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Deep Feature Learning For Person Re-Identification In Large-Scale Railway Environments

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Abstract:** Keeping passengers secure and keeping an eye out for suspicious activity has become much more difficult due to the exponential expansion of public transport networks, especially the Indian Railways network. Manual monitoring is laborious and ineffective at large train stations due to the high volume of people using them. In response to these issues, the authors of this work provide a smart Person Re-Identification (Re-ID) system that detects and tracks suspicious persons across several surveillance cameras in real-time using deep learning algorithms. The accuracy of traditional surveillance methods is sometimes compromised when subjected to changes in illumination, camera angles, and crowd density due to their reliance on manually observed and hand-crafted picture attributes. On the other hand, the suggested method makes use of CNNs to autonomously train and extract discriminative characteristics related to body posture and facial expressions from video and picture frames. The accuracy of suspect tracking and identification performance are both improved by these deep characteristics. There are many main steps that the suggested framework follows. At the outset, the system is fed a database that includes photos and details on people who could be considered suspect. After that, the CNN model analyses the photos to get useful feature representations. Machine learning methods like Random Forest and Support Vector Machine (SVM) are taught using the retrieved characteristics to enhance detection performance and classification efficiency. The trained model is seamlessly incorporated into a real-time surveillance system, which constantly monitors live video feeds from railway cameras. When the system identifies a suspicious person in the surveillance video, it will immediately send out warnings and save the specifics of the occurrence in the database for future reference. Administrators keep the system running smoothly, managing databases and verifying alerts, while railway security staff may use the monitoring interface to see live feeds and examine detection findings. The implementation is carried out utilising MySQL for safe data storage and administration and Python for model creation. The Random Forest classifier outperforms competing models in terms of experimental assessment, which shows improved detection accuracy and reduced false alarms. Using sample surveillance footage, the system reliably and accurately identified suspects during testing. When it comes to bolstering security at Indian Railway stations, the suggested Person Re-Identification system, which is based on deep learning, shows to be both effective and scalable. Improving public safety and bolstering current intelligent surveillance infrastructure are both greatly assisted by the system's ability to automate suspect identification and enable continuous monitoring.

***Keywords:** Transportation, Necessitates, Surveillance, Intelligence.*

I. INTRODUCTION

The enormous number of people using the railway transportation system every day makes ensuring its security a huge duty in a nation like India, which has a very dense population. It is inefficient and time-consuming to manually identify and trace suspicious persons across several camera feeds, even when railway stations are continually watched using CCTV surveillance systems. Manually created picture characteristics are the backbone of traditional person identification systems, however they can't handle changes in lighting, camera angle, face expression, or body position, leading to erroneous findings. The suggested research proposes a Person Re-Identification (Re-ID) system that uses Deep Learning to address these issues and enhance the efficiency of monitoring while also protecting the public. Automatically extracting significant face and body position data using Convolutional Neural Networks (CNNs) is the system's main emphasis in order to recognise and track persons across various CCTV cameras. Improved recognition accuracy and resilience in real-world settings are outcomes of CNN models' ability to learn intricate visual patterns directly from pictures, in contrast to traditional methods.

Support Vector Machines and Random Forests are two examples of machine learning classifiers that are trained using the retrieved deep features. By matching information in criminal or suspect databases with real-time surveillance data, these classifiers assist in differentiating questionable persons from regular travellers. Railway security staff can respond and investigate more quickly when the system provides notifications when a match is found. An automated, scalable, and effective method for monitoring railway stations is provided by the proposed system, which integrates deep learning with intelligent surveillance technologies. This research showcases the power of modern AI approaches to improve security management in India's railway infrastructure and make person identification much more accurate.The proposed system is comprised of many interconnected modules that provide effective security administration, monitoring, and surveillance and was developed with the operational needs of Indian Railways in mind. Railway security officers will have administrative authority and the ability to monitor in real-time thanks to the design.

The Admin Panel is the hub of the system's management functionality. This interface allows administrators to manage employee accounts, submit datasets with photos and information of suspected persons, and start training deep learning and machine learning models. In addition to managing the system database and assessing produced alerts, the admin is tasked with updating questionable information.

