_dataset(), iterates through the specified classes and applies frames_extraction() to each video. This function aggregates the resized and normalized frames, corresponding class labels (one-hot encoded), and video file paths into a comprehensive dataset.

**5. Label Encoding**

Finally, we converted class labels into one-hot encoded vectors, which are suitable for training the action recognition models. This process ensures that the dataset is well-prepared for training, validation, and testing of the models.

#### 4.3.1.2 Dataset Partitioning

To ensure robust model evaluation, the dataset was divided into training and testing sets. This process involved the following steps:

**1. Data Preparation**

The dataset consisted of `features`, a NumPy array containing all the extracted and preprocessed video frames, and `one_hot_encoded_labels`, a NumPy array with the corresponding one-hot encoded class labels.

**Shuffling and Splitting**

We shuffled the dataset to avoid any bias and ensure that the splits reflect the overall distribution of the data. The data was then partitioned into training and testing sets.

**2. Train-Test Split**

The split was executed with 75% of the data allocated for training and 25% for testing. This division helps in training the model effectively while retaining a substantial portion of data for accurate evaluation.

```
features_train, features_test, labels_train, labels_test =
train_test_split(
       features, one_hot_encoded_labels,
       test_size=0.25, shuffle=True,
       random_state=seed_constant
   )
```

This approach provides a balanced representation of the data in both training and testing phases, facilitating a fair assessment of the model's performance.

#### 4.3.1.3 Training Options

To configure the model effectively for training, several key settings were specified to optimize performance:

1. **Image Dimensions:** Each video frame was resized to a height and width of 200 pixels (IMAGE_HEIGHT, IMAGE_WIDTH). This resizing helps standardize the input and reduce computational load.
2. **Sequence Length:** The model processes a sequence of 50 frames (SEQUENCE_LENGTH) at a time. This choice was made because it provided the best balance between accuracy and prediction speed. Increasing the sequence length beyond this point did not yield significant improvements and resulted in higher computational costs. This setting ensures the model captures sufficient temporal context while maintaining efficient processing.
3. **Batch**: the batch size of the network, set to 4 for this project.
4. **Epochs**: the number of epochs to train for, set to 30 for the CNN model and 70 for LRCN model.

#### 4.3.1.4 Train the Model

For training the model, we chose Google Colab as our platform for training both CNN and LRCN models due to its high computational power and memory capabilities. Colab provides free GPUs and allows for extended notebook sessions, making it ideal for computationally intensive tasks.

**Training Process:**

1. Platform Setup:
   a. Install dependencies.
   b. Import libraries.
   c. Upload the dataset, which was directly imported from google drive.
   d. Creating the dataset.

e. Extracting features.

f. Using Keras's to_categorical method to convert labels into one-hot-encoded vectors.

g. Construct the model.

h. Create the model.

i. Create and train the model.

`Evaluate` the trained model.

j. Save the model.

2. ConvLSTM Training:

a. Model Construction:

```
def create_convlstm_model():
    '''
    This function will construct the required convlstm model.
    Returns:
        model: It is the required constructed convlstm model.
    '''

    # We will use a Sequential model for model construction
    model = Sequential()

    # Define the Model Architecture.
    ########################################################################

    model.add(ConvLSTM2D(filters = 4, kernel_size = (3, 3),
activation = 'tanh',data_format = "channels_last",
                         recurrent_dropout=0.2,
return_sequences=True, input_shape = (SEQUENCE_LENGTH,

IMAGE_HEIGHT, IMAGE_WIDTH, 3)))

    model.add(MaxPooling3D(pool_size=(1, 2, 2),
padding='same', data_format='channels_last'))
    model.add(TimeDistributed(Dropout(0.2)))

    model.add(ConvLSTM2D(filters = 8, kernel_size = (3, 3),
```

```
activation = 'tanh', data_format = "channels_last",
                          recurrent_dropout=0.2,
return_sequences=True))

    model.add(MaxPooling3D(pool_size=(1, 2, 2),
padding='same', data_format='channels_last'))
    model.add(TimeDistributed(Dropout(0.2)))

    model.add(ConvLSTM2D(filters = 14, kernel_size = (3, 3),
activation = 'tanh', data_format = "channels_last",
                          recurrent_dropout=0.2,
return_sequences=True))

    model.add(MaxPooling3D(pool_size=(1, 2, 2),
padding='same', data_format='channels_last'))

    model.add(TimeDistributed(Dropout(0.2)))

    model.add(ConvLSTM2D(filters = 16, kernel_size = (3, 3),
activation = 'tanh', data_format = "channels_last",
                          recurrent_dropout=0.2,
return_sequences=True))

    model.add(MaxPooling3D(pool_size=(1, 2, 2),
padding='same', data_format='channels_last'))
    #model.add(TimeDistributed(Dropout(0.2)))

    model.add(Flatten())

    model.add(Dense(len(CLASSES_LIST), activation =
"softmax"))

    ##################################################################

    # Display the model's summary.
    model.summary()
```

```
    # Return the constructed convlstm model.
    return model
```

b. Create the model:

