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Crowd Density Estimation in Railway Coaches

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Abstract

Crowd Density Estimation in Railway Coaches with the growing demand for public transportation and with the increasing use of unreserved coaches, overcrowding has become a major concern regarding passenger safety, comfort, and operational control. Traditional methods of monitoring crowd levels rely heavily on manual observation, which is ineffective and leads to errors. Currently, no effective crowd monitoring system is used in these compartments. The program processes captured images using Histogram of Oriented Gradients (HOG) to extract important visual patterns. The extracted features are classified into low, medium, and high crowd levels using multiple machine learning models trained and tested on railway coach images collected under different crowd density conditions. Performance is evaluated using Accuracy, Precision, Recall, and F1-score, with the MLP Neural Network achieving the highest accuracy of 94.7%. Whenever high crowd density is detected, an email alert along with the captured image is automatically sent to the railway authorities for timely action. By combining HOG-based feature extraction, multiple machine learning models, and an automated email alert mechanism, the proposed system provides a practical, cost-effective, and scalable solution for real-time crowd monitoring, improving passenger safety and efficient crowd management inside railway coaches.

Keywords

Crowd density, HOG, alert system, passenger, coach monitoring

Introduction

Railway transportation is one of the most widely used and affordable modes of travel, particularly in countries such as India, where millions of passengers rely on trains for daily commuting. Unreserved railway coaches frequently experience overcrowding during peak hours, weekends, and festive seasons, leading to passenger discomfort, restricted movement, reduced travel quality, and increased safety risks during emergency situations (Luan & Corman, 2022; Tjandra et al., 2024). Efficient crowd monitoring has therefore become an important requirement for ensuring passenger safety, improving operational efficiency, and supporting intelligent transportation management.

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Several studies have explored crowd management in public transportation. Meghana et al. (2020) developed an automated crowd management system for public bus transportation, demonstrating the effectiveness of automation in monitoring passenger density. Although these approaches provide promising results, their dependence on computationally intensive deep learning architectures may limit their applicability in low-resource environments. In addition, sensing-based crowd management solutions using IoT devices, surveillance sensors, and communication technologies have been extensively reviewed by Darsena et al. (2023). While these systems improve crowd monitoring and information dissemination, they often require expensive sensing infrastructure and complex deployment, increasing implementation costs in large-scale railway networks.

The major challenge is the absence of an efficient real-time crowd monitoring system inside railway coaches. Existing approaches mainly rely on manual observation, which is often inconsistent, time-consuming, and unsuitable for continuous monitoring (George et al., 2023). Consequently, overcrowding situations are frequently detected too late, affecting passenger safety and operational efficiency.

To address this issue, this study proposes a real-time crowd density estimation system using computer vision and machine learning techniques. Images captured inside railway coaches are preprocessed and transformed into numerical features using Histogram of Oriented Gradients (HOG). These features are then classified using Random Forest, XGBoost, LightGBM, and MLP Neural Network models to categorize crowd density into low, medium, and high levels. An automated email alert mechanism is also incorporated to notify railway authorities when overcrowding is detected.

The proposed system offers a practical and cost-effective solution for crowd monitoring in railway coaches. By enabling real-time density estimation and automated alerts, it enhances passenger safety, improves crowd management, and supports the development of intelligent railway transportation systems.

Methodology

The proposed system uses computer vision and machine learning techniques to estimate crowd density inside railway coaches in real time. The dataset consists of railway coach images collected from publicly available sources and categorized into three classes: Low, Medium, and High crowd density. Images captured by a camera are preprocessed, relevant features are extracted, and trained models classify the crowd level as Low, Medium, or High, while overcrowding conditions automatically trigger alerts to railway authorities for timely action.

A. Experimental Setup

The experimental setup of the proposed system is designed for real-time crowd density estimation inside railway coaches using image-based analysis. The dataset consists of images categorized into Low, Medium, and High crowd density classes and organized for efficient training. To improve robustness, data augmentation techniques such as horizontal flipping, Gaussian blurring, and brightness adjustment are applied. All images are resized to 128 × 128 pixels to maintain uniformity. The system supports both offline training and real-time testing using a webcam or laptop camera. Trained models and preprocessing components, including scalers, are stored using serialization techniques, enabling efficient reuse without retraining. Overall, the setup is simple, cost-effective, and suitable for practical real-world deployment.