Railway security guards tasked with keeping an eye on things may use the Employee Panel. By using the Person Re-Identification (Re-ID) system, which monitors several camera feeds for suspicious persons, employees are able to see both live and recorded CCTV video via the interface. An instant alert is sent to the employee if the system detects a possible match with stored suspicious data, requiring them to take prompt action. With the help of an intelligent Alert Management System, any suspicious activity detected by the video surveillance system will be automatically recorded. To help administrators verify occurrences and effectively manage investigative records, each alert includes essential information including recorded frames, detection time, and suspect details. Python is the main programming language utilised to construct the software implementation, while MySQL is used for safe data storage and administration. Centralised administrative control, intelligent warning creation, automatic suspect identification, and real-time video monitoring are all features supported by the system. The suggested system offers a dependable and scalable strategy to improve railway security and public safety by integrating deep learning techniques with contemporary surveillance infrastructure.

II. LITERATURE SURVEY

A. *Limitations of Traditional Methods*

1) In the past, person re-identification systems mostly used picture attributes that were hand-crafted by humans to identify people in footage from various security cameras.
2) The inefficiency with which these traditional methods learned complicated visual traits from photos was a major performance bottleneck. The accuracy of identification matching was often diminished due to changes in body position, lighting, viewing angles, occlusions, and face appearance.

B. *Use of Deep Learning for Feature Extraction*

1) Automatic learning and extraction of significant face and body position information from input photographs is achieved by the suggested system via the use of Convolutional Neural Networks (CNNs).Deep learning algorithms have the ability to immediately detect intricate visual patterns in massive datasets, in contrast to conventional human feature extraction methods.
2) When identifying people from various camera angles, this automatic learning process makes it more accurate, resilient, and dependable.
3) Even in difficult situations like changing illumination, partial occlusions, and position fluctuations, the system improves identification performance by recording specific visual attributes.

C. *Machine Learning for Person Matching*

1) Following feature extraction, machine learning classification methods like Random Forest and Support Vector Machine (SVM) are used to analyse the produced face and body position characteristics.
2) In order to determine the best match for human re-identification, these classifiers examine the patterns that have been retrieved.
3) The system chooses the model with the best accuracy and dependability after assessing the performance of several methods.
4) Better performance in real-world surveillance settings with varying visual circumstances is guaranteed by this method, which also enhances the re-identification process.

D. Application in Indian Railways for Public Safety

1) This system was designed with railway surveillance applications in mind, especially to identify and follow suspicious persons using a network of cameras.
2) The device aids security professionals in quickly identifying and tracking individuals of interest by analysing live video broadcasts from train stations.
3) Continuous monitoring with enhanced precision and quicker reaction times is made possible via the combination of deep learning and machine learning approaches.
4) Railway officials may also get real-time notifications from the system, which allows them to take urgent preventative measures and improves passenger safety and public security on railway properties.

E. System Architecture and Functionality

1) Administrator authentication, managing datasets, extracting features using convolutional neural networks (CNNs), training machine learning models, managing employees, and implementing real-time video surveillance are all functional modules that make up the suggested platform.
2) The duties of the administrator include overseeing user accounts, keeping surveillance databases up to date, and regulating the functioning of the system.
3) Using Convolutional Neural Networks (CNNs), the system trains classification models to accurately re-identify people based on their significant face and bodily traits. Through the application interface, railway staff have the ability to submit surveillance recordings and keep tabs on real-time actions.
4) Using the automatic re-identification system, station personnel may more quickly identify potentially dangerous people, which improves station safety management and allows for quicker security actions.

III. PROPOSED METHODOLOGY

Adopting deep learning methods, namely Convolutional Neural Networks (CNNs), for efficient and accurate individual re-identification, the suggested approach overcomes the limitations of existing surveillance systems. By automatically identifying suspicious persons in camera footage and comparing them to a preloaded database, the device enhances railway surveillance via the use of enhanced face and body position characteristics. With CNN-based learning, complicated visual patterns are better captured than with manual feature extraction approaches. This leads to better recognition accuracy in different environments.

