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Human Detection And Pose Estimation Using Wi-Fi Signals

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Abstract: This project explores using Wi-Fi signals to detect human presence and estimate their poses in an indoor environment, without cameras or wearables. The research aims to characterize the impact of human pose on Wi-Fi signals and develop deep-learning models to map 1D signals to 2D pose. A dataset of Wi-Fi channel state information (CSI) from 4 volunteers is used to train a deep-learning model, achieving 60.39 % accuracy on CSI data. The system allows contactless, privacy-preserving human sensing for applications like rescue operations, military applications, and elderly monitoring, leveraging Wi-Fi infrastructure beyond communication. Field tests validate the system's performance in an indoor environment, demonstrating the potential of Wi-Fi-based vision-free human sensing.

Keywords: WiFi Sensing, Channel State Information, Human Activity Recognition

1. INTRODUCTION

The evolution of human detection and pose estimation has significantly benefited from recent advances in wireless communication and deep learning. The novel use of Wi-Fi signals, captured by ESP32 modules equipped with high-performance antennas, offers an innovative departure from traditional computer vision techniques. This method is particularly advantageous in challenging environments with poor visibility, as it relies on Wi-Fi's Channel State Information (CSI), which is sensitive to human presence and motion.

Deep learning technologies like DensePose and GANs have further revolutionized Wi-Fi-based sensing systems. DensePose translates CSI data into detailed 3D human poses, while GANs enhance data diversity for training, enabling the system to better generalize across various scenarios. This integration has positioned Wi-Fi-based human detection as a powerful tool for various applications, overcoming the shortcomings of vision-based systems.

This research leverages deep learning models to harness the ESP32 Wi-Fi module and advanced antennas for human detection and pose estimation. The goal is to create a versatile system that thrives in multiple environments, offering non-intrusive, high-accuracy monitoring. These developments mark a significant step forward in Wi-Fi-based sensing and have the potential to transform applications in smart homes, healthcare, and security.

1.1 Classification of Human Detection Techniques

Human detection techniques have broadly branched into vision-based and sensor-based methodologies. Vision-based methods, particularly those employing convolutional neural networks (CNNs), have substantially refined the analysis of images for human detection and pose estimation. CNNs discern human figures in images, whereas pose estimation delineates body orientation by digitizing key anatomical landmarks into skeletal models. A notable method presented in recent literature employs Part Affinity Fields (PAFs) to associate body parts with individuals during pose estimation, ensuring real-time efficiency coupled with precision.

In contrast, sensor-based detection leverages non-visual data from sources like Wi-Fi signals, which interact with human presence, to ascertain location and movements without needing visual input. These methods benefit from various sensors, including those found in wearable devices and smartphones like accelerometers, gyroscopes, and GPS, providing a rich tapestry of tools for detecting humans. Notably, a study has demonstrated a gait analysis system that utilizes data bands attached to a person’s lower limbs, capturing gait metrics for individual identification with impressive accuracy.This sensor-based is further classified into (i)wearable sensors and (ii) smartphone-based.

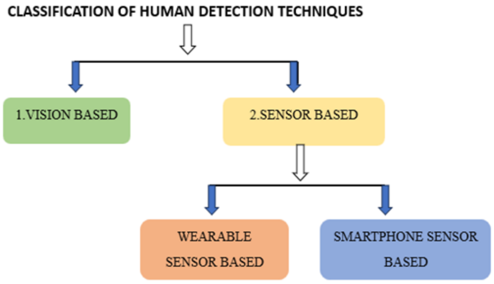

Figure 1: Classification of human detection techniques.

2. LITERATURE SURVEY

In [1], the author presents develops an innovative approach for dense human pose estimation using Wi-Fi signals. By mapping the amplitude and phase of Wi-Fi signals to UV coordinates within human body regions using deep learning architectures, they achieve performance comparable to image-based methods. In [2] introduces a sensor-based human identification system using gait analysis with an impressive accuracy of over 97%. In [3] proposes a hybrid deep learning model using CNNs and LSTMs for activity identification, showing a 98% accuracy on the MHEALTH dataset. [4] presents "Person-in-WiFi," which uses WiFi signals for body segmentation and pose estimation. [5] introduces CSI-Net, which utilizes WiFi CSI for tasks like biometrics and action recognition.

