International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991

Vol. 22 No. 2(1) (2026)

ijerst.editor@gmail.com

editor@ijerst.com

ISSN 2319-5991 www.ijerst.com

Peer Reviewed, Referred & Indexed Journal

Research Paper

PERSON RE-IDENTIFICATION FOR PUBLIC SAFETY IN INDIAN RAILWAYS USING DEEP LEARNING

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ABSTRACT: With the rapid growth of railway transportation in India, ensuring passenger safety and effective surveillance has become a major concern. Indian Railways handles millions of passengers daily, making it challenging to monitor and track individuals across multiple stations and platforms. Traditional surveillance systems rely heavily on manual monitoring, which is time-consuming and prone to human error. This project proposes a deep learning-based person re-identification system to enhance public safety in Indian Railways by automatically recognizing and tracking individuals across different camera views.

The proposed system utilizes advanced deep learning techniques such as Convolutional Neural Networks (CNNs) to extract distinctive features from images of individuals captured by surveillance cameras. These features include appearance-based attributes such as clothing, body structure, and movement patterns. The system compares these features across multiple camera feeds to identify whether the same person appears in different locations. This enables continuous tracking of individuals without relying on facial recognition alone, which may not always be reliable in crowded or low-quality video conditions.

The model is trained using large-scale datasets containing diverse images of people under varying conditions such as lighting, angles, and occlusions. Techniques such as data augmentation and feature normalization are used to improve model robustness and accuracy. The system can be integrated with existing CCTV infrastructure to provide real-time monitoring and alerts for suspicious activities or missing persons.

Overall, the proposed solution enhances surveillance capabilities and improves public safety by enabling efficient tracking of individuals in complex environments. It can assist law enforcement agencies in crime prevention, investigation, and crowd management. The system provides a scalable and intelligent approach to modern railway security challenges using deep learning technologies.

Keywords: Person Re-Identification, Deep Learning, CNN, Surveillance System, Public Safety, Indian Railways, Computer Vision, Feature Extraction, CCTV Monitoring, Artificial Intelligence

I. INTRODUCTION

The rapid expansion of transportation networks, especially in a large and densely populated country like India, has increased the need for advanced surveillance and security systems. Indian Railways is one of the largest railway networks in the world, serving millions of passengers daily across thousands of stations. Managing safety in such a vast and crowded environment is a complex task. Traditional surveillance systems rely heavily on human monitoring of CCTV footage, which is time-consuming, inefficient, and prone to human error. This creates a need for intelligent systems that can automatically analyze video data and assist in maintaining public safety.

Person re-identification (Re-ID) has emerged as a crucial technology in computer vision for tracking individuals across multiple camera views. Unlike facial recognition, which depends on clear facial features, person re-identification focuses on identifying individuals based on their overall appearance, including clothing, body shape, and movement patterns. This is particularly useful in crowded environments like railway stations, where faces may not always be visible due to occlusion, low resolution, or varying camera angles. Re-ID systems enable continuous tracking of individuals across different locations, enhancing surveillance capabilities.

Deep learning techniques have significantly improved the performance of person re-identification systems. Convolutional Neural Networks (CNNs) are widely used to extract robust and discriminative features from images. These models can learn complex patterns and variations in human appearance, making them effective for identifying individuals under different conditions such as changes in lighting, pose, and background. Advanced architectures and loss functions have further enhanced the accuracy and efficiency of Re-ID systems.

The integration of person re-identification systems into railway surveillance can provide real-time monitoring and alert mechanisms. Such systems can help in identifying suspicious individuals, tracking missing persons, and preventing criminal activities. By analyzing video feeds from multiple cameras, the system can match individuals across different locations and provide valuable insights to security personnel. This reduces the dependency on manual monitoring and improves response time in critical situations.