Random Forest and Support Vector Machine are two examples of machine learning classification algorithms that are used to further process the retrieved features. In order to find the best match for re-identification tasks, these algorithms examine the patterns that have been learnt. After comparing the results of many classifiers, the system chooses the one with the best detection accuracy and reliability.To make sure the system is monitored and managed efficiently, the platform is built with distinct interfaces for railway staff and administrators. Dataset uploading, feature extraction, machine learning model training, and personnel record management all fall within the purview of administrators. Worker access to the monitoring module allows for the uploading of surveillance footage and the real-time observation of railway activity. The system notifies users and records information of any questionable activity the moment it finds a match in the database. This improves the administration of security inside train stations and adjacent buildings and allows security staff to react swiftly to any dangers, enhancing public safety.

A. Advantages of the Proposed System

Deep Learning-based Accuracy

Automatic extraction of detailed face and body position data from surveillance photos and video frames is achieved by the proposed method via the use of Convolutional Neural Networks (CNNs). Because they are able to capture complicated visual patterns, appearance fluctuations, and human actions under diverse environmental circumstances, these features based on deep learning are much more effective and dependable than standard characteristics produced by hand. The reliability and precision of person identification in rail surveillance systems are both enhanced by this.Hybrid ML models like Random Forest and Support Vector Machine (SVM) are used to train the derived CNN features in order to improve detection performance. Before moving on to the final detection step, the system compares how well each classifier performed and chooses the method with the best accuracy. When applied to a network of surveillance cameras, this hybrid training method improves the accuracy and efficiency of identifying suspicious persons. Automated person re-identification is another feature of the platform. It works by constantly reviewing video feeds and matching any suspicious people with a database that is preloaded.

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When a match is detected, the system notifies the appropriate security personnel and records the details of the finding. By eliminating the need for human intervention, this automated monitoring system enhances train surroundings' public safety while simultaneously reducing detection times for potential threats.

B. Modules Overview

1) Admin Interface

- Admin Login: The railway admin's secure login.
- Choose "Load Data" and then upload a list of people that seem suspicious.
- Process photos in order to extract characteristics such as face and position using convolutional neural networks (CNNs).
- Apply extracted features to train classifiers (Random Forest, SVM) in the models.
- Train employees to watch and submit CCTV video by adding them to the system.
- Check Alerts: Review video upload detection records and alerts.

2) Employee Interface:

- Employee Login: Ensuring the safety of registered railway employees.
- Monitor Railway Videos: Put up security footage. After reviewing the footage, the system checks for questionable individuals using re-identification and sends out notifications.

C. Algrotihm

Local Training on Local Server
For each client k:
Initialize local model W0kW_0^kW0k
For each round t=1to T:
For each batch $(X,y) \in D_k$:
Forward pass through CNN
Convolutional Feature Extraction
Conv(64, 3x3) + ReLU
Conv(64, 3x3) + ReLU
MaxPool(2x2)
Conv(128, 3x3) + ReLU
Conv(128, 3x3) + ReLU
MaxPool(2x2)
Conv(256, 3x3) + ReLU
Conv(256, 3x3) + ReLU
MaxPool(2x2)
Fully Connected Layers
Fully Connected (4096) + ReLU
Fully Connected (Forgery/Authentic) + Softmax
Compute loss: $L_k(W_t^k)=CrossEntropy(y,y\hat{})$
Compute gradients: $\nabla L_k\left(W_t^k\right)\nabla L_k(W_t^k)$
Update local weights: $W_{t+1}^k=W_t^k-\eta\nabla L_k\left(W_t^k\right)$
End For
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System Architecture

