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Crowd Behaviour Monitoring using Anomaly Detection Approaches from Smart Phone Sensor Data

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ABSTRACT

Modern crowd-monitoring relies heavily on fixed CCTV networks and manual video analysis, which are costly, privacy-intrusive, and prone to human error and blind spots. Rule-based or simple vision analytics further struggle with occlusion, lighting variations, and lack adaptability across environments. To address these challenges, our work leverages ubiquitous smartphone inertial sensors (accelerometer and gyroscope) to detect and classify six human activities via machine learning. This sensor-driven approach offers a low-cost, privacy-preserving, and scalable solution for real-time anomaly detection in diverse public and private settings. This research presents a complete pipeline for monitoring crowd behaviour via anomaly detection on smartphone sensor data. We employ a public Human Activity Recognition dataset with 7,352 samples and 561 time- and frequency-domain features (accelerometer/gyroscope statistics), labeled across six activities (standing, sitting, laying, walking, walking_upstairs, walking_downstairs). A Tkinter GUI guides users through data upload, preprocessing (missing-value imputation, label encoding, visualization), model training, evaluation, and prediction. Two classifiers are compared: a single Decision Tree (DTC) and an ensemble Random Forest (RFC). The RFC attains a macro-averaged precision of 98.23%, recall of 98.24%, F1-score of 98.23%, and overall accuracy of 98.16%, versus the DTC's precision/recall/F1 around 94% and accuracy of 95%—an absolute accuracy gain of ~3.2 points and a 4-point lift in F1. ROC curves and confusion matrices confirm the RFC's superior discriminative power and reliability in both positive and negative predictions. Finally, the trained RFC can label new sensor recordings in real time via the same GUI.

Keywords: Anomaly Detection, Sensor Data, Decision Tree Classifier (DTC), Random ForestClassifer (RFC), Crowd Monitoring.

1.INTRODUCTION

Due to expeditious technological growth and pervasiveness, wearable sensing have become an integral part of many research areas such as, human activity recognition (HAR) [1]. HAR is an essential component in various application domains such as, smart healthcare [2], surveillance [3], human–computer interaction [4], and many more. Initially, videos were used in identifying anomalies in human action, especially in the surveillance domain [5]. However, smartphone sensors provide a infrastructure-free and privacy preserving approach to HAR. The distinct static or moving posture can be uniquely identified using self-contained inertial sensors, namely, accelerometer or a combination of accelerometer, gyroscope, and/or magnetometer. These sensors are commercially available with smartphones, smart watches, and other wearable devices [6].Since most citizens carry a smartphone nowadays, cost-effective ubiquitous systems could be designed for HAR based on smartphone sensing. Individual activity generates unique time-series signal pattern, although the extent of distinguishing characteristics varies depending on the nature of activity [7]. Dynamic activities (walk, run, jump etc.) produce distinguishable patterns due to separate rhythm of acceleration. In case of different static activities (stand, sit, lie etc.), the difference in time series signal patterns is minor. Lack of sufficient movements causes the acceleration information along the time scale insufficient to identify the static activities. Better analysis of static activities is possible using two-dimensional data, that is inter axis patterns could be meaningful here.

2.LITERATURE SURVEY

Machine learning based HAR systems [8] require these features to be extracted that necessitate specific domain knowledge about the set of activities to be recognized and hence, makes such systems difficult to customize for various applications. Existing research works on HAR as in [9, 10, 11] are mainly focused on the recognition of a given bunch of activities, and feature extraction and fusion [12, 13] for different sensors. A few works could be found that study the challenging effect of different sensor calibration of smartphone configurations and the several usage behaviors as in [14]. These works mostly apply an ensemble of supervised classifiers. Though a few recent works on smartphone-based HAR could be observed utilizing deep learning techniques, such as Long short-term memory (LSTM) as in [15, 16] we could not find any comprehensive deep learning framework for smartphone sensing that also handles the important challenge of different smartphone configurations and usage behavior.

