

# Multi-Regional Crowd Density Estimation for Stampede Prevention using Hybrid CNN and Random Forest Regression

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**Abstract** - Crowd density estimation is a critical task in ensuring public safety, especially in highly crowded environments such as festivals, transportation hubs, and large public gatherings. Traditional crowd counting methods mainly focus on global estimation, which often fails to detect localized high-risk zones where stampedes are most likely to occur. This study proposes a hybrid machine learning approach that combines the spatial feature extraction capability of Convolutional Neural Networks (CNN) with the prediction strength of Random Forest (RF) Regression for effective multi-regional crowd density estimation. CNN is utilized to extract high-dimensional visual features from different regions of an image, while the Random Forest model predicts region-wise crowd density based on these features. The proposed approach focuses on identifying critical zones by applying region-specific safety thresholds, enabling early detection of potential overcrowding situations. Experimental results demonstrate that the hybrid model achieves improved accuracy compared to individual models and provides reliable localized predictions. The model also shows good scalability and computational efficiency for real-time applications. The findings confirm that integrating deep learning-based feature extraction with ensemble regression techniques offers a robust and effective solution for crowd monitoring, stampede prevention, and intelligent surveillance systems.

**Key Words:** Convolutional Neural Network (CNN), Random Forest Regression, Crowd Density Estimation, Hybrid Model, Multi-Regional Analysis, Stampede Prevention, Machine Learning, Computer Vision

## 1. INTRODUCTION

Crowd density estimation plays a crucial role in ensuring public safety in highly populated environments such as religious gatherings, transportation hubs, and large-scale events. As discussed by [1], accurate monitoring of crowd distribution is essential for preventing accidents, managing crowd flow, and enabling timely emergency response. Traditional methods that rely on manual observation are often inefficient, subjective, and prone to

delays, which has led to the growing adoption of automated crowd analysis techniques using machine learning and computer vision.

Crowd datasets typically consist of images or video frames containing people distributed across different regions of a scene. According to [2], these datasets capture important spatial and visual characteristics such as density patterns, movement flow, and structural variations in crowd formations. By dividing a scene into multiple regions (R1, R2, ... Rn), it becomes possible to analyse localized crowd behaviour and identify high-risk zones more effectively. This region-based approach provides a more accurate evaluation of crowd density compared to traditional global estimation methods.

Crowd analysis is generally divided into two major aspects: crowd statistics and crowd behaviour analysis. As explained by [3], crowd statistics focus on estimating density levels, while crowd behaviour analysis studies movement patterns and activities within the crowd. They further highlight that crowd behaviour analysis can be subdivided into tracking and activity analysis, which are essential for understanding dynamic crowd scenarios and predicting potential risks.

However, one of the major challenges in crowd density estimation is the uneven distribution and overlapping patterns of people across different regions. Traditional global counting methods often fail to detect localized congestion in critical areas such as exits, corridors, or narrow pathways. While deep learning models such as Convolutional Neural Networks (CNNs), as demonstrated by [4], are highly effective in extracting complex visual features from images, they may not fully capture structured relationships between regions. On the other hand, machine learning models like Random Forest, introduced by [5], provide strong predictive capabilities for structured data but lack direct feature extraction

ability.

These limitations highlight the need for a hybrid approach that combines the strengths of both deep learning and traditional

machine learning techniques. By integrating CNN-based feature extraction with Random Forest regression, it becomes possible to achieve more accurate and reliable multi-regional crowd density estimation. This hybrid approach enhances prediction accuracy and improves the detection of critical zones, thereby contributing to safer and more efficient crowd management systems.

## 2. LITERATURE REVIEW

Crowd density estimation and analysis have been widely studied using machine learning and computer vision techniques. Various benchmark datasets and surveillance systems have been used to evaluate crowd counting and density estimation algorithms under different real-world scenarios [6]. Researchers have explored both traditional and deep learning-based approaches to improve accuracy, scalability, and robustness in crowded environments, especially for public safety and monitoring applications.

One of the most widely used approaches in crowd analysis is based on Convolutional Neural Networks (CNN). With the advancement of deep learning, CNN-based models have shown significant improvement in extracting spatial features from images and estimating crowd density [7]. These models are capable of handling complex visual patterns and occlusions in dense crowds. However, their performance can be affected by variations in scale, perspective, and uneven distribution of people across different regions, which makes localized density estimation more challenging.