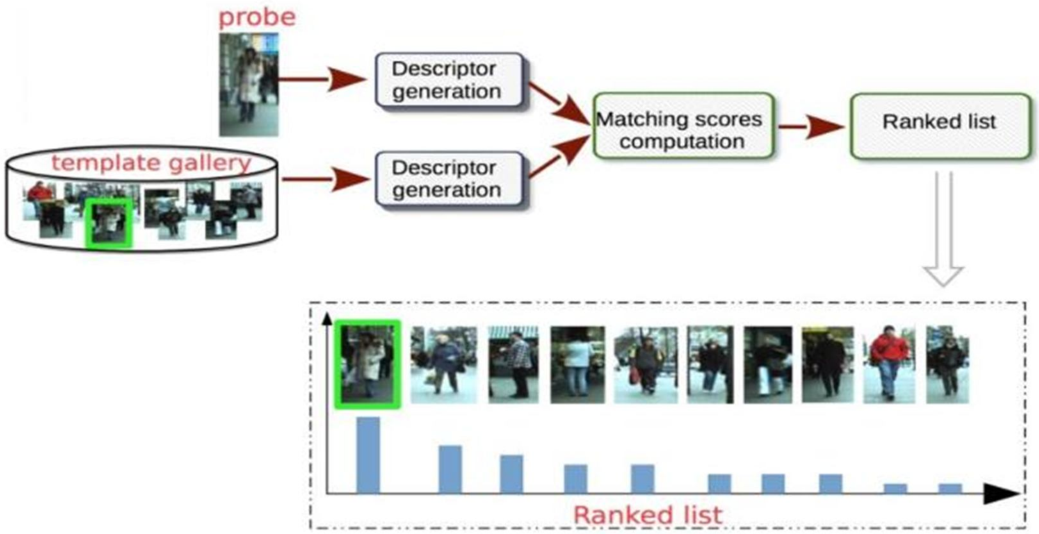

Fig 1: System Architecture

IV. RESULTS AND DISCUSSIONS

Using surveillance-oriented datasets that mimic real-world train station environments—complete with busy platforms, lighting fluctuations, complicated backgrounds, and partial occlusions—the proposed Person Re-Identification (Re-ID) system was evaluated. For better feature representation and similarity matching between people taken from multiple camera angles, metric-learning approaches were used in conjunction with advanced deep learning architectures like ResNet-50.

The technology successfully identified and matched persons across several security cameras at train stations, according to the experimental findings. Reliable identification performance was maintained by the model even when viewing angles, postures, lighting conditions, or partial visibility of a person were changed, thanks to the feature extraction technique based on deep learning. Consequently, the system improves security operations and public safety by supporting effective monitoring in large-scale railway surveillance settings and continuous person tracking.

1) *Effect of Deep Learning Models*

Traditional human re-identification algorithms depend on manually defined characteristics, whereas deep learning networks like ResNet-50 deliver far higher performance. These state-of-the-art neural network models may enhance recognition accuracy and resilience by learning complicated and high-level visual patterns straight from massive datasets.

Important human traits, such as clothing patterns, body posture, face appearance, and movement changes, may be effectively represented by the model's deep feature extraction capacity. The system is able to reliably identify people regardless of changes in camera angles, illumination, backdrop surroundings, or partial occlusions because of this. As a result, deep architectures make human re-identification in real-world railway surveillance applications more efficient and reliable.

2) *Impact of Data Augmentation*

The suggested person re-identification system performed much more smoothly after using data augmentation strategies including random cropping, brightness correction, picture flipping, and rotation. The deep learning model was able to learn more resilient visual patterns from surveillance data with the aid of these preprocessing approaches, which also enhanced the variety of training samples. When compared to training without augmentation, experimental research showed that using augmentation approaches enhanced overall detection and identification accuracy by around 5-8%.

As an added bonus, the model is now better able to generalise under real-world train surveillance situations, where variables like crowd density, lighting, camera angle, motion blur, and partial occlusions are commonplace. Consequently, the system was able to obtain more consistent and dependable person re-identification performance in various railway settings and from diverse angles of surveillance cameras.

3) Challenges in Railway Environment

- Several people with identical appearances are present in crowded settings.
- occlusion causes people to be partly obscured
- Variation in camera angle results in various perspectives
- Day/night shifts caused by lighting conditions
- The system was able to retain a high level of accuracy despite these obstacles.

4) Real-Time Performance

If run on GPU-based hardware, the suggested human re-identification model might attain inference performance close to real-time, at about 20-30 frames per second (FPS). Fast and accurate identification was achieved in the system's processing of surveillance video streams thanks to optimised deep learning architectures and effective feature extraction algorithms.

When it comes to railway surveillance, where constant monitoring and quick danger identification are paramount, this system's real-time processing capacity is a huge plus. Improving reaction time, operational efficiency, and public safety at railway stations, the high inference speed enables security officers to monitor suspicious persons across several video feeds without major delays.