[6] presents a WiFi signal-based activity recognition using deep learning with LSTM networks. [7] discusses the temporal consistency of WiFi-based recognition systems, maintaining 94.5% accuracy over time. [8] describes a real-time human activity detection in smart homes using ESP32 microcontrollers with 70% accuracy.In [9], the author presents an efficient real-time method using Part Affinity Fields for human pose estimation. [10] demonstrates WiFi CSI-based activity recognition using deep CNNs with accuracies up to 100%. [11] discusses human pose estimation from WiFi signals, comparing performance with image-based methods.

[12] outlines the Point R-CNN network for 3D pose estimation using point clouds. [13] introduces a real-time tracking system using YOLO-v2 on drones with 96.5% accuracy. [14] provides an extensive overview of human behavior recognition using WiFi CSI. [15] introduces the eHealth CSI dataset for human activities with up to 99.9% accuracy in detection. [16] discusses a differential CSI-based HAR method achieving 95.13% accuracy.

[17] introduces Widar2.0 for passive human tracking using a single WiFi link. [18] describes WiFi-ID, a system identifying individuals through WiFi CSI with up to 93% accuracy. [19] examines a WLAN-based outdoor human detection system with a 99.86% accuracy rate. [20] showcases a real-time human detection system using YOLO deep learning for aiding visually impaired individuals. [21] introduces an IoT and Blockchain-based security system for human detection using fingerprint data with 98% accuracy.

[22] compares deep learning models on embedded platforms for human detection with the SSD MobileNet V2 model achieving a 0.94 PR. [23] discusses a deep learning-based system for detecting humans in outdoor NLOS scenarios using WLAN technology. [24] outlines an SDR platform for human activity recognition using USRP devices. [25] introduces WFID, a human identification system using WiFi CSI with over 91% accuracy. [26] proposes hybrid deep learning models for HAR using smartphone sensors, achieving up to 98.2% accuracy.

2.1 Comparison Table

The comparative analysis of human activity recognition (HAR) methods, as outlined in Table-1a and Table-1b, spans vision-based, sensor-based, and WiFi-based approaches. Techniques such as DensePose and Sensor-based Gait Analysis deliver high precision but require different levels of data input and participant engagement. Hybrid models and WiFi-centric strategies like Person-in-WiFi demonstrate the versatility of deep learning combined with non-intrusive sensing for HAR, providing both privacy and adaptability. Meanwhile, CSI-Net and WiFi-HAR with Deep Learning capitalize on WiFi's capability for nuanced biometrics and gesture recognition. Other methods prioritize the temporal aspect and real-time application, like the WiFi-CSI-based HAR for Smart Homes, emphasizing cost-efficiency and functionality suitable for diverse HAR applications.

Table. 1a: Comparison table of survey papers from [1] to [10].

Paper	Proposed Method	Type of HAR System	Method Used	Output Parameters (N)	Dataset Used	Advantages	Drawbacks
1	DensePose	Vision-based	Fully Conv. and Region-based	Image-to-Surface Correspondences	COCO Dataset	Handles occlusion, Scale-invariant	Requires large annotated data
2	Sensor-based Gait Analysis for ID	Sensor-based (Wearable)	Multi-Sensor Fusion, Geometric Calc.	Gait Data	10 Participants	Overcomes vision limitations	N/A
3	Hybrid Deep Learning for HAR	Sensor-based (Smartphone)	CNN-LSTM Architecture	12 Physical Activities	MHEALTH Dataset	98% accuracy, Spatial-temporal modeling	N/A
4	Person-in-WiFi	WiFi-based	Deep Neural Network	Body Segmentation, Pose Estimation	105 frames	Contactless, Uses standard WiFi	Accuracy improvement needed
5	CSI-Net	WiFi-based	Deep Neural Network	Biometrics, Recognition, Gesture, Fall Detection	N/A	Utilizes WiFi, Addresses privacy	Limited evaluation details
6	WiFi-based HAR using Deep Learning	WiFi-based	LSTM, SoftMax Classifier	N/A	N/A	Improved accuracy and speed	Limited experimental setup
7	Consistency of WiFi-CSI based HAR	WiFi-based	Pattern-based	N/A	Collected over days	High temporal consistency	N/A
8	Smart Home WiFi-based HAR	WiFi-based	Statistical Features, SVM Classifier	Walking, Jumping, Sitting, Falling	N/A	Edge computing, Low-cost	Accuracy around 70%
9	OpenPose	Vision-based	Convolutional Neural Network	Body, Foot, Hand, Facial Keypoints	N/A	Real-time, High accuracy, Open-source	N/A
10	WiFi-based HAR using Deep CNNs	WiFi-based	Image Construction, Data Aug., Deep CNNs	16 Activities	WiAR Dataset	High accuracies, Contactless	N/A