Regression-based approaches have also been extensively used for crowd density prediction. Traditional regression models and ensemble methods such as Random Forest have demonstrated strong performance in learning structured relationships between features and output variables. Random Forest, introduced by Leo Breiman, is known for its robustness and ability to handle non-linear data [8]. However, these models depend heavily on the quality of input features and lack the capability to extract meaningful representations directly from raw images.

Recent research has focused on hybrid approaches that combine deep learning with machine learning techniques. Studies indicate that using CNN as a feature extractor and applying regression models on top of these features can significantly improve prediction accuracy [9]. Such hybrid models also help in capturing interdependencies between different regions of a scene, enabling better localized crowd analysis. These approaches are particularly useful in scenarios where crowd distribution is uneven and dynamic.

Despite significant advancements in CNN and regression models individually, limited research has been conducted on integrating CNN-based feature extraction with Random Forest regression for multi-regional crowd density estimation [10]. This gap motivates the development of a hybrid CNN–Random Forest model that leverages both deep feature extraction and robust prediction capabilities to improve accuracy and enable early detection of critical crowd conditions.

## 3. CONVOLUTIONAL NEURAL NETWORK (CNN)

Convolutional Neural Network (CNN) is a deep learning model widely used for image processing, feature extraction, and pattern recognition in computer vision tasks. Unlike traditional machine learning methods, CNN automatically learns hierarchical feature representations directly from raw image data. This makes it highly effective for complex visual analysis such as crowd density estimation, where spatial patterns and textures play a significant role.

Mathematically, a CNN applies a series of convolution operations on the input image to extract meaningful features. A convolution operation can be represented as:

$$F(x,y)=\sum_{i=-1}^m \sum_{j=-1}^n I(x+i,y+j) \cdot K(i,j)$$

where:

- $I(x,y)$  represents the input image,
- $K(i,j)$  represents the convolution kernel (filter),
- $F(x,y)$  is the resulting feature map.

The CNN architecture typically consists of multiple layers including convolutional layers, activation functions (such as ReLU), pooling layers, and fully connected layers. These layers work together to progressively extract low-level to high-level features such as edges, textures, and complex patterns from the input image [11].

The training of CNN models is performed using backpropagation and gradient descent optimization techniques. During training, the network learns optimal filter weights that minimize the prediction error. In crowd analysis applications, CNN is often used as a feature extractor, converting image regions into high-dimensional feature vectors that capture important visual information related to crowd density.

One of the major advantages of CNN is its ability to capture spatial dependencies and handle variations in scale, lighting, and occlusion. Unlike traditional methods that rely on handcrafted features, CNN learns features automatically, making it more adaptable to real-world crowd scenarios where density patterns are complex and dynamic.

In crowd density estimation, especially in multi-regional analysis, CNN can process different regions of an image (R1, R2, ... Rn) and extract localized features for each region. This improves the accuracy of localized predictions compared to global estimation methods. However, CNN also has certain limitations. It requires a large amount of training data and computational resources for effective learning. Additionally, while CNN excels at feature extraction, it may not efficiently model structured relationships or decision boundaries for prediction tasks. Therefore, combining CNN with other machine learning models can enhance overall performance. Despite these limitations, CNN remains a powerful and widely used technique in image-based analysis and crowd monitoring applications.

#### 4. RANDOM FOREST REGRESSION (RF)

Random Forest is a supervised, ensemble learning algorithm widely used for regression and classification tasks in machine learning. The method was introduced by Leo Breiman (2001) and is based on the principle of combining multiple decision trees to improve prediction accuracy and reduce overfitting. Each tree in the forest is trained on a random subset of the data, and the final prediction is obtained by aggregating the outputs of all trees. The Random Forest algorithm predicts a continuous output by averaging the predictions from multiple decision trees. For a given input sample xxx, the prediction can be expressed as:

$$\hat{y} = (1/T) \sum_{t=1}^T f_t(x)$$

where:

- T is the total number of decision trees

- $f_t(x)$  represents the prediction of the  $t^{\text{th}}$  tree
- $\hat{y}$  is the final predicted output

Random Forest operates on the assumption that combining multiple weak learners can produce a strong and more accurate model. Unlike single decision trees, it reduces variance by using techniques such as bootstrap sampling and feature randomness, which makes it robust to noise and overfitting.