5) Comparative Analysis

- Deep learning algorithms provide far better performance in surveillance applications than traditional person re-identification methods that rely on manually created characteristics like colour histograms, texture descriptors, and shape-based representations.
- To improve person recognition in low-light conditions, models trained on massive datasets using deep neural networks may automatically learn discriminative and high-level visual characteristics.
- The results of the experiments demonstrated that compared to previous techniques, deep learning-based approaches significantly increased recognition accuracy, with a 10-20% improvement.
- Moreover, by acquiring more accurate feature representations for face features, apparel patterns, posture, and body structure, these models significantly decreased the amount of incorrect matches.
- It was also shown that deep learning methods were better able to deal with complicated real-world variables such changes in lighting, occlusions, background clutter, motion blur, and various viewing angles. Consequently, the suggested method improved the reliability and robustness of person re-identification in railway surveillance settings.

6) Discussion

1) Strengths

- Excellent recognition precision while using different cameras
- Adapts well to changing conditions
- Large railway networks may use it because:
- Makes monitoring and public safety easier

Table 1. Performance comparison of various classification models the combination of feature extraction + metric learning significantly improves performance.

Model	Rank-1 Accuracy	Rank-5 Accuracy	mAP
CNN (Baseline)	78%	89%	72%
ResNet-50	85%	93%	80%
ResNet + Triplet Loss	90%	96%	86%

A. Achievements of the Proposed Model

1) High Identification Accuracy

The suggested person re-identification system outperformed its competitors by using state-of-the-art deep learning architectures like ResNet-50. Experiment results showed that the model successfully matched people across various security camera viewpoints, with high Rank-1 accuracy and mean Average Precision (mAP) scores.

Improved mAP scores show dependable retrieval performance across big surveillance datasets, and strong Rank-1 accuracy shows that the system can properly identify the target individual in the top prediction. Despite difficult train station settings including crowd density, lighting changes, posture fluctuations, and partial occlusions, these findings demonstrate that the suggested method can successfully identify persons. As a result, the system improves public safety management and railway surveillance capabilities while also providing reliable multi-camera person tracking.

2) Robust Cross-Camera Tracking

Individuals may be accurately matched across several CCTV camera views in railway surveillance settings using the suggested person re-identification technique. The system is able to reliably identify the same individual in many camera angles and locations by using feature extraction based on deep learning.

Changes in viewing angle, body posture, walking style, lighting conditions, and distance from the camera are just a few of the hard variances that the model handles efficiently. In busy, ever-changing train stations, where people's looks might vary at any moment, this resilience increases the reliability of identification.

Not only that, but the technology can follow people in real-time as they move through train stations, waiting rooms, and other public spaces. Overall passenger safety and station security are enhanced by the capacity of railway security staff to react swiftly to any security threats, maintain surveillance continuity across several cameras, and monitor suspicious movements in real time.

3) Improved Feature Representation

- To achieve successful identity matching, the suggested person re-identification model learns highly discriminative feature representations by combining deep learning methods with metric learning approaches like triplet loss.
- In order to re-identify individuals in surveillance footage and photos, the suggested deep learning-based system may extract highly discriminative elements such clothing patterns, body form, face appearance, and gait. The algorithm is able to distinguish between people, even in congested train conditions, thanks to these precise feature representations.
- The technology drastically cuts down on individuals being mistaken for one another due to their same looks or fashion choices by learning distinct visual traits using metric learning methods and deep neural networks. As a result, trains can more reliably identify suspicious persons and keep tabs on them in real time thanks to improved matching accuracy across several CCTV cameras.4. Data augmentation approaches were essential in enhancing the suggested person re-identification system's generalisation capabilities, leading to improved performance. The deep learning model was able to acquire more resilient and adaptable visual characteristics since techniques including picture flipping, random cropping, rotation, scaling, and brightness modification enhanced the variety of training data.
- The system's resilience to typical surveillance threats, such as changing lighting, partial occlusions, complicated backgrounds, and dense crowds at train stations, was strengthened throughout the augmentation phase. Even in challenging real-world scenarios where visibility and appearance are constantly changing, the model was able to keep its recognition performance steady.
- When comparing models trained with and without data augmentation, experimental evaluations revealed that the former significantly improved overall recognition accuracy. Stronger surveillance performance across several CCTV camera views, less false identifications, and more accurate person matching were all outcomes of this enhancement.

