# MULTI-INSTRUMENT RECOGNITION AND TUNING SYSTEM[GUITAR & VEENA]


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***Abstract*— This project presents a real-time multi-instrument recognition and tuning system focused on the guitar and veena. In live performance scenarios, multiple instruments often produce overlapping audio, making individual tuning challenging. Existing tuners struggle to isolate and identify instruments in polyphonic environments. This project addresses that limitation by integrating advanced machine learning models such as Demucs**

**and Spleeter for source separation and convolutional neural networks (CNNs) for instrument classification using spectrogram-based features. The system distinguishes and isolates individual instruments from a complex soundscape, enabling precise pitch detection and tuning. A comprehensive audio pre-processing pipeline—comprising silence trimming, volume normalization, spectrogram conversion, and feature extraction (e.g., MFCCs, chroma, ZCR)—enhances model accuracy and robustness. Additionally, data augmentation improves generalization across diverse acoustic conditions. This work is novel in its unified approach to instrument identification and tuning in polyphonic environments, specifically addressing the unique challenges of Indian classical instruments like the veena, with an emphasis on real-time performance. The system holds promise for professional musicians seeking efficient and accurate tuning tools in dynamic settings.**



***Keywords*— *Real-time tuning, Multi-instrument recognition,***

*Source separation, Demucs, Spleeter, CNN, Spectrogram features, Pitch detection, Audio pre-processing, MFCC*


## I. INTRODUCTION

Accurate instrument tuning is critical in music to ensure harmonic coherence and consistent sound reproduction. Human auditory perception struggles with distinguishing fine pitch differences, especially in polyphonic settings. Instrument tuners, both hardware and software-based, address this by analyzing audio signals to detect pitch deviations and guide tuning adjustments.

Conventional tuners are typically designed for single-instrument input and rely on frequency analysis techniques. While numerous online and mobile applications exist, their effectiveness is limited in multi-instrument environments where overlapping sound sources introduce noise and interfere with pitch detection. This highlights the need for advanced systems capable of isolating and tuning specific instruments in real-time, even amidst concurrent audio signals.

## II. LITERATURE SURVEY:

Musical instrument recognition and automated tuning have gained significant traction in recent years due to the increasing application of machine learning (ML) and deep learning (DL) techniques in music information retrieval (MIR). These technologies have shown promise in addressing the limitations of traditional tuning systems, particularly in polyphonic audio environments and with non-Western instruments such as the veena. This literature survey categorizes the research landscape into two primary areas: Instrument Recognition and Automated Tuning Techniques.

### *A. Convolutional Neural Network (CNN)-Based Recognition*

A deep CNN framework for recognizing predominant instruments in polyphonic music using Mel-spectrograms as input features. Their model used an eight-layer CNN architecture with ReLU activation, Max Pooling, and dropout regularization. The final classification was performed using a Softmax layer. The model achieved a classification accuracy of 92.8%, demonstrating the efficacy of spectrogram-based CNNs for instrument recognition in real-world audio scenarios.

### *B. Multi-Feature, Multi-Architecture Approaches*

Combining different audio features—such as MFCCs, spectrograms, and scalograms—has led to improved

classification results. These features are processed through various architectures, including deep neural networks (DNNs), CNNs, recurrent neural networks (RNNs), and hybrid models like CNN-LSTM. Deeper networks generally outperform shallow ones due to their enhanced ability to capture complex temporal and frequency dependencies.

### C. Sequence-Based and Retrieval-Oriented Models

Sequence-based models that use recurrent units, such as LSTMs, have been effective in audio retrieval and recognition tasks where temporal structure is essential. However, these models tend to be computationally heavy, limiting their usability in real-time applications.

### D. High-Frequency Enhancement for Improved Recognition

To enhance audio quality and recognition accuracy, especially in compressed or noisy environments, high-frequency reconstruction techniques are employed. The Modified Discrete Cosine Transform (MDCT) is used to isolate low-frequency information from input audio lacking high-frequency components. Using phase space reconstruction the model predicts and reconstructs the missing high-frequency components. A harmonic adjustment step then refines the output to maintain tonal consistency.
The overall pipeline is depicted in the below figure, where low-frequency audio features are used to reconstruct missing high-frequency information. The inverse MDCT (IMDCT) combines both low and reconstructed high-frequency data to restore the full frequency spectrum.