B. Proposed Framework

The proposed methodology begins with image acquisition using a camera to capture crowd conditions inside railway coaches. The captured images are resized to 128 × 128 pixels and converted into grayscale during preprocessing. HOG is then used to extract meaningful features representing crowd patterns and human presence. These features are scaled and used to train Random Forest, XGBoost, LightGBM, and MLP Neural Network models. The dataset is divided into training and testing sets, and the models are evaluated using Accuracy, Precision, Recall, and F1-score. In real-time deployment, the trained model classifies crowd density as Low, Medium, or High, and automatically generates an alert when overcrowding is detected.

Image Acquisition and Preprocessing

The methodology begins with image acquisition using a camera inside the railway coach, where a laptop webcam is used in the prototype to capture images under low, medium, and high crowd conditions. The captured images are resized to 128 × 128 pixels and converted to grayscale format to ensure consistency, reduce computational complexity, minimize lighting and background variations, and provide reliable input for feature extraction and classification.

Feature Extraction Phase

After preprocessing, feature extraction is carried out using the Histogram of Oriented Gradients (HOG) technique. This method analyzes gradient directions and edge orientations within the image to capture important structural information. The image is divided into smaller cells, and gradient information is computed for each cell. These gradients are then grouped into histograms and normalized across blocks to reduce the effect of illumination changes. Figure 1 shows the original to HOG Feature Vector and Figure 2 shows the original Crowd Image versus Gradient Directions.

Table 1. Visual Perception

S. NO	HUMAN PERCEPTION	COMPUTER INTERPRETATION
1.	People	Pixel values
2.	Crowd	Intensity changes
3.	Body shapes	Gradient directions
4.	Density	Histogram Pattern

Figure 1. Original to HOG Feature Vector

Figure 2. Original Crowd Image VS Gradient Directions

HOG focuses on shape and edge information rather than color, making it robust to lighting and background variations. It captures human silhouettes and crowd patterns as fixed-length feature vectors, improving classification accuracy while reducing noise and computational complexity.

Training and Model Evaluation

The extracted features are used to train machine learning models. The dataset is divided into training and testing sets using an 80:20 ratio with stratified sampling to maintain class balance. To address class imbalance, Random Under Sampling is applied. Feature scaling is performed using StandardScaler to normalize the data, ensuring that all features contribute equally during training. The performance of each model is evaluated using standard metrics. These evaluation measures provide a clear understanding of the effectiveness of each model and help in selecting the most suitable approach for accurate crowd density classification.

Decision Logic and Alert System

After training, the selected model is deployed in a real-time system to classify crowd density as Low, Medium, or High from captured images. If a high crowd level is detected, the system automatically sends an email alert containing the crowd level, date and time, coach number, and captured image, enabling timely response and effective crowd management. Figure 3 shows the High Crowd Alert Email Output.