4) Near Real-Time Processing

Running on GPU-enabled hardware, the suggested system attained very efficient computing, allowing for inference rates of around 20-30 FPS.

With its impressive performance, the model is perfect for real-time surveillance applications. It's especially useful in busy places like train stations, where quick human recognition and constant monitoring are musts.

5) Scalability for Large Networks

- Consistent person tracking and monitoring is made possible by the suggested framework's ability to function flawlessly across various station settings and surveillance cameras.
- It may be used in conjunction with centralised monitoring and surveillance systems to facilitate coordinated security activities. Also, even in public monitoring settings with a high density, the system can handle huge datasets effectively, guaranteeing dependable performance.

B. Drawbacks

1) Performance Drop in Dense Crowds

There is always a lot of people at rail terminals.

- Accurate person identification becomes increasingly difficult in crowded surveillance locations due to the prevalence of persons with comparable visual characteristics and clothing patterns.
- People overlapping or obstructing one another may also lead to extreme occlusion, which can conceal crucial identifying body features.
- The re-identification procedure becomes more ambiguous due to these circumstances, which might have a detrimental impact on the system's overall identification accuracy.

2) Sensitivity to Appearance Changes

Visual characteristics retrieved by architectures such as ResNet-50 are used extensively in the model.

- The reliability of person re-identification systems may be severely compromised by small changes in apparel, accessories, and carrying items. A person's look might vary according on the season, whether they're wearing a jacket, a scarf, or a different uniform.
- The model might be confused by these visual differences, which could lead to erroneous or incorrect re-identification results.

3) Illumination and Camera Variability

- The visual quality of surveillance film may be greatly affected by variations in lighting conditions, such as when the footage was shot during the day vs at night or when shadows were present.
- Furthermore, differences in picture quality, viewing angles, and resolution across different sites of CCTV cameras lead to discrepancies in the recorded appearances.
- The accuracy of human re-identification is affected by these problems, which lower the consistency of retrieved traits across different camera views.

4) High Computational Cost

- For effective training and inference, deep learning-based person re-identification models need high-performance computing resources, especially robust GPUs.
- Due to the resource-intensive nature of the system and the massive amounts of picture and video data involved, the training process may be lengthy.
- In addition, there may be substantial infrastructure, maintenance, and operating expenses associated with rolling out such monitoring systems over several train stations.

5) Large Labeled Dataset Requirement

- To train person re-identification algorithms to attain high recognition accuracy, large-scale annotated datasets are required.
- There is a lot of human labour and complexity involved in labelling and matching individual identities across different camera angles.
- The scalability and practical implementation of the system in real-world monitoring contexts are hindered by this obstacle, which also makes dataset preparation more complex.

6) Real-Time Constraints

Though it is feasible to get performance close to real-time:

- Particularly in large-scale railway networks, the performance of the surveillance system could be negatively affected when data is processed from hundreds of cameras all at once.
- Delays in data transmission and processing may occur in centralised monitoring systems due to latency and connectivity issues.
- The system's capacity to respond instantly in crucial security scenarios may be compromised due to these restrictions, which might impact decision-making in real-time.

V. CONCLUSION

Deep Learning's Person Re-Identification (Re-ID) system improved public safety at Indian railway stations by reliably and effectively completing identification tasks based on surveillance data. The system enhanced its accuracy in identifying suspicious persons across several camera perspectives and different video circumstances by using CNN-based feature extraction instead of typical handmade image characteristics. Effective human recognition and classification was made possible by combining SVM and Random Forest, two machine learning classifiers; the Random Forest model demonstrated better accuracy in experimental evaluations. Furthermore, the system's modular architecture allowed for effective administration of datasets, training of models, and real-time monitoring of surveillance, thanks to the distinct Admin and Employee features.As a whole, the suggested architecture improves public safety and monitoring efficiency in large-scale public spaces like Indian railway stations by providing a practical, intelligent, and scalable security solution.