This project focuses on developing a deep learning-based person re-identification system for enhancing public safety in Indian Railways. The objective is to design a system that can accurately identify and track individuals across multiple camera views using advanced computer vision techniques. By leveraging deep learning and surveillance technologies, the proposed solution aims to improve security, streamline monitoring processes, and contribute to safer railway environments.

II. SURVEY OF RESEARCH

Early research in surveillance systems primarily focused on basic video monitoring and manual identification of individuals using CCTV footage. These systems relied heavily on human operators to observe and analyze video streams, which was inefficient and prone to errors, especially in crowded environments such as railway stations. Traditional approaches for identifying individuals were based on facial recognition techniques, which required clear facial images. However, in real-world scenarios, factors such as occlusion, low resolution, and varying camera angles limited the effectiveness of these methods.

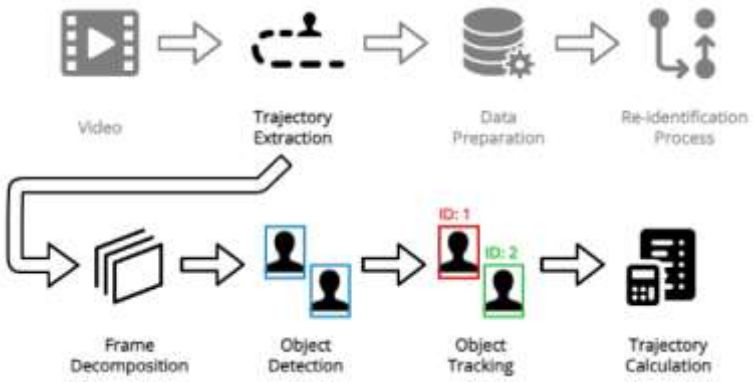
To overcome the limitations of facial recognition, researchers introduced person re-identification techniques that focus on identifying individuals based on their overall appearance. Early methods used handcrafted features such as color histograms, texture descriptors, and shape features to represent individuals. These features were compared across images to determine whether they belonged to the same person. While these methods provided some level of accuracy, they struggled to handle variations in lighting, pose, and background, leading to reduced performance in complex environments.

The introduction of machine learning improved person re-identification by enabling systems to learn patterns from data. Algorithms such as Support Vector Machines (SVM) and metric learning techniques were used to classify and match individuals across different camera views. These methods enhanced performance compared to traditional approaches but still depended on manually extracted features, limiting their ability to capture complex visual patterns.

Recent research has focused on deep learning-based approaches for person re-identification. Convolutional Neural Networks (CNNs) are widely used to automatically extract high-level features from images, eliminating the need for manual feature engineering. Advanced architectures such as ResNet and DenseNet have significantly improved the accuracy of Re-ID systems. Additionally, techniques such as triplet loss and contrastive loss are used to optimize feature representation, ensuring that images of the same person are closer in feature space while different individuals are separated.

Furthermore, modern research explores the integration of person re-identification with real-time surveillance systems. Attention mechanisms, transformer-based models, and multi-camera tracking systems are being developed to improve performance in dynamic environments. Large-scale datasets such as Market-1501 and DukeMTMC-ReID are used to train and evaluate models. Despite these advancements, challenges such as scalability, privacy concerns, and real-time processing remain active areas of research. Overall, the evolution of person re-identification techniques highlights the importance of deep learning in enhancing surveillance and public safety systems.