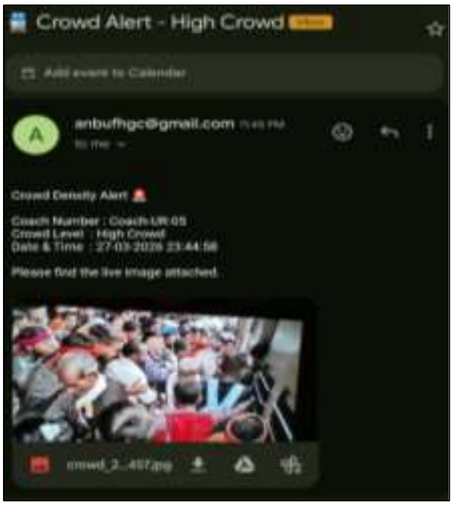

Figure 3. High Crowd Alert Email Output

C. System Architecture

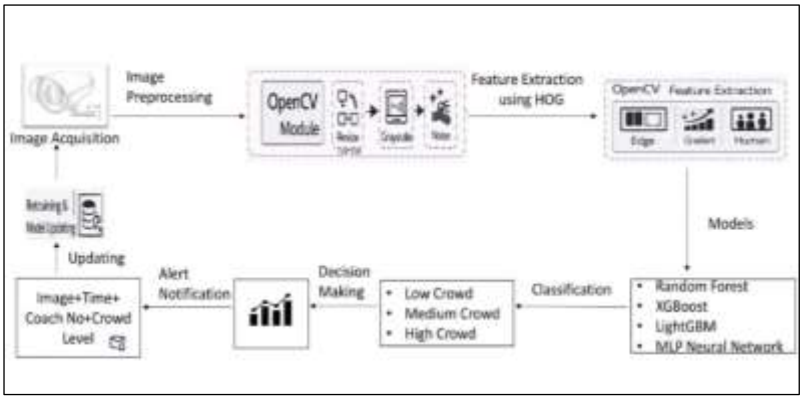

Figure 4. Architecture Diagram

The system architecture in figure 4 begins with capturing images inside a railway coach using a camera. The images are preprocessed using OpenCV by resizing them to 128 × 128 pixels, converting them to grayscale, and reducing noise. HOG is then used to extract edge and gradient-based features, which are classified by Random Forest, XGBoost, LightGBM, and MLP Neural Network models to predict crowd levels as Low, Medium, or High, with MLP achieving the best performance. Based on the prediction, the system generates email alerts during high crowd conditions and supports continuous improvement through periodic model retraining with new data. The architecture follows a sequential workflow, ensuring that each processing stage contributes to accurate crowd density estimation. The modular design allows individual components, such as preprocessing, feature extraction, or classification, to be updated without affecting the overall system. This approach improves the system's reliability, scalability, and suitability for real-time railway crowd monitoring applications.

Results and Discussion

This part explains the findings achieved after deploying the suggested crowd density estimation system within railway coaches. Some machine learning models that had been trained on HOG based features derived on live images were used to test the system. The review generally analyzes the extent to which the models are correct in categorizing the various levels of crowds, each level is accurately predicted, and the overall performance of the system is dependable and reliable under real-life circumstances.

Performance Evaluation: There are some simple evaluation measures that are used to review the overall performance of each model as indicated in the table below. These findings provide a straightforward clue of the level of identification of the various crowd levels by each model.

Table 2. Performance Metrics

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	0.9318	0.9336	0.9318	0.9318
XGBoost	0.9091	0.9140	0.9091	0.9091
LightGBM	0.9192	0.9225	0.9192	0.9191
MLP Neural Network	0.9470	0.9489	0.9470	0.9469

Based on the outcomes, MLP Neural Network is more effective than other models. It performs best overall and has minimal mistakes during the process of determining the levels of the crowds.

Model Accuracy Comparison: The region plot is the best demonstration of the overall trend of the performance of all the classifiers. The Accuracy Area Chart is an effective comparison of the accuracy of each model and it is easily comprehensible to see how the performance of each model compares with the performance of the other. Figure 5 shows the accuracy area chart.

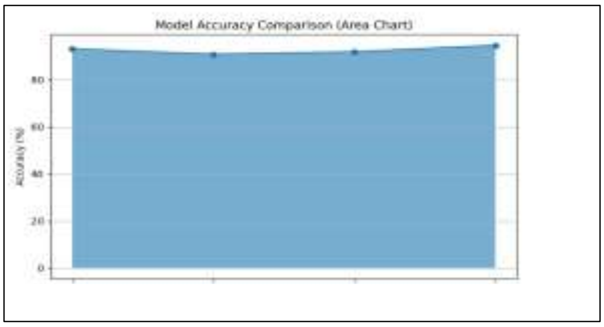

Figure 5. Accuracy Area Chart

Confusion Matrix Analysis: The performances of the various models were observed using normalized confusion matrices to read the performance of each model over the different different crowd levels. Most of the predictions are correctly classified along the diagonal, indicating that all four models effectively distinguish between the Low, Medium, and High crowd density categories. A small number of misclassifications occur mainly between the Low and Medium classes because these crowd levels share similar visual characteristics. Figure 6 shows the confusion matrix of the XGBoost while figure 7 shows the confusion matrix of the LightGBM.