Few works [17] could be found where activity continuously monitored with other factors like heart rate, temperature to identify several diseases. The HAR works that focused on user, position, and/or device independence have also been discussed. During the last decade, smartphones have become a part of our daily life, and this fact was reflected in HAR research works too. An online activity recognition system for the Android platform was proposed in [18]. Data was collected with preferred window size and the training set for each of the activities was reduced into smaller subsets using clustered k-nearest neighbor (kNN). However, online activity recognition with kNN [19] is practically a time-consuming process as it requires high computational complexity for the lazy learning nature. Activities can be recognized in phases, as proposed in the two-layer approach [20]. In the first layer, similar activities are classified into separate groups like, static and dynamic. Then, different strategies and suitable classifiers were used according to the type of activities of each group. For dynamic activities, a position-assisted classifier was proposed as the position and orientation of smartphones highly affect the time-series signal pattern of dynamic activities. Static activities were identified with the help of transition recognition like sit-to-stand or vice-versa. Another similar approach was proposed in [21], the group-based context-aware HAR (GCHAR) approach, which outperforms single ML classifiers when evaluated on the UCI HAR dataset.

Recognizing transition and sequence of activities were the main objective in [22], using a smartphone-based Multi-Instance Multi-Label (MIML) ensemble model considering kNN distance metrics. Transition among two or three consecutive activities was successfully recognized in this work. Hand-gesture activities can also be recognized with higher accuracy, when smartphone is used along with wrist-worn sensors, as shown in [23]. The main challenge was to recognize less-repetitive activities like smoking, talking, eating, etc. with smaller window sizes. The system was evaluated with seven different window sizes considering thirteen activities to analyze this matter. Naive Bayes, decision tree, and kNN were used for classification.Multiple features increase the time complexity of any HAR system. Identifying optimal feature set and combine with machine learning model is a crucial task for building any system. The author in [24] has selected a few meta-heuristic techniques for identifying relevant and optimal features from the overall feature space. The wolf search, elephant search and cuckoo search are combined with the correlation-based feature selection to perform as filter for identifying relevant feature set. The overall performance has increased with feature subsets compared to whole feature set. In [25], Fast Fourier Transform (FFT) and Discrete Cosine Transform (DCT) are used to calculate the frequency component of time domain signals. The Welch's power spectral density algorithm has applied to extract the detailed distribution of the power for different frequency related components of entire accelerometer signal. Breaking the chain of supervised learning, the unsupervised learning-based HAR method was proposed in [26]. The activities were recognized by applying the clustering method on smartphone data using the Jaccard distance measure. Applying C-index and FM-index before and after clustering respectively, researchers explained how this uncommon distance measurement can outperform popular Euclidean distance-based HAR approaches.

Like smartphones, smartwatches are also being popular day by day, making their usage obvious in HAR research works.In [27], authors proposed a new HAR approach for detecting sitting positions. Office Workers Syndrome (OWS), that is having pain in the body due to sitting in a fixed position for a long time, is a common problem among numerous working people. The system identifies six different activities including sitting and computing approximate the time period of sitting using the accelerometer and gyroscope data of the smartwatch using an ensemble learning-based technique. Support Vector Machine (SVM), Decision Tree (DT) and Random Forest (RF) are used to identify abnormal activities in [28]. The RF algorithm is more efficient for identifying the activity like climbing up and down as there are more spikes and changes of the features. The author in [29], explore the XGBoost algorithm for HAR. Examine the impact of the gyroscope on HAR results and compared results of existing models Decision Tree, SVM, Multilayer Perceptron, Naive Bayes, KNN, Random Forest. More training data improves the accuracy of each activity in [30], audio sensor of the Samsung Gear S3 smartwatch was included, along with an accelerometer and gyroscope for recognizing three basketball activities: handling, passing, and dribbling. Approximately 20% improvement in performance was observed after involving the audio sensor.

3.PROPOSED METHODOLOGY

This researchautomatically detects and monitor "anomalous" crowd behaviors (sitting, standing, walking, walking upstairs/downstairs, laying) using only the accelerometer/gyroscope data captured by a smartphone carried by each person. In addition, it demonstrates a complete "data → model → deploy" cycle: from raw smartphone signals through preprocessing, model development, evaluation, and finally an end-user application that both trains and applies the anomaly-detection classifiers.