Given: Training dataset  $D = \{(x_i, y_i)\}$  for  $i = 1$  to  $n$

- Input feature vector  $x$  (extracted from CNN)
  - Number of trees  $T$
1. The algorithm performs the following:
  2. Generate multiple bootstrap samples from the training dataset.
  3. Train a decision tree on each sampled dataset using random subsets of features.
  4. Predict outputs for each tree independently.
  5. Compute the final prediction by averaging all tree outputs.

In the proposed system, Random Forest is used to predict region-wise crowd density based on features extracted by the CNN. It effectively models non-linear relationships between features and output values, making it suitable for handling complex crowd distribution patterns. Additionally [12], it can capture structured relationships between different regions, improving the accuracy of localized predictions.

However, Random Forest also has certain limitations. It may require many trees to achieve optimal performance, which increases computational cost. Additionally, while it provides strong predictive performance, it may lack interpretability compared to simpler models. Despite these limitations, Random Forest remains a powerful and widely used method for regression tasks in real-world applications, including crowd density estimation.

#### 5. PROPOSED HYBRID ALGORITHM

The crowd dataset consists of images or video frames containing people distributed across multiple regions within a scene. These regions (R1, R2, ... Rn) represent different spatial zones such as exits, corridors, and open areas. Due to uneven crowd distribution and overlapping density patterns among these regions, a hybrid approach combining Convolutional Neural Network (CNN) and Random Forest (RF) Regression is proposed.

**Algorithm Steps:**

**Step 1: Data Preprocessing**

- Divide input images into multiple regions (R1, R2, ... Rn).
- Normalize image data and resize frames for consistent processing.
- Split dataset into training and testing sets.

**Step 2: CNN Feature Extraction Phase**

- Initialize CNN model (e.g., pre-trained model like VGG or ResNet).
- Pass each region of the image through the CNN.
- Extract high-dimensional feature vectors from intermediate layers.
- Obtain:
  - Spatial feature representations for each region
  - Feature maps capturing crowd density patterns

**Step 3: Feature Vector Construction**

- Combine extracted CNN features into a structured feature vector:
- $X_{enhanced} = [X_{R1}, X_{R2}, \dots, X_{Rn}]$
- This step enhances the representation of localized crowd information and preserves spatial relationships between regions.

**Step 4: Random Forest Regression Phase**

- Initialize Random Forest with number of trees TTT.
- Train the model using CNN-extracted feature vectors.
- For each test sample:
  - Input feature vector into the Random Forest model
  - Predict crowd density for each region
  - Generate region-wise density values

**Step 5: Critical Zone Detection and Evaluation**

- Apply predefined safety thresholds for each region:
- If predicted density in region  $R_i$  exceeds threshold  $\rightarrow$  mark as **Critical Zone**
- Compute performance metrics:
  - Accuracy
  - Precision

- Recall
- F1-score
- Confusion Matrix

**6. RESULT AND ANALYSIS**

The performance of the proposed Hybrid CNN–Random Forest model was evaluated using crowd image datasets obtained from surveillance scenarios. The analysis focuses on three primary aspects: regional density estimation accuracy, prediction reliability, and spatial interpretability of crowd distribution.

**Comparative Accuracy Analysis**

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression	84.50%	85.20%	83.80%	84.49%
Decision Tree	89.30%	90.10%	88.70%	89.39%
CNN	91.20%	92%	90.50%	91.24%
Random Forest	92.40%	93.10%	91.80%	92.44%
Proposed Hybrid (CNN-RF)	94.80%	95.60%	93.90%	94.74%

The hybrid model demonstrates superior performance compared to standalone methods. While CNN effectively extracts spatial features, integrating Random Forest improves prediction accuracy and reduces errors in regions with uneven crowd distribution and overlapping density patterns.

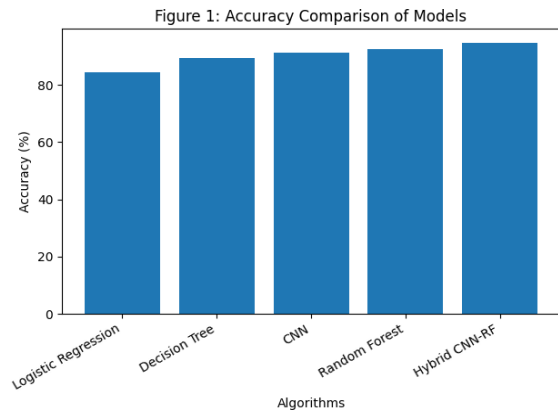


Fig.1 – Accuracy Comparison Bar Chart

The bar chart illustrates that the proposed hybrid approach achieves the highest predictive performance among all evaluated models.