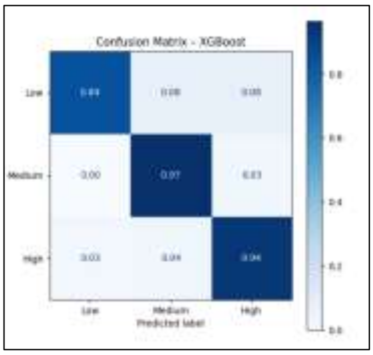

Figure 6. Confusion Matrix of the XGBoost

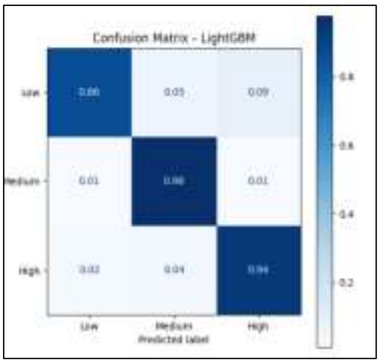

Figure 7. Confusion Matrix of the LightGBM

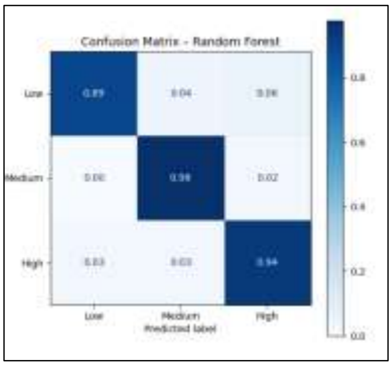

Figure 8 Confusion Matrix of the Random Forest

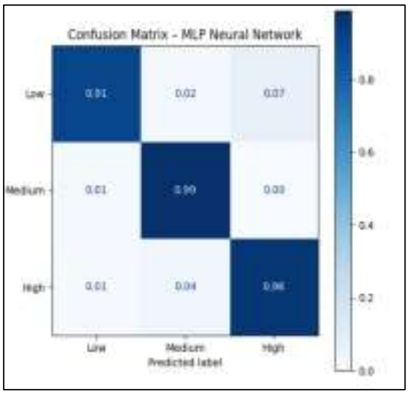

Figure 9. Confusion Matrix of the MLP Neural Network

Random Forest and LightGBM show better class separation than XGBoost, while the MLP Neural Network achieves the best overall performance with the highest number of correct predictions and the fewest classification errors. These results demonstrate that the proposed framework can reliably classify crowd density levels and is suitable for real-time railway coach monitoring. Figure 8 shows the confusion matrix of the random forest and figure 9 shows the confusion matrix of the MLP neural network.

The results of the confusion matrix indicate that the system is a steady and balanced system across all levels of crowds.

- The highest accuracy reached is 94.7%.
- Among all the models, the MLP Neural Network gives the best results.
- The predictions for each crowd level are fairly even, with only a few mistakes.
- The results show that the system can clearly tell the difference between the crowd levels.
- It can be used for real-time monitoring and sending alerts when needed.

The study demonstrates that a machine learning–based framework can effectively estimate crowd density inside railway coaches with a focus on real-time and practical deployment. The results show that the system is capable of accurately classifying crowd levels into low, medium, and high categories using visual pattern analysis. Unlike many existing approaches that rely on complex deep learning models, the proposed method uses Histogram of Oriented Gradients (HOG) to capture structural features such as shapes, spacing, and human presence, which contributes to efficient and reliable performance. This observation aligns with earlier studies that emphasize the importance of feature-based methods for reducing computational complexity while maintaining accuracy. The ability of the system to operate on standard computing devices highlights its practicality and suitability for real-world railway environments, where cost and scalability are important considerations. Furthermore, the integration of an automated alert mechanism ensures timely communication with authorities, enabling quicker response to overcrowding situations. However, the system's performance may be influenced by factors such as variations in lighting conditions, camera angles, and occlusions, which were not extensively addressed in the current setup. Overall, the findings indicate that lightweight machine learning approaches can provide an effective alternative to resource-intensive models for real-time crowd monitoring applications.

Conclusion

This study presented an intelligent and cost-effective system for crowd density estimation in railway coaches using computer vision and machine learning techniques. The proposed approach employs image preprocessing and Histogram of Oriented Gradients (HOG) for feature extraction, followed by classification using multiple machine learning models. The experimental results demonstrated that the system can accurately classify crowd density into low, medium, and high levels, with the MLP Neural Network achieving the highest performance among the evaluated models, and the system also operates successfully in a real-time setup by generating automated alerts when overcrowding is detected. The findings emphasize the importance of lightweight and efficient machine learning models for real-world applications, particularly in environments with limited computational resources, as the system enables real-time monitoring, improves passenger safety, enhances travel comfort, and supports better decision-making for railway authorities, while also showcasing the practical application of artificial intelligence in transportation systems. However, the study has certain limitations, including the use of a controlled experimental setup, a relatively small dataset, and reliance on single-camera inputs; therefore, future research can focus on extending the system to continuous video analysis, incorporating multi-camera setups for better coverage, improving robustness under varying conditions such as lighting and occlusions, integrating mobile and IoT-based alert systems, and utilizing larger and more diverse datasets, along with continuous model updates and real-world deployment to enhance reliability and scalability.

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