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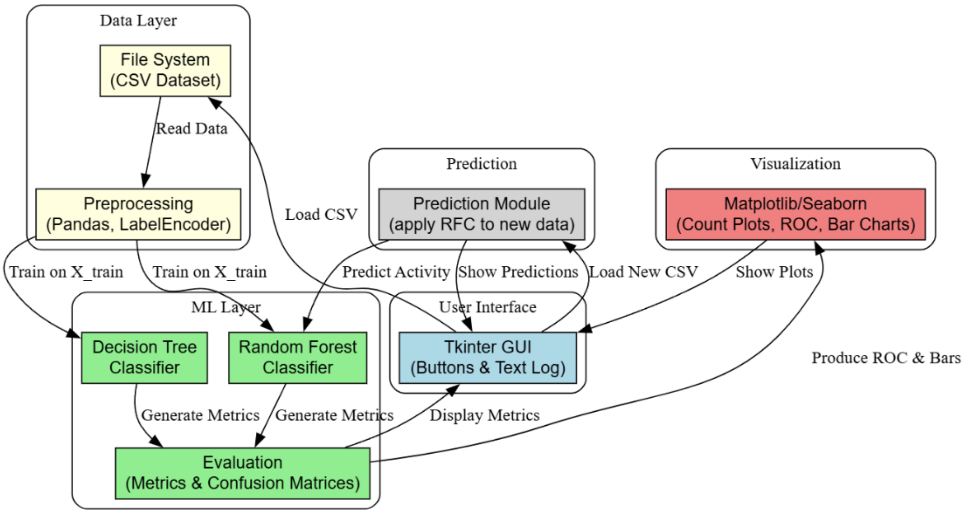


Fig. 1: Proposed system architecture of crowd behaviour monitoring system.

Here's a high-level overview of the entire system and workflow:

Step-1: Data

The system uses a public "Human Activity Recognition" dataset that contains 7352 samples. Each sample includes 561 normalized sensor-feature columns, representing time and frequency domain statistics (e.g., tBodyAccmean() X, tGravityAccstd() Y), along with an "Activity" label. During preprocessing, missing values are filled with zero, categorical labels are encoded numerically, and the data is split into 80% for training and 20% for testing.

Step-2: Models

Two models are implemented for activity recognition. The first is a Decision Tree Classifier (DTC), a single-tree model that captures hierarchical splits based on sensor features. The second is a Random Forest Classifier (RFC), which consists of an ensemble of randomized trees, offering improved stability and accuracy.

Step-3: Evaluation Metrics

The models are evaluated using several metrics. Positive metrics include precision, recall, F1 score, and accuracy (both macro averaged and per class). Negative metrics include confusion matrices, true/false negative rates, and Negative Predictive Value. Additionally, ROC curves are plotted for each model to compare the trade-offs between true positive and false positive rates.

Step-4: User Interface

A graphical user interface (GUI) is built using Tkinter. The application guides the user through six interactive steps:

1. Upload the dataset (CSV format).
2. Preprocess and normalize the data, which includes filling missing values, encoding labels, and visualizing class distributions.
3. Train the Random Forest Classifier.

4. Train the Decision Tree Classifier.
5. Predict activities using new sensor data files.
6. Plot a comparison chart displaying performance metrics.

A scrollable text area in the GUI logs the outputs and metrics for each operation. Separate Matplotlib windows are used to display the count plot, ROC curves, and performance comparison bar chart.

Step-5: Key Findings

The Random Forest Classifier consistently outperforms the Decision Tree Classifier across all positive metrics including precision, recall, F1 score, and accuracy, as well as in terms of the reliability of negative predictions. The GUI enables non-programmers to interact with the entire machine learning pipeline easily by uploading raw data, clicking buttons, and immediately viewing model performance and predictions.

3.1 Random Forest Classifier

A Random Forest builds an ensemble of independently trained Decision Trees (as shown in Fig. 3), each on a bootstrap sample of the data and considering only a random subset of features at each split. By aggregating their predictions through majority voting, it dramatically reduces the variance and overfitting typical of single trees, yielding high accuracy and robustness to noisy or highly correlated features.