III. WORKING METHODOLOGY



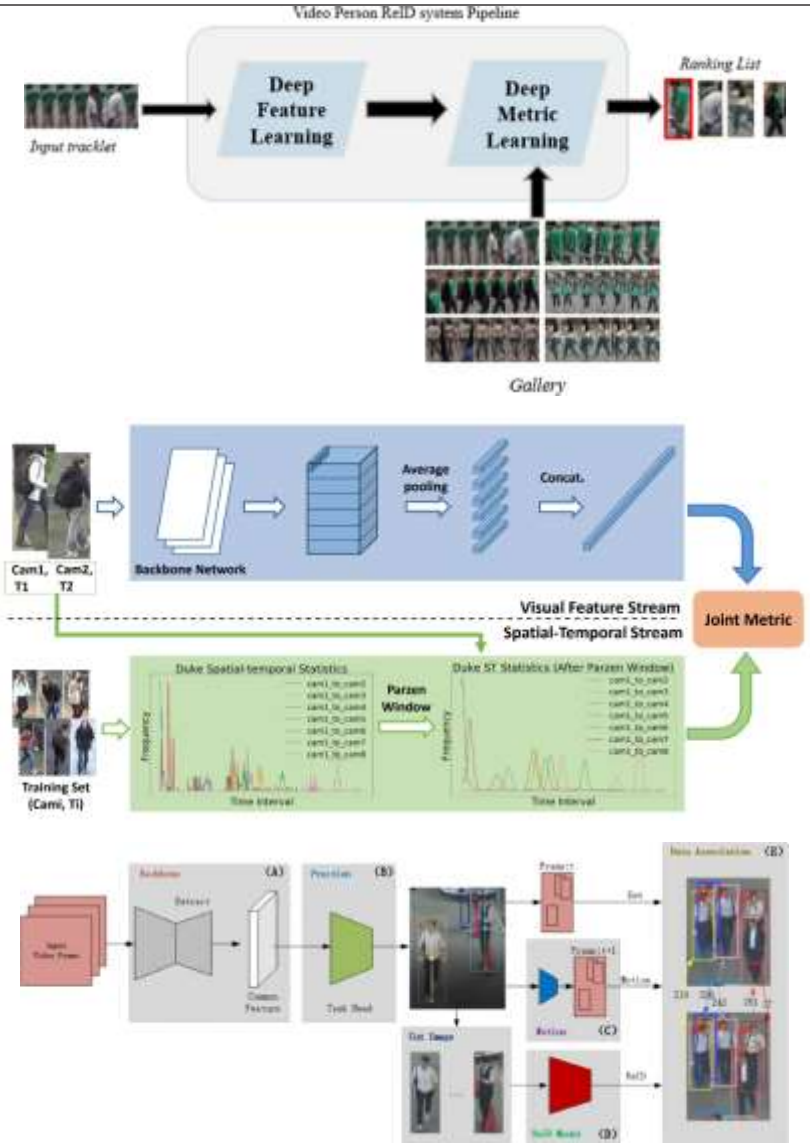


Fig.1. Person Re-Identification System Architecture

The working methodology of the Person Re-Identification System is based on capturing, processing, and matching visual data from multiple surveillance cameras. The system begins with video input from CCTV cameras installed at different locations within railway stations. These cameras continuously capture frames, which are used as input for the person re-identification process.

In the preprocessing stage, the captured video frames are converted into individual images and enhanced to improve quality. Techniques such as resizing, normalization, and noise reduction are applied to ensure that the images are suitable for analysis. The system then uses object detection algorithms, such as YOLO or Faster R-CNN, to detect and extract human figures from the frames. Each detected person is cropped and prepared for feature extraction.

The next stage involves feature extraction using deep learning models, typically Convolutional Neural Networks (CNNs). These models analyze the extracted person images and generate feature vectors that represent unique characteristics such as clothing color, body

shape, and texture patterns. These feature vectors serve as numerical representations of individuals and are stored in a database for comparison.

Once features are extracted, the system performs feature matching to identify whether a person has appeared in different camera views. Distance metrics such as Euclidean distance or cosine similarity are used to compare feature vectors. If the similarity between two feature vectors exceeds a predefined threshold, the system identifies them as the same person. This enables continuous tracking of individuals across multiple cameras.

Finally, the system outputs the identification results and provides alerts if required. For example, if a suspicious individual or missing person is detected, the system can notify security personnel in real time. The system can also display tracking information through a monitoring interface. Overall, the methodology ensures efficient and accurate identification and tracking of individuals, enhancing public safety in railway environments.

