**EXISTING SYSTEM:**

Human Surveillance:

The existing system relies heavily on human operators who monitor multiple video feeds simultaneously. This approach is susceptible to human error, fatigue, and decreased efficiency over prolonged periods without visual stimulation.

The current system functions more like a recording system, which is primarily useful for forensic analysis rather than real-time anomaly detection.

Machine Learning Techniques:

Various machine learning techniques have been applied in different studies for anomaly detection. These include k-nearest neighbor, decision tree, linear regression, logistic regression, ordinal regression, and ensemble logistic regression. For example, Kim et al. achieved 69% accuracy using techniques like logistic regression and decision trees, while another study by Elharrouss et al. used the levenerg-marquardt technique with an accuracy of 78%​

**DISADVANTAGES OF EXISTING SYSTEM:**

Inconsistent Performance: Human operators' performance can be inconsistent due to fatigue and decreased attention over time.

High Error Rate: Traditional machine learning methods used in the existing system have a high error rate and low accuracy.

Limited Real-Time Utility: The existing system primarily serves forensic purposes rather than real-time anomaly detection, limiting its effectiveness in preventing incidents.

Resource Intensive: Requires continuous human monitoring, which is resource-intensive and not scalable.

**PROPOSED SYSTEM:**

Deep Learning Approach:

The proposed system leverages deep learning techniques, specifically Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), for detecting anomalies in pedestrian pathways.

The system uses a large dataset of images collected from various security cameras. These images undergo image processing techniques to analyze and recognize patterns.

System Architecture:

The system architecture includes input data in various forms such as pictures, audio, and video. For this study, preprocessed pedestrian picture data are used to remove duplicates.

Feature extraction and selection methods are employed to retrieve and select the most relevant features from the images.

The dataset is split into training and testing sets, and the deep learning model is trained to predict anomalies in the input images.

Implementation Steps:

Data Collection: The UCSD anomaly detection dataset is used, which includes videos captured by cameras mounted in pedestrian pathways.Data Preprocessing: Object detection and optical flow techniques are used to identify anomalies based on motion, speed, and appearance of objects in video frames.

Batch Normalization: This technique is used to accelerate the training process of the model, making it easier to understand and faster to learn from the training data​.

**ADVANTAGES OF PROPOSED SYSTEM:**

Higher Accuracy: Deep learning models, particularly CNNs, have shown improved accuracy in anomaly detection compared to traditional methods.

Real-Time Detection: The system can detect anomalies in real-time, enabling immediate response to potential threats.

Scalability: Capable of handling large datasets and can be scaled to monitor multiple locations simultaneously.

Reduced Human Error: Automates the detection process, significantly reducing the likelihood of human error.

Versatility: Can process various forms of input data, including images, audio, and video