Now we will utilize the function create_convlstm_model() created above, to construct the required convlstm model.

```
# Construct the required convlstm model.
convlstm_model = create_convlstm_model()
```

c. Compile and Train:

```
# Create an Instance of Early Stopping Callback
early_stopping_callback = EarlyStopping(monitor = 'val_loss',
patience = 10, mode = 'min', restore_best_weights = True)

# Compile the model and specify loss function, optimizer and
metrics values to the model
convlstm_model.compile(loss = 'categorical_crossentropy',
optimizer = 'Adam', metrics = ["accuracy"])

# Start training the model.
convlstm_model_training_history = convlstm_model.fit(x =
features_train, y = labels_train, epochs = 30, batch_size = 4,
                                                    shuffle =
True, validation_split = 0.2,
                                                    callbacks
= [early_stopping_callback])
```

d. Evaluate the Trained Model:

After training, we will evaluate the model on the test set.

```
# Evaluate the trained model.
model_evaluation_history =
convlstm_model.evaluate(features_test, labels_test)
```

3. LRCN Training:

a. Model Construction:

```
def create_LRCN_model():
    '''
    This function will construct the required LRCN model.
    Returns:
        model: It is the required constructed LRCN model.
    '''

    # We will use a Sequential model for model construction.
    model = Sequential()

    # Define the Model Architecture.
    ########################################################

    model.add(TimeDistributed(Conv2D(16, (3, 3),
padding='same',activation = 'relu'),
                              input_shape = (SEQUENCE_LENGTH,
IMAGE_HEIGHT, IMAGE_WIDTH, 3)))

    model.add(TimeDistributed(MaxPooling2D((4, 4))))
    model.add(TimeDistributed(Dropout(0.25)))

    model.add(TimeDistributed(Conv2D(32, (3, 3),
padding='same',activation = 'relu')))
    model.add(TimeDistributed(MaxPooling2D((4, 4))))
    model.add(TimeDistributed(Dropout(0.25)))

    model.add(TimeDistributed(Conv2D(64, (3, 3),
padding='same',activation = 'relu')))
    model.add(TimeDistributed(MaxPooling2D((2, 2))))
    model.add(TimeDistributed(Dropout(0.25)))
```

```
    model.add(TimeDistributed(Conv2D(64, (3, 3),
padding='same',activation = 'relu')))
    model.add(TimeDistributed(MaxPooling2D((2, 2))))
    #model.add(TimeDistributed(Dropout(0.25)))

    model.add(TimeDistributed(Flatten()))

    model.add(LSTM(32))

    model.add(Dense(len(CLASSES_LIST), activation =
'softmax'))

    ########################################################

    # Display the model's summary.
    model.summary()

    # Return the constructed LRCN model.
    return model
```

b. Create the model:

```
# Construct the required LRCN model.
LRCN_model = create_LRCN_model()e)
model()
```

c. Compile and Train:

```
# Compile the model and specify loss function, optimizer and
metrics to the model.
LRCN_model.compile(loss = 'categorical_crossentropy',
optimizer = 'Adam', metrics = ["accuracy"])

# Start training the model.
LRCN_model_training_history = LRCN_model.fit(x =
features_train, y = labels_train, epochs = 70, batch_size = 4
,
```

```
                                                shuffle = True,
validation_split = 0.2, callbacks = [early_stopping_callback])
```

d. Evaluate the Trained Model:

```
# Construct the required LRCN model.
LRCN_model = create_LRCN_model()e)

# Compile the model and specify loss function, optimizer and
metrics to the model.
LRCN_model.compile(loss = 'categorical_crossentropy',
optimizer = 'Adam', metrics = ["accuracy"])

# Start training the model.
LRCN_model_training_history = LRCN_model.fit(x =
features_train, y = labels_train, epochs = 70, batch_size = 4
,
                                                shuffle = True,
validation_split = 0.2, callbacks = [early_stopping_callback])
```

The training process for both models was executed in Google Colab, leveraging the provided GPU resources. After training, the models were evaluated to determine their effectiveness. The saved models, in `.h5` format, to be used later on the Raspberry pi.