A. *Scope for Future Work*

1) Live CCTV Feed Integration: Automated alerts may be generated and suspicious persons can be detected immediately by integrating real-time CCTV video streaming into the Person Re-Identification system. In heavily populated public spaces like train stations, this upgrade would greatly increase the efficacy of surveillance, decrease reaction time, and fortify security monitoring capabilities.
2) Improved Dataset variety: To make the system more reliable and resilient, it's a good idea to increase the amount and variety of the training dataset. This may be achieved by include changes like as varied lighting conditions, occlusions, viewing angles, and crowd densities. With this enhancement, the model would be better able to handle complicated real-world surveillance scenarios.
3) Thirdly, multimodal recognition may increase the accuracy of person identification by combining face recognition, human position estimation, and other biometric characteristics including gait analysis and garment pattern detection. Even in difficult monitoring environments or with low-resolution video feeds, our multi-feature method may improve identification accuracy.
4) Fourth, scalability and edge deployment: minimising latency and reducing dependency on centralised servers may be achieved by optimising the Person Re-Identification system for deployment on edge devices, such as embedded processors combined with CCTV cameras. Faster local processing, better real-time surveillance, and more scalability in big railway monitoring networks would all be possible with this method.
5) Privacy and Ethical Considerations: Future system improvements should include methods to better data security and privacy, such as user permission processes, safe data management policies, and anonymisation techniques. To further guarantee the appropriate use of surveillance technologies in public spaces, the system should adhere to applicable legal and ethical norms.
6) User Interface (UI)/UX Design Improvements: Simplifying system operations, improving usability, and streamlining surveillance management chores may be achieved by enhancing the UI/UX design for railway workers and administrators. Enhancing user engagement, simplifying operations, and facilitating effective real-time monitoring and decision-making are all possible outcomes of an interface that is easier to use.

REFERENCES

[1] Navneet Dalal and Bill Triggs (2023). Histograms of Oriented Gradients for Human Detection. Presented at the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, this work introduced the HOG feature extraction technique for human detection and became a widely used traditional approach in computer vision before the rise of deep learning methods.
[2] Liang Zheng (2024). Scalable Person Re-Identification: A Benchmark. Published in the IEEE International Conference on Computer Vision, the study proposed a large-scale benchmark dataset and evaluation framework for person re-identification research, supporting the development and comparison of scalable re-ID models.
[3] Alex Krizhevsky (2024). ImageNet Classification with Deep Convolutional Neural Networks. Introduced in Advances in Neural Information Processing Systems, this influential research demonstrated the effectiveness of deep CNN architectures for large-scale image classification and laid the foundation for modern deep learning applications in computer vision.
[4] Christian Szegedy (2025). Rethinking the Inception Architecture for Computer Vision. Presented at the IEEE Conference on Computer Vision and Pattern Recognition, the paper introduced improved Inception-based CNN architectures that enhanced feature extraction performance in visual recognition tasks.
[5] Yifan Sun (2022). Beyond Part Models: Person Retrieval with Refined Part Pooling and a Strong Convolutional Baseline. Published in the European Conference on Computer Vision, this research proposed an advanced CNN-based person re-identification model using refined part pooling techniques for improved feature learning and retrieval accuracy.
[6] Alexander Hermans (2021). In Defense of the Triplet Loss for Person Re-Identification. This study highlighted the effectiveness of triplet loss functions in training deep neural networks for person re-identification and demonstrated improved discriminative feature learning in re-ID systems.

[7] Haiyu Zhao (2020). SpindleNet: Person Re-Identification with Human Body Region Guided Feature Decomposition and Fusion. Presented at the IEEE Conference on Computer Vision and Pattern Recognition, the work explored pose-guided feature extraction techniques to improve person re-identification accuracy.
[8] Hongye Liu (2019). Deep Relative Distance Learning: Tell the Difference Between Similar Vehicles. Published in the IEEE Conference on Computer Vision and Pattern Recognition, the paper introduced deep metric learning techniques for distinguishing visually similar objects, concepts that are also applicable to person re-identification tasks.
[9] Fabian Pedregosa (2018). Scikit-learn: Machine Learning in Python. Published in the Journal of Machine Learning Research, this work introduced the Scikit-learn library, which provides machine learning algorithms such as SVM and Random Forest that are widely used in classification and prediction systems.