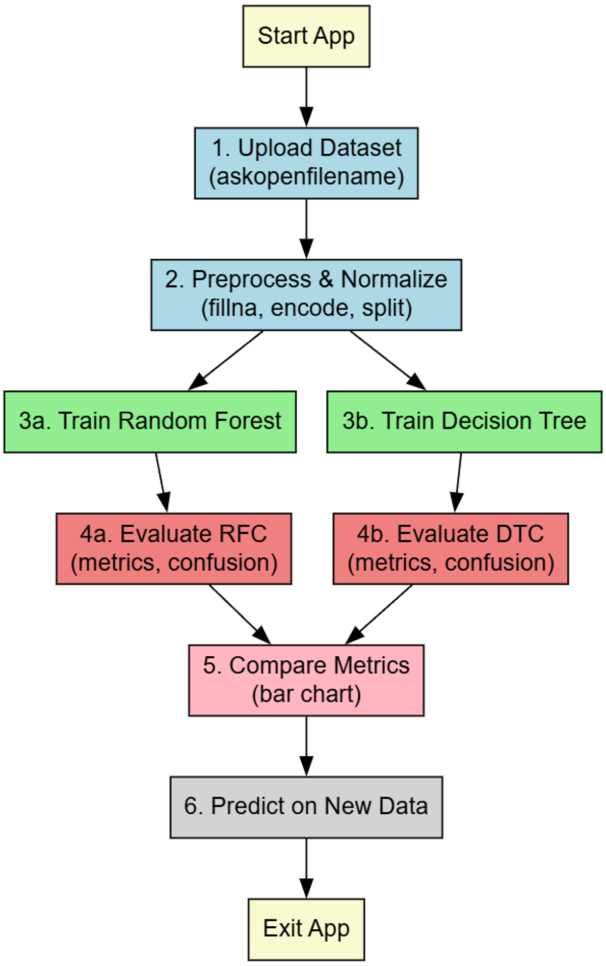


Fig. 2: Workflow of proposed crowd behaviour monitoring using anomaly detection from smart phone sensor data.

Explanation:

1. Bootstrap Sampling: Each tree is trained on a random sample (with replacement) of the original dataset.
2. Feature Subspace: For each split in a tree, a random subset of features is considered, adding decorrelation between trees.
3. Tree Ensemble: Multiple Decision Trees independently learn their splits on their bootstrap samples and chosen feature sets.
4. Voting: When predicting, each tree casts a vote for its predicted class; the Random Forest outputs the class with the most votes, reducing variance and improving generalization over a single tree.

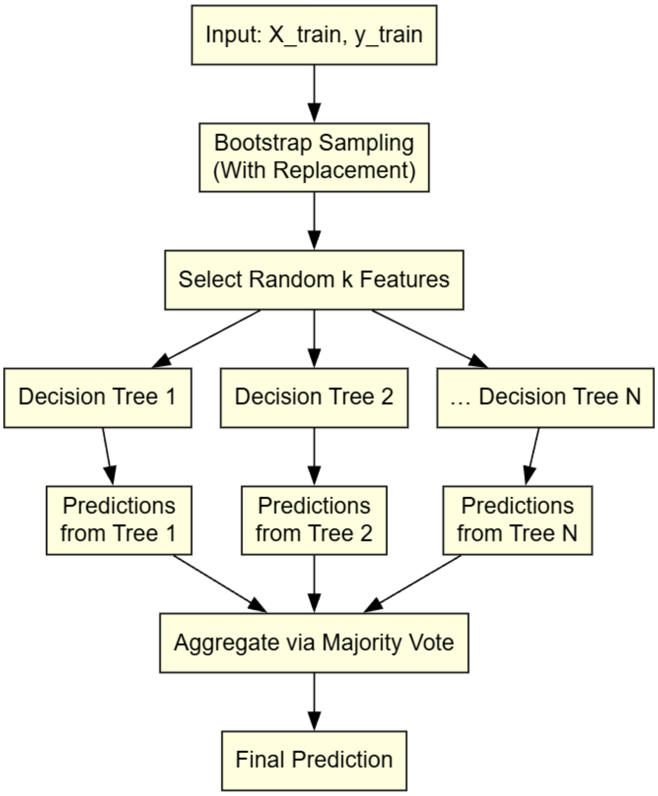


Fig. 3: Internal workflow of RFC model.