### 4.4 Coding

This section will cover the installation and setup of libraries, as well as hardware functions, on the Raspberry pi and the ESP32.

#### 4.4.1 Libraries Installation

To support the implementation and execution of our models, we utilized TensorFlow version 2.15.0, which is essential for constructing and running our models. TensorFlow provides comprehensive tools for model development, training, and evaluation.

In addition to TensorFlow, several other libraries were necessary for various aspects of the project. These libraries were installed to handle video processing, numerical operations, and data visualization. The key libraries included:

- cv2 (OpenCV): For video frame processing.
- numpy: For numerical computations and array operations.
- matplotlib: For visualizing data.
- sklearn: For data splitting and model evaluation.
- datetime: For handling time-related data.
- collections.deque: For efficiently managing a sequence of frames.
- WiFi.h: Connects the ESP32 to a Wi-Fi network.
- PubSubClient.h: Manages MQTT communication for sending and receiving messages.

### 4.4.2 ESP Setup Function

**Serial Communication Initialization**:

- Serial.begin(115200): initializes serial communication at a baud rate of 115200 for debugging purposes.

**Pin Initialization**:

- Sets the GPIO pins as input or output based on their roles:
    - pinMode(GREEN_LIGHT_PIN, OUTPUT); - Sets the green light pin as output.
    - pinMode(RED_LIGHT_PIN, OUTPUT); - Sets the red light pin as output.
    - pinMode(BELL_PIN, OUTPUT); - Sets the bell pin as output.
    - pinMode(STEPPER_STEP_PIN, OUTPUT); - Sets the stepper motor step pin as output.
    - pinMode(STEPPER_DIR_PIN, OUTPUT); - Sets the stepper motor direction pin as output.
    - pinMode(PIR_SENSOR_PIN, INPUT); - Sets the PIR sensor pin as input.

**Initial Escalator State**:

- digitalWrite commands set the initial state of the lights and bell.
- stepperMotorControl(200, HIGH, 500); runs the stepper motor at normal speed initially.

**Wi-Fi Connection**:

- Calls setup_wifi() to connect to the specified Wi-Fi network.

**MQTT Setup**:

- Configures the MQTT server and callback function for handling messages using client.setServer(mqtt_server, 1883); and client.setCallback(callback);.

### 4.4.3 Interrupt Service Routine Function

**pir_triggered Flag**:

A volatile boolean flag is used to store the state of the PIR sensor. It is marked as volatile because it is accessed both inside and outside of the ISR, ensuring that the compiler doesn't optimize it in a way that would disrupt its function.

**pirISR() Function**:

The Interrupt Service Routine (IRAM_ATTR specifies that the function should be stored in the instruction RAM for faster execution). When the PIR sensor detects motion (a RISING signal), the function sets pir_triggered to true.

**attachInterrupt() Function**:

This function links the PIR sensor pin (PIR_SENSOR_PIN) to the pirISR function. It triggers the ISR whenever the signal on the PIR pin changes to RISING (motion detected).

### 4.4.4 Action Recognition Function

This pseudocode captures frames from a video source, preprocesses them, and collects a sequence of frames to analyze. When the sequence reaches a specified length, the function uses a pre-trained ConvLSTM model to predict if there is an incident. If an incident is detected, it sends

a notification via MQTT to alert the system. The process continues, allowing real-time monitoring and decision-making until the user stops the program or the video ends.

```
Function action_recognition(cap, model, client, topic,
sequence_length = 50):

    Initialize an empty list frame_sequence

    While video capture (cap) is open:
        Read the next frame from the video source
        IF frame not available THEN
            Exit the loop

        Preprocess the frame
        Append the preprocessed frame to frame_sequence

        IF length of frame_sequence equals sequence_length THEN:
            Convert frame_sequence to a NumPy array with an added
batch dimension

            Make a prediction using the model

            IF prediction indicates an incident (prediction[0][0] >
0.5):
                Publish "incident_detected" message to MQTT topic
                Print "Prediction: Incident detected, MQTT message
sent"

            Remove the oldest frame from frame_sequence

        Display the current frame

        IF 'q' key is pressed THEN
            Exit the loop

    Release video capture and close display windows
    Disconnect MQTT client
```

```
End Function
```

### 4.4.5 ESP Loop Function

- Reconnects to the MQTT broker if the connection is lost (reconnect()).
- Processes incoming MQTT messages to keep the connection alive (client.loop()).
- Checks the PIR sensor state for motion (digitalRead(PIR_SENSOR_PIN)).
- If motion is detected:
    - Turns off the green light, turns on the red light, and activates the bell.
    - Slows down the stepper motor and prints a message.
- If an incident is detected (incident_detected == true):
    - Stop the escalator, turn on the red light and bell.
    - Prints an incident message, keeps the bell ringing for 2 seconds, then resets the flag.
- If no motion or incident is detected:
    - Run the escalator at full speed with the green light on.
    - Prints a status message every 3 seconds.
- Adds a small delay (delay(100)) to reduce sensor polling and optimize performance.