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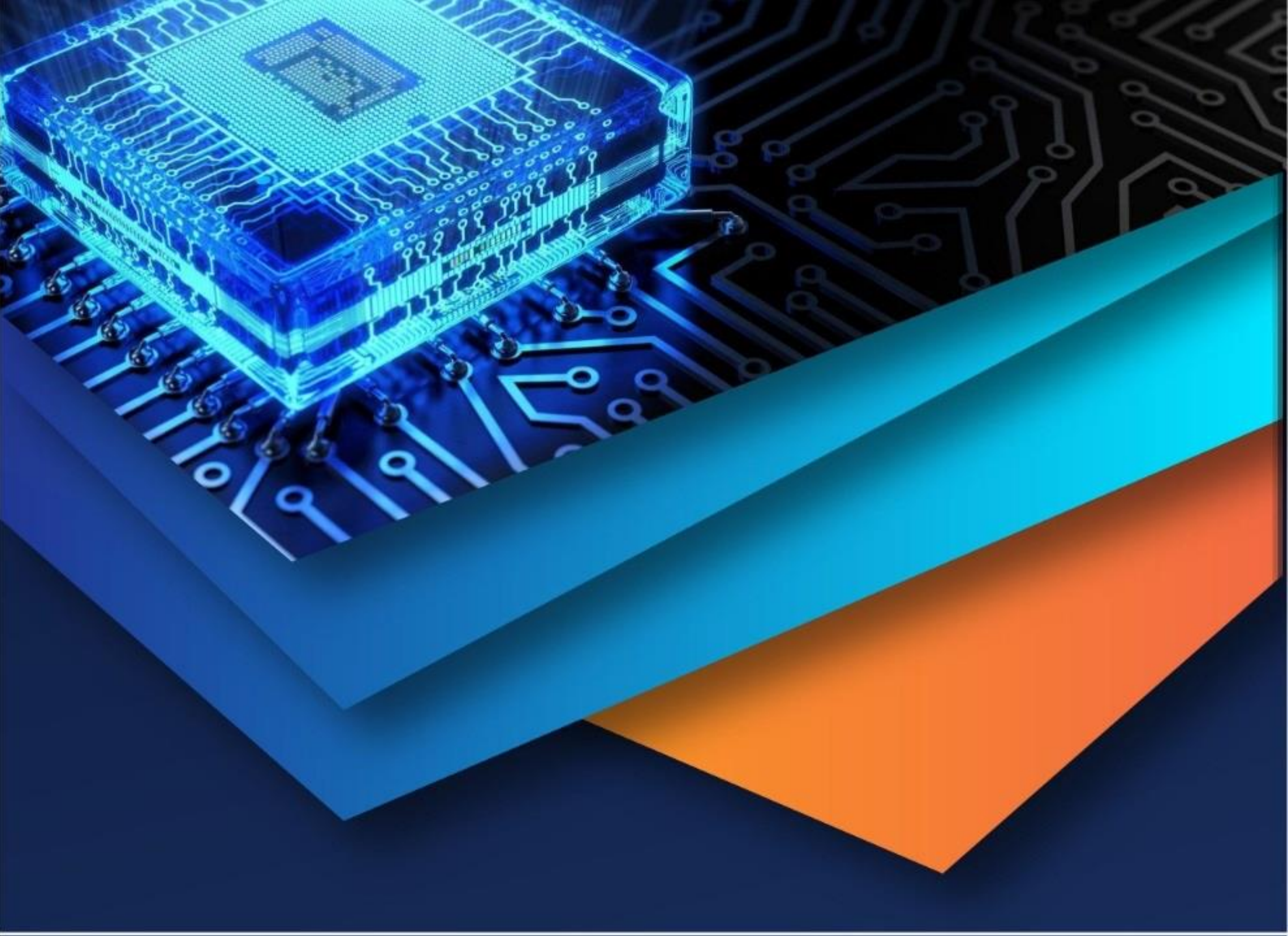

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