4.RESULTS AND DISCUSSION

4.1 Dataset description

This is a fully-numeric, normalized dataset of smartphone sensor readings (time and frequency domain) for human activities, with 7352 samples and 561 features—ready for training classifiers after encoding the activity labels.

Here's an overview of the uploaded Train_Data.csv:

1. **Size & Rows**: 7352 observations (rows). No missing values in any column.
2. **Features (Columns)**: There are 561 numeric sensor-feature columns, each named following the format <signal>-<statistic>()-<axis>. For example, tBodyAcc-mean()-X represents the mean of body acceleration in the X direction, while tBodyAcc-std()-Y represents the standard deviation of body acceleration in the Y direction. Similar naming conventions apply to body and gravity signals, gyroscope data, and frequency-domain transforms. Additionally, there is one target column, which is not shown in the excerpt above, that indicates the activity label (e.g., walking, sitting, laying).
3. **Data Types & Completeness**: All sensor-feature columns are float64.Every column has 7352 non-null values—no missing data.
4. **Descriptive Statistics**: Many features range between –1.0 and +1.0, reflecting normalized sensor readings.Means for acceleration signals hover near zero (e.g. ~0.27 on X axis, –0.01 on Y, –0.11 on Z).Standard deviations exhibit wide spans (e.g. some features span –1.0 to +1.0).The quartile splits (25th/50th/75th percentiles) confirm roughly symmetric, normalized distributions for most features.

4.2 Results description

Fig. 4displays the distribution of activity labels in the uploaded dataset. Each bar corresponds to one activity category (e.g. walking, sitting, laying, walking_upstairs, walking_downstairs, standing), and the bar heights show how many samples belong to each. The exact counts are annotated above each bar, revealing any class-imbalance that could affect model training.

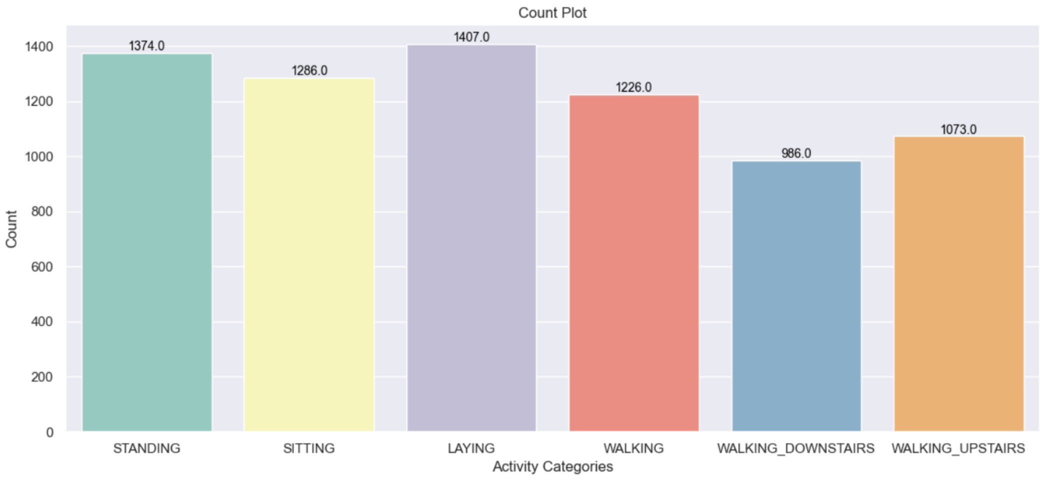
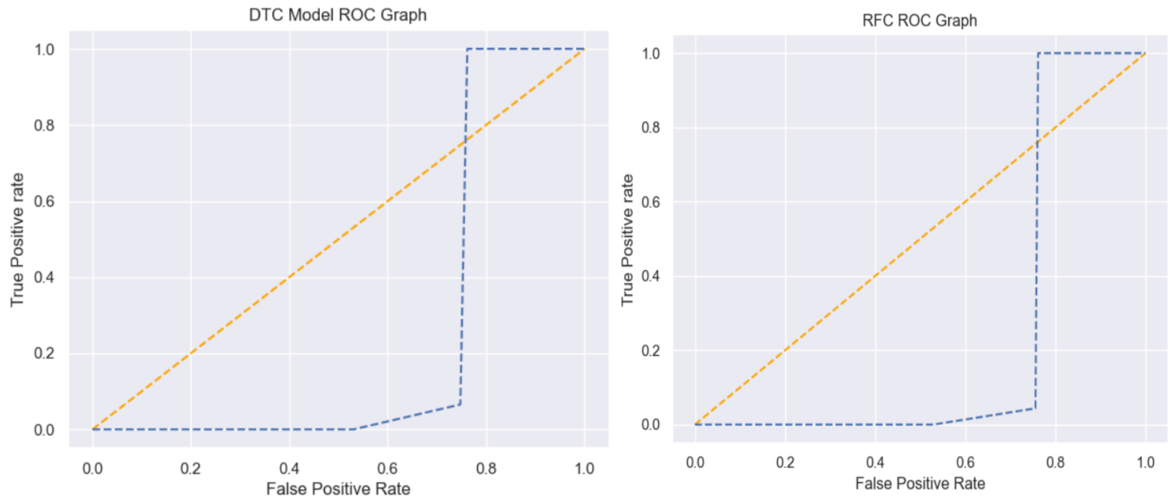