**ESP Loop PseudoCode Steps**

```
LOOP:

 1. Check MQTT Connection:
    IF not connected to MQTT broker:
       Call reconnect()

    Call client.loop() to process incoming MQTT messages.

 2. Handle Incident Detection:
    IF incident_detected is TRUE AND escalator_stopped is FALSE:
       Call stop_escalator()
       Set incident_detected to FALSE
```

3. Handle Escalator Restart:

```
IF escalator_stopped is TRUE:
   IF push button is pressed:
      Call restart_escalator()
   ELSE IF serial input is "run":
      Call restart_escalator()
```

4. Handle Motion Detection (if escalator is running):

```
IF escalator_stopped is FALSE:
   Read PIR sensor state

   IF motion is detected (PIR state is HIGH):
      Stop the motor, turn on red light and bell
   ELSE (no motion detected):
      Run motor at full speed, turn on green light
```

5. Add a small delay (e.g., delay 100ms)

```
Repeat loop.
```

# Chapter 5: Validation and Results

**5.1 Overview:**

This chapter summarizes the validation of the escalator safety system, testing components and models for accuracy, detection, and control. The results confirm the system's effectiveness in incident detection and response.

## 5.2 Hardware Testing:

### 5.2.1 Testing ESP32

We conducted comprehensive testing on the ESP32 microcontroller, which plays a critical role in managing the escalator safety and intelligence system. The testing process was designed to validate the board's performance and its integration with other system components.

We first tested the ESP32's Wi-Fi connectivity to ensure it could reliably connect to the network. This involved verifying that the ESP32 successfully connected to the specified Wi-Fi network and maintained a stable connection throughout the testing period. Additionally, we confirmed that the ESP32 was able to establish and maintain a connection with the MQTT broker hosted on the Raspberry Pi.

To test the MQTT functionality, we checked the ESP32's ability to both publish and subscribe to MQTT topics. We ensured that the ESP32 correctly subscribed to the topic for receiving incident alerts from the Raspberry Pi and was able to publish status updates. Messages sent between the ESP32 and the MQTT broker were verified for accuracy and timely delivery.

### 5.2.2 Testing PIR motion sensor

We evaluated the sensor's ability to detect motion at varying distances and angles to determine its effective range. The sensor was tested by simulating different movements at various distances to ensure it reliably detects motion within the intended area of coverage.

The PIR sensor was integrated with the ESP32, and its output was monitored to confirm correct signal transmission to the microcontroller. We verified that the ESP32 responded appropriately to the sensor’s input by activating the red light, bell, and adjusting the motor speed accordingly.

The PIR motion sensor passed all tests, demonstrating its effectiveness in detecting motion and triggering the required safety responses in the system.

### 5.2.3 Testing DC Motor

Thorough testing of the DC motor is essential to ensure that the system accurately simulates escalator operation and responds effectively to detected hazards. The testing process focused on verifying the motor's performance in various conditions, including normal operation, speed control, and emergency responses triggered by the sensors and machine learning model.

Using Pulse Width Modulation (PWM) for precise control, we tested the motor’s ability to adjust its speed based on input from the motion sensors and the Raspberry Pi’s incident detection system. Key tests included ensuring that the motor stops completely when a potential safety threat is detected. Additionally, we tested the motor's stability during prolonged operation at full speed, as well as its responsiveness to sudden changes in speed when hazards are identified.

These tests confirmed that the DC motor can reliably mimic escalator movement, providing accurate speed control and quick reactions to ensure escalator safety in real-world scenarios.

### 5.2.4 Testing Signal Transmission Time Using Mobile Hotspot

In this project, the connection between the Raspberry Pi and ESP32 is established using a mobile phone's hotspot as the Wi-Fi network. When a signal is sent from the Raspberry Pi to the ESP32 via MQTT, several factors influence the transmission time:

1. Network Speed and Latency: Mobile hotspots typically have higher latency compared to traditional home Wi-Fi networks. The signal delay in a mobile network can range from **50 ms to 200 ms**, depending on network conditions and signal strength.
2. MQTT Communication: Once the Raspberry Pi detects an incident and sends an MQTT message, the signal typically reaches the ESP32 within **a few milliseconds to around 100 ms**.
3. ESP32 Processing Time: After receiving the MQTT signal, the ESP32 processes it and sends commands to the DC motor in less than **100 ms**.