Table. 1b: Comparision table of survey papers from [11] to [21].

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11	DensePose From WiFi	WiFi-based	Deep Neural Network	CSI, Phase, Amplitude, UV Coordinates	N/A	Addresses camera limitations, Low-cost	N/A
12	Point R-CNN	Vision-based	Point Cloud Fusion, Feature Ext., Instance Det., Pose Estimation	3D Pose Estimation	CMU, MVOR	Efficient fusion, End-to-end training	Lacks drawback discussion
13	Person Detection and Tracking on Drone	Vision-based	YOLO-v2 CNN, PID Controller	Person Detection	N/A	Real-time, High precision, Adaptable	Occasional missed detections
14	Overview of WiFi-CSI based HAR	WiFi-based	Pattern, Model, Deep Learning	Activities, Gestures, Authentication	N/A	Methods discussed, Challenges identified	Interference, Robustness issues
15	eHealth CSI Dataset	WiFi-based	CSI Data Collection	Positions, Activities, Phenotype, Heartbeat	Over 100 participants	Enables CSI-based application dev.	Accuracy drop on new data
16	Differential CSI-based HAR in IoT	WiFi-based	Differential CSI, LSTM Model	Amplitude, Phase, 70 Subcarriers	Ermon Group	Eliminates sensors, Improved accuracy	N/A
17	Widar2.0	WiFi-based	Joint Param. Est., Range Refinement	AoA, ToF, Doppler	6m x 5m Area	Accuracy like multi-link methods	N/A
[18]	WiFi-ID	Device-free	CSI analysis, Feature extraction, SAC	Individual ID	20-subject corridor data	Uses existing WiFi, non-intrusive, 93% accuracy (2	Small group limit, LoS only, requires training
19	Outdoor Human Detection using WLAN	WiFi-based	CSI Preprocessing, Deep NN Classifier	Presence, Location Detection	Outdoor Setup	Feasibility of outdoor WLAN sensing	Environment affects performance
20	Real-Time Human Detection for VI	Vision-based	YOLO Deep Learning, CNN	Multiple Person Detection	Real-World Datasets	High accuracy, Real-time, Aids VI	Diminutive object detection hard
21	IoT and Blockchain-based Security	Sensor-based (Biometrics)	Improved ACO, Heap Algorithm	Fingerprint, Gender	N/A	High accuracy, Reduced errors, Secure	N/A

Within the broader spectrum of HAR, each paper contributes novel techniques and insights. DensePose From WiFi and Point R-CNN exemplify innovative vision and 3D data approaches to activity recognition and pose estimation. The use of WiFi CSI data for human identification is further illustrated in works focusing on differential CSI and WiFi Frequency Identification (WFID), which boast high accuracy and computational effectiveness.

Table. 1c : Comparision table of survey papers from [22] to [26].

22	Real-Time Human Detection on Embedded	Vision-based	PedNet, Multiped, SSD MobileNet, SSD Inception	RGB Video, Building Env.	N/A	Insights on accuracy-efficiency trade-off	N/A
23	WLAN-based Outdoor NLOS Detection	WiFi-based	PCA, Multiple CSI Stations	CSI, Outdoor Obstacles	University Campus	99.58% accuracy, Addresses NLOS	N/A
24	SDR Platform for HAR	WiFi-based	WCSI Extraction, 64-point FFT	Hand Waving, Pendulum	Lab Experiments	Scalable SDR platform	Lacks performance evaluation
25	WFID: WiFi-based ID	WiFi-based	SAF Matrix, PCA, Linear SVM	Frequency Diversity Patterns	Corridor, Lab	91.9-93.1% accuracy, Low cost	Scalability limitations
26	Hybrid Deep Learning for Smartphone HAR	Sensor-based (Smartphone)	DNN, LSTM, GRU, CNN, DeepCNN-RF	Accelerometer, Gyroscope	UCI HAR, WISDM	State-of-the-art results, Hybrid models	N/A