Fig. 4: Anomaly category versus number of samples.



(a) (b)

Fig. 5: ROC curve obtained using (a) DTC model. (b) RFC model.

Fig. 5 demonstrate two ROC plots side-by-side:

(a) Decision Tree Classifier (DTC) – The dashed orange line shows the random-guess baseline; the solid line shows the tree's true positive rate vs. false positive rate as the discrimination threshold varies.

(b) Random Forest Classifier (RFC) – Similarly plotted, typically hugging the top-left corner more closely, indicating stronger separability and higher AUC.

These ROC curves visually compare each model's ability to distinguish between normal vs. anomalous activities across all threshold settings.The goal is to categorize and list each sample with its respective detected posture, such as "laying," "sitting," "standing," or "walking," within the sequence. Here's a concise summary of each test input vector and its detected "anomaly" posture represented in Table.1:

1. Samples 1–3 all triggered the model's "laying" anomaly profile.
2. Samples 4–6 fell into the "sitting" anomaly.
3. Samples 7–10 keyed as "standing."
4. Samples 11–13 were flagged as "walking."

Sample	Detected Posture
1	laying
2	laying
3	laying
4	sitting
5	sitting
6	sitting
7	standing

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8	standing
9	standing
10	standing
11	walking
12	walking
13	walking

Table. 1: Posture predictions on test data**.**

Table. 2: Performance evaluation of DTC, and RFC models.

Model	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
Random Forest (RFC)	98.23	98.24	98.23	98.16
Decision Tree (DTC)	95.00	95.00	95.00	95.00

Table. 2 summarizes as follows:

1. Precision: RFC's 98.23% vs. DTC's 95.00% means that of all instances each model labeled as positive, RFC was correct about 3.2 points more often—fewer false positives overall.
2. Recall: RFC at 98.24% vs. DTC at 95.00% shows RFC also captures more of the true positives, missing far fewer actual cases.
3. F1-Score: As the harmonic mean of precision and recall, RFC's 98.23% vs. DTC's 95.00% confirms a consistently stronger balance between precision and recall.
4. Accuracy: RFC's accuracy is about 3 points higher, meaning it simply makes fewer total classification errors across the entire dataset.

5.CONCLUSION

Through end-to-end integration of scikit-learn classifiers into a user-friendly Tkinter application, this work demonstrates that ensemble methods substantially outperform single-tree models for smartphone-based crowd-activity recognition. The Random Forest classifier achieved a 98.16% accuracy, improving upon the Decision Tree's 95% by more than three points; its macro-averaged precision, recall, and F1-score all exceeded 98%, compared to roughly 94% for the DTC. Confusion matrices show that RFC dramatically reduces both false positives and false negatives, yielding near-perfect Negative Predictive Values across all six activity classes. ROC analysis further illustrates the RFC's tighter trade-off between true and false positive rates. The GUI effectively abstracts away coding details, enabling domain experts to upload raw CSVs, visualize class distributions, train both models, inspect detailed metrics, and perform live predictions—all with a few clicks. This accessibility paves the way for scalable deployment in real-world crowd-monitoring scenarios.

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