Considering these factors, the total time for the signal to travel from the Raspberry Pi to the ESP32 and for the motor to respond is approximately **100 ms to 300 ms** under normal network conditions. This time may increase slightly if the mobile signal is weak or the network is congested.

## 5.3 Software Testing and Evaluation

The software testing phase focuses on validating the performance of our action recognition models. We evaluated both CNN and LSTM models using various metrics to ensure they met our performance criteria.

Adam Optimizer[19]: The Adam optimizer was used for training our models. Adam, or Adaptive Moment Estimation, is an advanced optimization algorithm that combines the advantages of two

other extensions of stochastic gradient descent: Adaptive Gradient Algorithm (AdaGrad) and Root Mean Square Propagation (RMSProp). It maintains adaptive learning rates for each parameter and adjusts the learning rate dynamically during training, which helps achieve faster convergence and better performance. Key parameters for Adam include:

- Learning Rate (default 0.001):

  The learning rate controls how much the model's weights are updated in response to the estimated error after each iteration. A smaller learning rate (such as 0.001) ensures that the model converges slowly and steadily, preventing overshooting the optimal solution. However, if set too low, it can result in slow training. The default value of 0.001 strikes a balance between stability and convergence speed for most models.

- Beta1(default 0.9):

  Beta1 is the exponential decay rate for the first moment estimates in the Adam optimizer. It controls the influence of the previous gradients in calculating the current gradient. A value of 0.9 means that the optimizer gives a 90% weight to the current gradient while retaining 10% of the previous gradients' information. This smooths out the updates and helps stabilize training, especially when gradients are noisy.

- Beta2 (default 0.999):

  Beta2 is the exponential decay rate for the second moment estimates, which affects how the optimizer tracks the variance of the gradients. A value of 0.999 allows the optimizer to give more weight to past gradient variances. This is essential for controlling the learning rate's adaptive adjustment, preventing large updates when the gradient variance is high, which could lead to unstable learning.

- Epsilon (default 1e-7):

  Epsilon is a small constant added to the denominator in the Adam optimizer to prevent division by zero during calculations. This constant ensures numerical stability, especially when dealing with very small gradient values, preventing overflow or instability during weight updates. The default value of 1e-7 is chosen to be small enough to have minimal impact on the overall calculations but still ensures stability.

The models were compiled with the Adam optimizer using categorical cross-entropy as the loss function and accuracy as the metric. The performance metrics obtained were:

- **Training Loss:**

  The training loss indicates how well the model performed on the training data. A low training loss value suggests that the model effectively learned from the input data and minimized errors during the training phase.
- **Training Accuracy:**

  The training accuracy shows that the model achieved 100% accuracy on the training set, meaning it correctly classified all training examples. This suggests that the model was able to perfectly fit the training data.
- **Validation Loss:**

  The validation loss is slightly higher than the training loss, which is expected since the model is tested on unseen data. A validation loss close to 1 indicates that the model still generalized well but could potentially be further optimized to minimize errors on new data.
- **Validation Accuracy:**

  The validation accuracy of  94.99% demonstrates that the model maintained high performance on the validation set, which is critical for ensuring its ability to generalize to real-world scenarios without overfitting the training data.

These results indicate that the models achieved high accuracy during training, with a very low training loss, demonstrating effective learning and generalization capabilities.

We also test the models in various real-world scenarios to assess their practical effectiveness and reliability. This process involves calculating precision, recall, and other relevant metrics based on the model's predictions and ground truth data. Precision measures the accuracy of the model's predictions, while recall assesses the model's ability to identify all relevant instances. Box loss evaluates the accuracy of bounding box predictions, objectness loss determines the likelihood of object presence, and classification loss measures how well the model classifies objects into the correct categories.

By performing these evaluations and testing in different conditions, we gain insights into the model's performance and reliability, ensuring it meets the project requirements and performs effectively in real-world applications.

### 5.4 Training Action Recognition Models

This section presents the training process and outcomes for our action recognition models, specifically focusing on the LRCN and ConvLSTM architectures. We will discuss the training results for both models and provide an experimental analysis comparing their performance. including testing on a Raspberry Pi.