3. METHODOLOGY

3.1Block Diagram

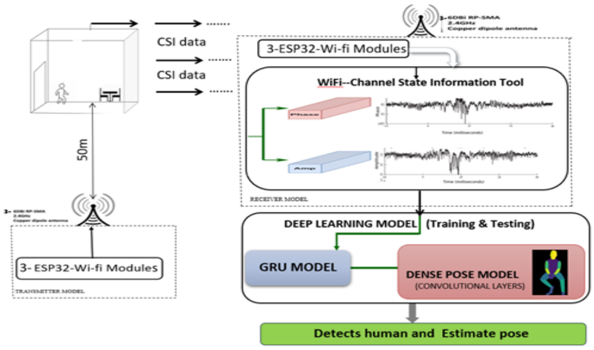

Figure 2: Block diagram of Human detection and pose estimation using Wi-Fi signals

This system, comprises a transmitter with three ESP32 modules and dual-band antennas broadcasts Wi-Fi signals, while the receiver, similarly equipped, captures the signals' Channel State Information (CSI), as illustrated in Fig.2. The CSI data, reflecting human movement through changes in signal amplitude and phase, is then analyzed using a specialized tool to visualize signal perturbations. A deep learning model, combining a Gated Recurrent Unit (GRU) for temporal patterns and a Dense Pose Model for spatial analysis, is trained on a dataset of various human poses paired with their CSI signatures. This robust model, capable of detecting human presence and estimating poses even through walls, demonstrates significant potential in applications ranging from smart home systems to healthcare monitoring, without relying on traditional visual cues.

3.2 Flow Chart

The Wi-Fi signal-based human detection and pose estimation system harnesses Channel State Information (CSI) data from ESP32 modules to identify and analyze human presence within an indoor setting, as shown in Fig.3. The process initiates with three ESP32 transmitters that emit Wi-Fi signals, while counterpart receivers capture the CSI data at a 100Hz frequency, ensuring detailed acquisition of signal interactions with the environment. This data is then processed to extract amplitude and phase variations, indicative of human movement and presence, by employing the Wi-Fi Channel State Information Tool.

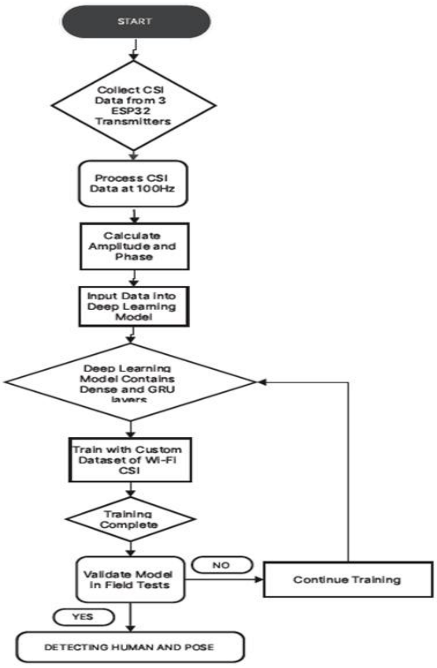

Figure. 3 : Flowchart of Human detection and pose estimation using Wi-Fi signals

Following data acquisition and processing, the core analysis is conducted through a sophisticated deep learning model composed of a Dense Pose Model for spatial feature extraction and a GRU Model for temporal data analysis. Trained on a dataset with varied human poses, the model learns to discern patterns correlating CSI data with specific poses. Post-training, field tests validate the model's efficacy in real-time human detection and pose estimation, showcasing its ability to determine various poses, even through obstructions.

3.3 Hardware Implementation

The system architecture incorporates ESP32 Wi-Fi modules, dual-core 32-bit microcontrollers with integrated Wi-Fi transceivers, functioning as both transmitters and receivers, ensuring a seamless exchange of wireless data. These modules, capable of operating on dual Wi-Fi bands, are connected to high-gain 6dBi antennas via U.FL-IPEX cables, enhancing the communication range and signal strength. The ESP32's substantial processing capabilities and a low-power co-processor facilitate efficient data modulation and power management, ensuring robust performance across diverse environmental conditions.