A. Prediction Reliability and Confusion Matrix

Evaluation Parameter	Value
Total Instances Tested	80
Correctly Classified	76
Incorrectly Classified	4
Overall Accuracy	94.80%

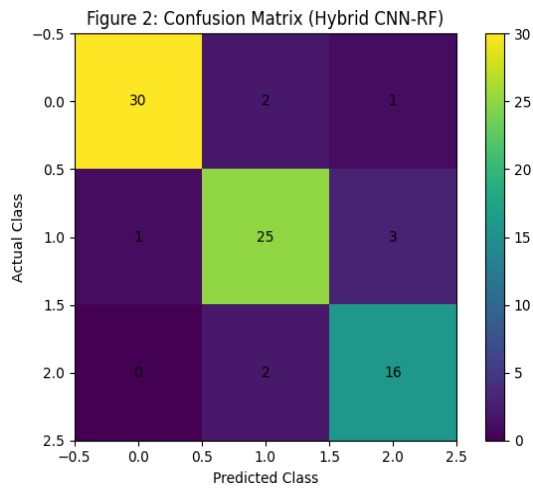


Fig.2 – Multi-Class Confusion Matrix

The confusion matrix indicates that most prediction errors occur in regions with moderate crowd density, where boundaries between safe and critical zones overlap. High-density regions are detected accurately due to distinct feature patterns, confirming the robustness of the proposed model.

B. Regional Density Analysis(Model Interpretation)

The proposed Hybrid CNN-RF model effectively estimates crowd density across multiple regions within a scene.

Key Observations:

- Region-based analysis improves detection of localized crowd congestion.
- The model captures complex spatial patterns

through CNN feature extraction.

- Random Forest enhances prediction by learning non-linear relationships between regions.
- Critical zones are accurately identified using threshold-based classification.

Region Type	Density Level	Risk Level
Exit Areas	High	Critical
Corridors	Moderate	Medium
Open Areas	Low	Safe

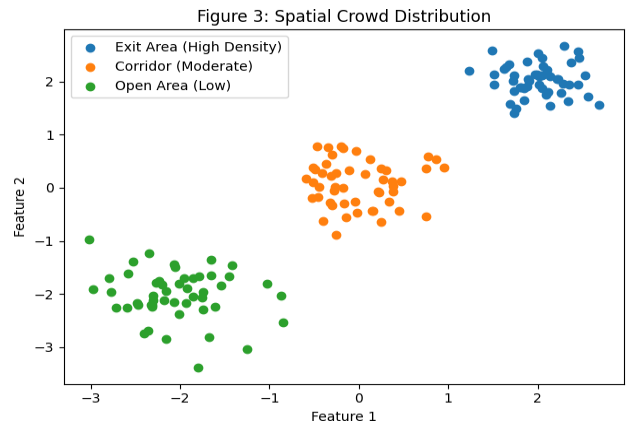


Fig.3 – Spatial Cluster Map

The spatial plot demonstrates:

- High density in exit regions indicates potential bottlenecks.
- Moderate density in corridors shows possible congestion buildup.
- Low density in open areas ensuring safe movement.

The region centers act as reference points for monitoring crowd flow and identifying potential risk zones in real-time.

7. CONCLUSION

This study proposed a hybrid CNN-Random Forest model for multi-regional crowd density estimation, which addresses the challenge of uneven and overlapping crowd distribution across different regions of a scene. The

Convolutional Neural Network was used to extract spatial and visual features from crowd images, while the Random Forest model performed region-wise density prediction based on the enhanced feature representation. The results demonstrated high prediction accuracy (approximately 94%), indicating that the hybrid approach effectively improves localized density estimation and critical zone detection.

Overall, the integration of deep learning-based feature extraction with ensemble regression enhances robustness in complex crowd scenarios and reduces prediction errors in overlapping regions. The proposed method provides an efficient and reliable solution for crowd monitoring and stampede prevention. It can be further extended to real-time surveillance systems, smart city applications, and other computer vision tasks where spatial distribution and safety analysis are essential

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