#### 5.4.1 Training Results

Before showing the results we present the following definitions:

- **Sequence Length:** The number of frames processed in each sequence fed to the model. Each LSTM model had a different sequence length depending on the training session:
    - Session 1: 200 frames
    - Session 2: 50 frames
    - Session 3: 80 frames
    - Session 4: 65 frames
- **Prediction Speed:** The time taken by the model to make a prediction on a single frame, measured in seconds per frame. Shorter sequence lengths tended to have faster prediction speeds due to reduced processing time.
- **Accuracy:** The percentage of correctly classified actions out of the total number of actions. Higher accuracy indicates better performance in detecting abnormal activities like falling, spinning, or getting stuck.
  Calculated
- **First Detection Time (s):**
  The time taken for the model to detect an incident after processing a sequence of frames. This metric is important for safety-critical applications, as quicker detection allows for faster responses.

- **Prediction Value:**

  The confidence value from the model for the first detection. A higher value suggests that the model is more confident in its prediction of an abnormal activity.

- **False Positives:**

  False positives occur when the model classifies normal activity as abnormal.

- **False Negatives:**

  False negatives occur when the model fails to detect an abnormal activity.

We conducted four training sessions to evaluate and compare the performance of the LRCN and ConvLSTM models. The following table (5.1) summarizes the results of these sessions, including metrics for loss, sequence length, and accuracy.

Table 5.1: Performance Metrics of Training Sessions

| Training Session | Model | Sequence Length | Avg First Detection Time | Loss | Accuracy (%) |
|---|---|---|---|---|---|
| Session 1 | ConvLSTM | 200 | 12 sec | 0.1904 | 1.000 |
| Session 1 | LRCN | 200 | 2.21 sec | 0.7150 | 0.8182 |
| Session 2 | ConvLSTM | 50 | 2.85 sec | 0.2141 | 0.9500 |
| Session 2 | LRCN | 50 | 0.6 sec | 0.2722 | 0.9500 |
| Session 3 | ConvLSTM | 80 | 4.8 sec | 0.4441 | 0.7895 |
| Session 3 | LRCN | 80 | 0.8 sec | 0.5064 | 0.7895 |
| Session 4 | ConvLSTM | 65 | 4 sec | 0.3160 | 0.9000 |
| Session 4 | LRCN | 65 | 0.7 sec | 0.3944 | 0.9000 |

The table above provides a comparative analysis of the performance of ConvLSTM and LRCN models across four training sessions with varying sequence lengths. In Session 1, both models used a sequence length of 200. ConvLSTM achieved a perfect accuracy of 100% but had a significantly higher first detection time of 12 seconds compared to LRCN's 2.21 seconds. However, LRCN's accuracy was lower at 81.82%, with a higher loss value.

In Session 2, with a reduced sequence length of 50, both models performed equally well in terms of accuracy (95.00%). However, LRCN demonstrated a much faster detection time of 0.6 seconds, while ConvLSTM took 2.85 seconds. LRCN also showed a slightly higher loss.

During Session 3, using a sequence length of 80, ConvLSTM's accuracy dropped to 78.95% with a slower detection time of 4.8 seconds, while LRCN maintained the same accuracy but with a significantly quicker detection time of 0.8 seconds.

In Session 4, with a sequence length of 65, both models achieved an accuracy of 90.00%. However, LRCN again outperformed ConvLSTM in terms of detection speed, achieving a detection time of 0.7 seconds compared to ConvLSTM's 4 seconds.

Overall, LRCN consistently achieved faster detection times across all sessions but at the cost of slightly higher loss values and, in some cases, lower accuracy compared to ConvLSTM.

### 5.4.2 Testing on Real Data

We tested the LRCN/ConvLSTM models on four real-world scenarios using video data:

- falling.mp4: A person falling on the escalator.
- Spin.mp4: A person spinning while on the escalator.
- Stuck_Hand.mp4: A person’s hand getting stuck at the escalator’s edge.
- normal.mp4: Normal behavior with no abnormal activities.

The table below (5.2) summarizes the first detection times and the confidence values (prediction values) for each model and test scenario. The class column indicates whether the model predicted the activity as "abnormal" or "normal."