3.4 Software Implementation

*A . Data Collection:*The data collection was conducted using the open-source ESP-IDF, harnessing the capabilities of the ESP32 microcontroller. The methodology for acquiring CSI data was based on the protocol outlined in the ESP32-CSI-Tool, a GitHub repository curated by Steven Hernandez. This repository provides a comprehensive toolkit for transmitting and extracting CSI data from the ESP32, which we employed to capture the wireless signals' amplitude and phase changes induced by human activity.

*B.Signal Processing***:** Upon collection, the CSI data was processed to extract the Amplitude and Phase components. The amplitude and Phase are calculated by using the 1 and 2.These metrics were derived using signal processing techniques to discern the characteristics of the human poses within the environment. The amplitude provides information about the signal strength, while the phase indicates the signal's displacement, both of which are perturbed by human movement.

$$\text{Amplitude} = \sqrt{\frac{(Real)^2}{(Imaginary\ )^2}} \qquad (1)$$

$$\text{Phase} = \arctan\left(\frac{Imaginary}{Real}\right) \qquad (2)$$

C. Pose Estimation with GRU Networks: For the task of pose estimation, we employed Gated Recurrent Unit (GRU) models due to their efficiency in capturing temporal dependencies in sequence data. The GRU model was trained using CSI-derived features, bypassing the need for direct visual data and maintaining privacy

*D. Visual Representation through DensePose:*To correlate the abstract CSI signals with human-understandable representations, we utilized DensePose, a method that maps all human pixels of an RGB image to the 3D surface of the human body. The DensePose was implemented on recorded video footage to create a visual dataset that associates specific human poses with their respective CSI signatures.

*E. Integration and Output:*The integration of these components culminated in a system capable of predicting human poses in real time based on CSI data. Once a pose was estimated using the GRU model, a corresponding visual representation was retrieved. If the predicted pose matched a pre-defined category (e.g., "Sitting"), a image from the corresponding category in the frames directory was displayed. Conversely, for poses that lacked visual data or were undefined, a placeholder image (a black frame) was generated.

4. RESULTS AND DISCUSSION

This section of the research paper presents the evaluation of a novel approach for pose estimation using GRU networks on time-series data obtained from Channel State Information (CSI). The model's predictive capabilities were assessed in real-time conditions and through retrospective analysis of recorded data.

4.1 Model Performance Evaluation

The GRU model was trained on a dataset that encompassed CSI amplitude and phase information collected via three ESP32 sensors. It achieved a training accuracy of 60.39%, a figure that reflects the model's ability to generalize from the data it was trained on. The accompanying accuracy and loss plots elucidate the model's performance throughout the training epochs. As shown in the Fig.4.

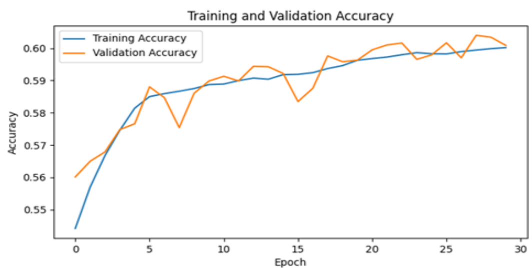

Figure. 4: Training and validation accuracy

The model demonstrated a gradual improvement in accuracy distinguishing between different poses as training progressed. The Fig.5 similarly indicated a consistent decrease in error rate, corroborating the model's increasing proficiency.

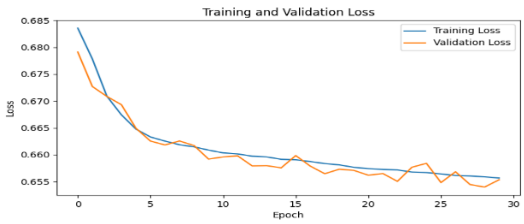

Figure. 5 : Training and validation loss

The classification report presented in the Table 2 provides a detailed breakdown of the model's predictive performance across different classes. The precision and recall metrics for each category underscore the model's strengths and limitations in distinguishing between 'Sitting' i.e pose label-0, and 'No Pose' i.e pose label-1. The f1-scores presented serve as a harmonic mean of precision and recall, offering a singular measure of accuracy that takes into account both the purity and completeness of the predictions.