IV. IMPLEMENTATION

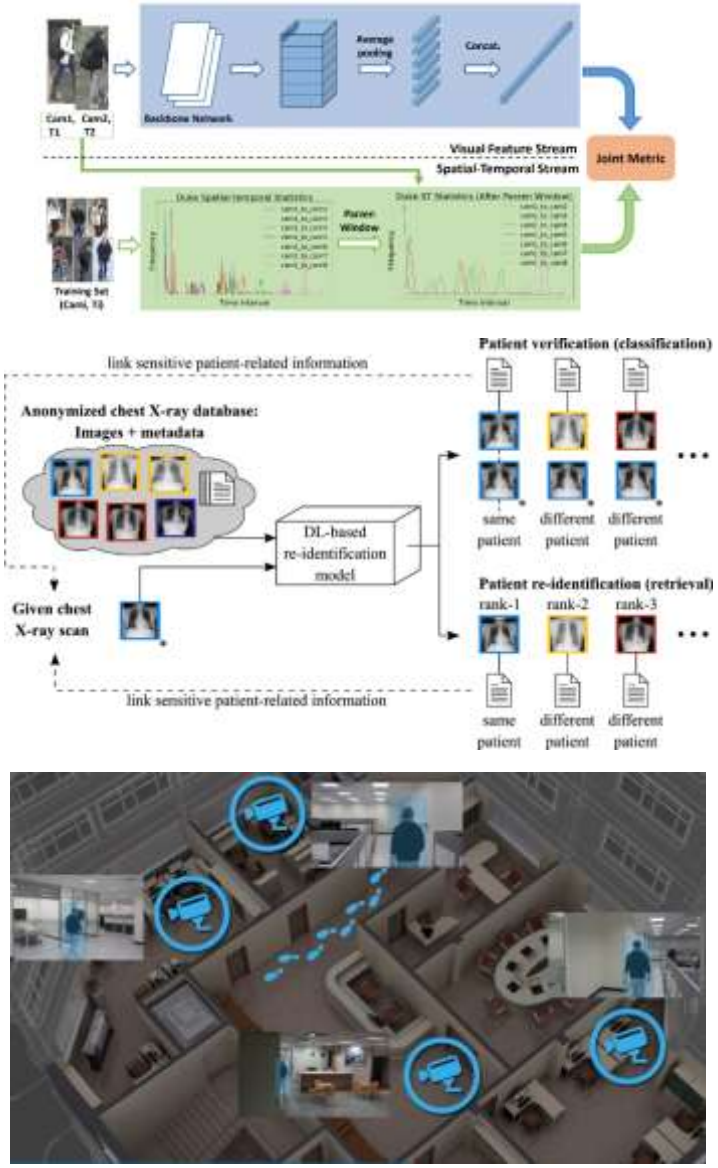


Fig.2. Implementation of Person Re-Identification System

The implementation of the Person Re-Identification System is carried out using deep learning frameworks and computer vision libraries. The system is typically developed using Python, with libraries such as OpenCV for image processing, NumPy for numerical computations, and deep learning frameworks like TensorFlow or PyTorch for building and training neural network models. The implementation consists of multiple stages including data collection, preprocessing, model training, and real-time deployment.