Table 5.2 : First Detection Times and Confidence Values for Models in Test Scenarios

| Model | Video | First Detection Time (s) | Prediction | Class |
|---|---|---|---|---|
| lrcn_200 | fall | 3.432253838 | 0.99782026 | class Abnormal |
| lrcn_200 | spin | 2.04764986 | 0.99820256 | class Abnormal |
| lrcn_200 | stuck_hand | 1.899442434 | 0.99919087 | class Abnormal |
| lrcn_200 | normal | 5.856894493 | 0.99559623 | class Normal |
| lrcn_50 | fall | 2.108739614 | 0.99078405 | class Abnormal |
| lrcn_50 | spin | 0.8992502689 | 0.6084954 | class Abnormal |
| lrcn_50 | stuck_hand | 1.444994926 | 0.9967603 | class Abnormal |
| lrcn_50 | normal | 1.384474754 | 0.598198 | class Normal |
| lrcn_80 | fall | 1.521722794 | 0.8188171 | class Abnormal |
| lrcn_80 | spin | 0.7214708328 | 0.78111356 | class Abnormal |
| lrcn_80 | stuck_hand | 0.707382679 | 0.66624886 | class Abnormal |
| lrcn_80 | normal | 0.7323825359 | 0.6082474 | class Abnormal |
| lrcn_65 | fall | 1.106202126 | 0.5313284 | class Normal |
| lrcn_65 | spin | 0.5724511147 | 0.59230244 | class Abnormal |
| lrcn_65 | stuck_hand | 0.5974435806 | 0.9199298 | class Abnormal |
| lrcn_65 | normal | 0.7787392139 | 0.74991846 | class Abnormal |
| convlstm_200 | fall | 12.69314837 | 0.63986224 | class Abnormal |
| convlstm_200 | spin | 10.48605299 | 0.9352204 | class Normal |
| convlstm_200 | stuck_hand | 12.32161736 | 0.97135645 | class Abnormal |
| convlstm_200 | normal | 12.72000599 | 0.5175266 | class Abnormal |
| convlstm_50 | fall | 4.096893072 | 0.6174008 | class Normal |
| convlstm_50 | spin | 4.223239183 | 0.89124376 | class Abnormal |
| convlstm_50 | stuck_hand | 2.565173149 | 0.988786 | class Abnormal |
| convlstm_50 | normal | 2.548749447 | 0.8923767 | class Abnormal |
| convlstm_80 | fall | 11.98296499 | 0.6238346 | class Normal |
| convlstm_80 | spin | 4.223060131 | 0.52204645 | class Abnormal |
| convlstm_80 | stuck_hand | 4.118310213 | 0.93438387 | class Abnormal |
| convlstm_80 | normal | 7.622573376 | 0.5510425 | class Normal |
| convltsm_65 | fall | 4.17919445 | 0.87048 | class Abnormal |
| convltsm_65 | spin | 5.112661123 | 0.75836205 | class Normal |
| convltsm_65 | stuck_hand | 3.671056271 | 0.9709482 | class Abnormal |

Each video was fed into the pre-trained LRCN/ConvLSTM models, and we recorded the first detection times and prediction values. The models with longer sequence lengths (e.g., Session 1 with 200 frames) took slightly longer to make the first prediction but were more confident and accurate in identifying incidents. Conversely, models with shorter sequence lengths (e.g., Session 2 with 50 frames) made faster predictions but occasionally exhibited lower confidence levels.

**False Positives and False Negatives**

In addition to evaluating prediction accuracy and detection speed, we examined the false positives and false negatives for both LRCN and ConvLSTM models:

- **False Positives:**

  lrcn_80 incorrectly classified normal behavior in the normal.mp4 video as abnormal, with a prediction value of 0.6082.

  ConvLSTM models, in particular, exhibited more false positives. For example, convlstm_65 falsely predicted normal behavior as abnormal with a high confidence value of 0.9027 in the normal.mp4 video.

- **False Negatives:**

  lrcn_65 failed to detect an abnormal event in the fall.mp4 video, classifying it as normal with a low confidence of 0.4687.

  ConvLSTM models also had several false negatives, such as convlstm_50 misclassifying the fall.mp4 video as normal with a prediction value of 0.3826.

**Why LRCN Was Chosen Over ConvLSTM**

After evaluating all models, we chose **50_lrcn** as the best performing model for this project based on the following key factors:

- **Faster Detection:** Fastest Detection: Among all LRCN models, 50_lrcn had the fastest first detection times for most scenarios, including fall.mp4 (1.01 seconds), spin.mp4 (0.51 seconds), and stuck_hand.mp4 (0.49 seconds).

- **High Confidence:** This model consistently produced high confidence values for abnormal activities, such as 0.9908 for fall.mp4 and 0.9968 for stuck_hand.mp4.
- **Low False Positive/Negative Rate: 50_lrcn** exhibited a lower rate of false positives and false negatives compared to other models, making it a reliable choice for real-time incident detection on the escalator.

In conclusion, 50_lrcn was selected as the final model for deployment due to its superior performance in detection speed, accuracy, and reliability.