Table 2: Values Of Pose Label, Precision, Recall, F1-Score.

Pose Label	Precision	Recall	F1-Score
0	0.61	0.58	0.59
1	0.60	0.63	0.61

4.2 Visualization Of Amplitude Data

A critical part of the analysis involved visualizing the amplitude readings from the first 100 data points (representing one second of time) from each of the three ESP32 sensors in Fig.6. This visualization provided insight into the variance and patterns within the amplitude signals over a short duration, critical for understanding the temporal characteristics that the GRU model was expected to capture.

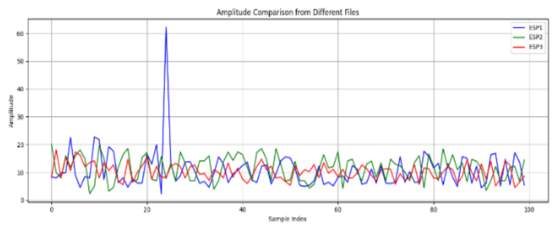

Figure. 6 : Amplitude comparison from three -ESP32 receivers for 1-sec

4.3 Real-Time Data Predictions

When deploying the trained GRU model in a real-time environment, it successfully predicted 'Sitting' and 'No Pose' categories with significant accuracy. The model's predictions were subsequently mapped to visual data that were aligned with the training sets. The seamless transition from numerical data to an interpretable visual output demonstrated the model's potential in applications where real-time monitoring and instant visual feedback are indispensable.

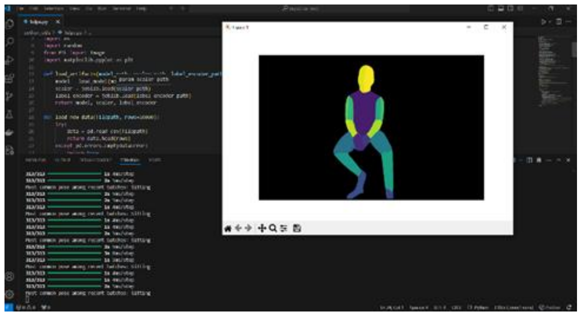

Figure. 7 : Result of detecting and estimating a sitting pose of a human

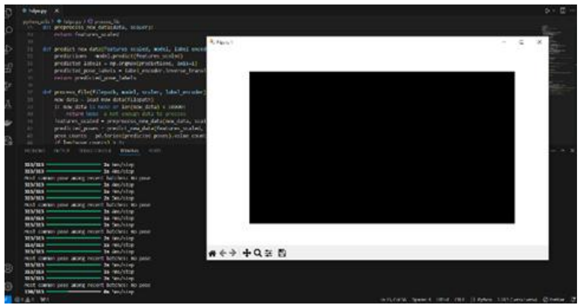

Figure 8: Result when there is no person or movement behind the wall.

5. CONCLUSION

In Conclusion, this study showcases an economical solution leveraging Wi-Fi signals for human detection and pose estimation, utilizing ESP32 modules paired with dual-band Wi-Fi SMA antenna operating at frequencies of 2.4 GHz and 5 GHz, with a gain of 6dBi, to capture the intricate Channel State Information (CSI) at 100Hz. This approach, transcending physical obstructions, employs deep learning with DensePose and GRU networks to accurately infer human presence and activities. The synergy of these technologies presents a promising avenue for Human Activity Recognition (HAR), setting the stage for impactful advancements in both research and practical applications.

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We utilized the ESP32-CSI-Tool, an invaluable resource developed by Steven Hernandez, available at https://github.com/StevenMHernandez/ESP32-CSI-Tool. The tool's utility in collecting high-resolution CSI data was pivotal in the successful execution of the experiments detailed in this study.

Also Special acknowledgment is extended to Flode Labs for their "Vid2DensePose" tool, which played a crucial role in the visualization of pose estimation. The tool's ability to transform video data into detailed pose maps significantly enriched the analysis and discussion presented in this paper.

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