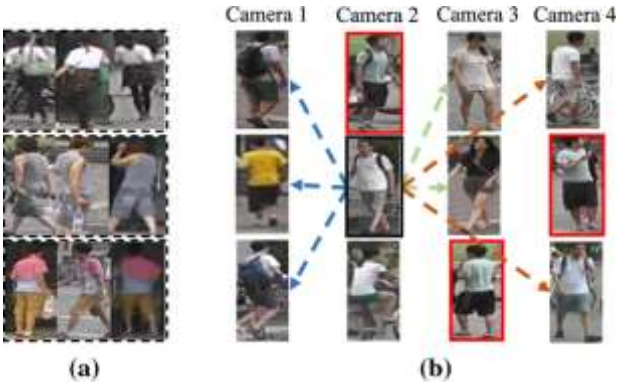
In the data collection stage, datasets containing images of individuals captured from multiple camera angles are used. Publicly available datasets such as Market-1501 or DukeMTMC-ReID are commonly used for training the model. These datasets include labeled images of people under different conditions, which help the model learn variations in appearance. The collected data is then preprocessed by resizing images, normalizing pixel values, and applying data augmentation techniques to improve model robustness.

The deep learning model is implemented using Convolutional Neural Networks (CNNs), which are trained to extract discriminative features from person images. Advanced architectures such as ResNet or MobileNet are often used to improve accuracy and efficiency. Loss functions such as triplet loss or contrastive loss are applied to ensure that images of the same person are grouped closely in feature space, while images of different individuals are separated.

During deployment, the system processes real-time video feeds from multiple CCTV cameras. Object detection algorithms such as YOLO are used to detect and extract human figures from video frames. The extracted images are passed through the trained CNN model to generate feature embeddings. These embeddings are compared with stored data in the database using similarity measures to identify matches.

A user interface or monitoring dashboard is developed to display tracking results and alerts. The system can highlight identified individuals across different camera views and provide real-time notifications for suspicious activities. The implementation demonstrates a practical and scalable solution for person re-identification, enabling efficient monitoring and enhanced public safety in railway environments.