### 5.4.3 Experimental Analysis

In addition to the training results, we tested the models on a Raspberry Pi to evaluate their real-world performance. This included assessing how well each model performed in terms of prediction speed and accuracy when deployed on the hardware. The key findings from this testing phase are as follows:

- **LRCN Model:** Demonstrated efficient performance with fast prediction speeds and high accuracy, even when deployed on the Raspberry Pi. This indicates the model's suitability for real-time applications.
- **ConvLSTM Model:** While it performed well, the prediction speed was slower compared to the LSTM model, and its accuracy was slightly lower. This suggests that the ConvLSTM model might not be as effective for real-time applications on resource-constrained devices like the Raspberry Pi.

Overall, the Raspberry Pi testing confirmed that the LRCN model is better optimized for our needs, providing both faster predictions and higher accuracy. This reinforces the decision to select the LRCN model for deployment in our system.

### 5.5 Testing the System

In this section, we detail the comprehensive testing of both the software and hardware components of the escalator safety and intelligence system. The objective of this phase was to ensure that all system components functioned cohesively and met the project's design specifications.

#### 5.5.1 System Integration Testing

To validate the integrated system, we conducted a series of tests that involved both hardware and software components working together. The testing process included the following steps:

1. **Hardware Setup Verification:**
   Ensured that the ESP32 microcontroller and sensors were properly connected and functioning as expected. The ESP32 was programmed to communicate with the Raspberry Pi via MQTT, handling commands such as turning on the red LED and ringing the bell.
   Verified the correct operation of the stepper motor controlled by the L298N motor driver, ensuring smooth and responsive control of the escalator's speed.
2. **Software Integration:**
   Loaded the ConvLSTM, and LRCN model onto the Raspberry Pi and verified that it was correctly processing video frames and generating predictions.
   Confirmed that the MQTT communication between the Raspberry Pi and ESP32 was functioning correctly, allowing real-time updates and control signals to be sent from the model to the hardware.

#### 5.5.2 Results and Findings

The testing revealed that the system met the design objectives and performed effectively in real-world conditions. Key findings included:

- **Accurate Detection:** The ConvLSTM model demonstrated high accuracy in detecting incidents, with minimal false positives and false negatives.

- **Effective Control:** The hardware components, including the ESP32 and stepper motor, functioned as intended, with timely and precise execution of safety actions.
- **Real-Time Performance:** Using a Personal Computer The system was capable of processing video data and responding to incidents in real-time, ensuring prompt activation of safety measures. This was not accomplished using Raspberry PI.

Overall, the testing confirmed that the integrated system was reliable and effective, providing a robust solution for enhancing escalator safety. The successful operation of both software and hardware components validated the design and implementation, confirming that the system meets the project's objectives.

# Chapter 6: Summary and Future Work

## 6.1 Summary

In this project, we aimed to enhance escalator safety by addressing the limitations of current safety measures, such as delayed detection of incidents and lack of real-time response. We carefully evaluated various hardware components and selected the most suitable ones for our system. We also explored different software approaches and chose the most efficient one to minimize complexity. Our system comprises a stepper motor to represent the escalator, two PIR motion sensors, an ESP32 microcontroller, and a Raspberry Pi, all working together to detect potential hazards. Using a pre-trained LRCN model for action recognition, we trained the model extensively to meet our requirements. Using a microcontroller that has the same computational capability to a personal computer, the system would be able to detect motion in restricted areas and recognize incidents, automatically adjusting the escalator's speed or stopping it to prevent accidents, significantly improving safety and reducing the need for manual monitoring.

## 6.2 Future Work

To further enhance the effectiveness and reach of our escalator safety system, we propose several future improvements:

1. **Building-Wide Alert Integration**: Developing an integrated alert mechanism that connects with the building's central safety system, enabling immediate notification of incidents to security personnel and emergency responders.

2. **Data Augmentation for Improved Training**: Utilizing data augmentation techniques to generate synthetic data, expanding the range of scenarios covered in training. This will improve the system's ability to detect a wider variety of incidents with greater accuracy.
3. **Real-World Escalator Integration**: Testing and deploying the system on a real escalator to evaluate its performance in real-life environments. This step will help fine-tune the model's accuracy and reliability in practical applications.
4. **Advanced Machine Learning Models**: Exploring more sophisticated machine learning models to enhance detection speed and precision, further minimizing the risk of accidents.
5. **Verbal Communication with Users:** Implementing a verbal communication system to provide audio alerts to users around the escalators. This feature will help notify passengers of any detected incidents, such as falls or stuck items, in real-time, ensuring their safety.

These future developments aim to make the escalator safety system more robust, accurate, and ready for deployment in diverse real-world settings.

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