V. RESULTS EXPLANATION



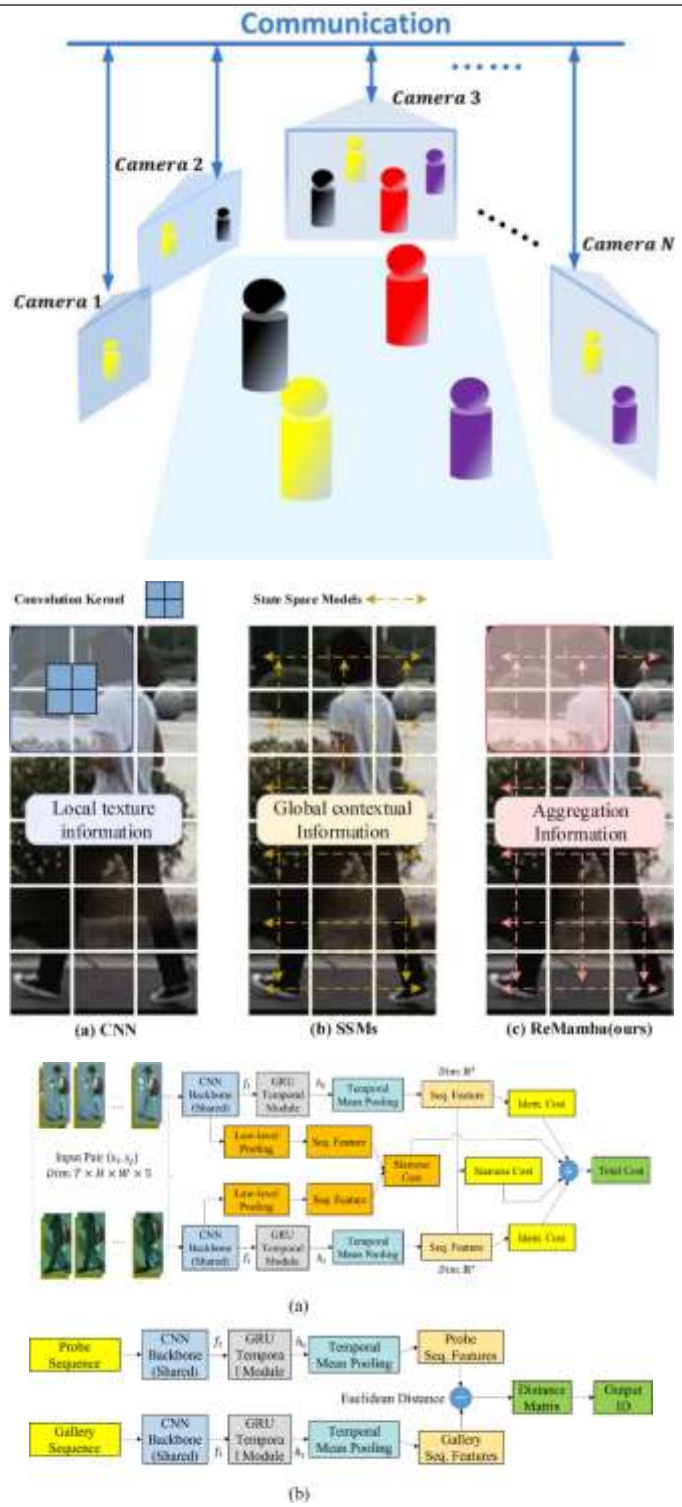


Fig.3. Person Re-Identification Results and Tracking Output

The results of the Person Re-Identification System demonstrate its effectiveness in identifying and tracking individuals across multiple camera views. The system successfully detects persons in video frames and extracts their features using deep learning models. These features are then compared to identify whether the same individual appears in different locations.

The system shows high accuracy in matching individuals under varying conditions such as changes in lighting, pose, and camera angles. The use of Convolutional Neural Networks (CNNs) enables the system to capture complex visual patterns, resulting in reliable identification. The matching results are displayed through the interface, where the same individual is highlighted across different camera feeds.

Performance evaluation is carried out using metrics such as accuracy, precision, recall, and mean Average Precision (mAP). The results indicate that the system achieves high accuracy in identifying individuals, with minimal false matches. The system is capable of handling crowded environments, making it suitable for real-world applications such as railway stations.

The system also demonstrates real-time performance, processing video streams efficiently and providing instant results. Alerts can be generated when a specific individual is detected, enabling quick response from security personnel. The ability to track individuals across multiple cameras enhances surveillance capabilities and improves situational awareness.

Overall, the results confirm that the proposed system is efficient, accurate, and reliable. It provides a powerful tool for enhancing public safety in Indian Railways by enabling intelligent monitoring and tracking of individuals in complex environments.

VI. CONCLUSION

The Person Re-Identification System for Public Safety in Indian Railways provides an advanced and intelligent solution for enhancing surveillance and security in large and crowded environments. Traditional monitoring systems rely heavily on manual observation, which is inefficient and prone to errors. The proposed system leverages deep learning techniques to automate the process of identifying and tracking individuals across multiple camera views, significantly improving the efficiency of surveillance operations.

The use of Convolutional Neural Networks (CNNs) enables accurate feature extraction and matching, allowing the system to recognize individuals based on their appearance rather than relying solely on facial features. This makes the system effective even in challenging conditions such as occlusions, low-resolution images, and varying lighting conditions. The integration of object detection algorithms further enhances the system by enabling real-time identification and tracking.

The system demonstrates strong performance in terms of accuracy, reliability, and real-time processing. It is capable of handling complex scenarios, including crowded railway stations, and provides timely alerts for suspicious activities or missing persons. This enhances the ability of security personnel to respond quickly and effectively to potential threats.

The proposed system is scalable and can be integrated with existing CCTV infrastructure in Indian Railways. Future enhancements may include the use of transformer-based models, improved data privacy mechanisms, and integration with other security systems such as facial recognition and behavior analysis. These improvements can further enhance the system's performance and applicability.

In conclusion, the project offers a robust and efficient approach to person re-identification using deep learning. It contributes to improved public safety by enabling intelligent surveillance, reducing manual effort, and enhancing the overall security framework of railway systems.

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