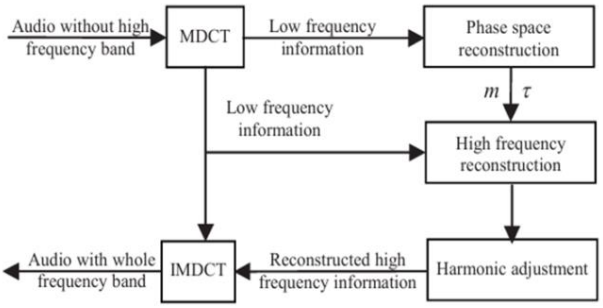



Figure 1. Block diagram of the proposed method

### E. Hybrid GMM-DNN Frameworks with Timbral Feature Fusion

Instrument recognition in polyphonic audio often struggles due to overlapping harmonics and shared frequency bands among instruments. To overcome this, hybrid modeling techniques that combine the strengths of traditional statistical models with modern deep learning frameworks have proven highly effective. One such approach involves the integration of Gaussian Mixture Models (GMMs) and Deep Neural Networks (DNNs), using a fusion of timbral audio features. Gaussian Mixture Models (GMMs) GMMs are probabilistic models that assume that the data is generated from a mixture of several Gaussian distributions. In the context of instrument recognition, GMMs are used to model the probability distribution of audio features corresponding to different instrument classes. GMMs are particularly effective for modeling variability in feature space and can provide useful initial class probability estimates.Deep Neural Networks (DNNs): DNNs, with their multiple layers of nonlinear transformations, can learn complex mappings between audio features and instrument classes. When used in conjunction with GMMs, DNNs refine and enhance the classification process by learning discriminative features from the probabilistic output of GMMs or directly from low-level features.
Feature Fusion Strategy: The hybrid GMM-DNN approach employs early feature fusion, where multiple types of timbral features are combined into a single representation before being input to the model. This comprehensive representation improves the model's ability to capture subtle differences between instruments.

### F. Attention Mechanisms for Feature Emphasis

Attention-based models selectively focus on important frequency bands while suppressing noise and irrelevant components. These mechanisms enhance model performance by emphasizing unique spectral patterns specific to each instrument.

## III. AUTOMATED TUNING TECHNIQUES

Tuning involves identifying and correcting deviations in pitch relative to a standard reference frequency. ML methods have extended this process by improving accuracy, adaptability, and speed.

### A. Conventional Tuning Methods

Traditional methods rely on harmonic matching and frequency analysis using Fourier-based algorithms. These are effective for isolated signals but perform poorly in the presence of background noise or other instruments. .

### B. Machine Learning-Based Tuning

Supervised models trained on labeled pitch data can estimate pitch deviation and suggest corrective tuning. CNNs and other DL models have been successfully used with features such as MFCCs, chroma vectors, and zero-crossing rates to predict pitch and guide tuning adjustments.

### C. Traditional Tuning Methods

Conventional tuning systems, such as handheld tuners or mobile apps, primarily use frequency analysis techniques like**:**

- Fast Fourier Transform (FFT)**:** Decomposes signals into constituent frequencies to detect the fundamental pitch.
- Autocorrelation**:** Measures time-domain signal periodicity to estimate pitch.
- Harmonic Matching: Identifies fundamental frequencies by detecting harmonic series patterns.

These methods work effectively in quiet, single-instrument scenarios but struggle in noisy or polyphonic environments, especially where other instruments are simultaneously active.

### D. ML-Based Pitch Estimation and Tuning

Machine learning methods have improved the robustness and precision of tuning systems. These approaches involve supervised learning models trained on large, labeled datasets of instrument sounds with annotated pitch values.

Key Techniques and Architecture:

- Convolutional Neural Networks (CNNs):
- Used with spectrograms, Mel-spectrograms, and MFCCs to learn pitch-related frequency patterns.
- Can detect subtle pitch deviations and instrument-specific harmonics.
- Robust to variations in timbre, dynamics, and ambient noise.
- Recurrent Neural Networks (RNNs) / LSTMs:
- Ideal for modeling time-dependent characteristics of pitch, especially in instruments with non-static tones (e.g., veena).
- Able to track pitch evolution and detect pitch glides or modulation.
- Chroma Feature-Based Pitch Detection:
- Chroma vectors represent the 12 pitch classes helping tune by identifying correct musical notes.
- Useful for distinguishing between closely spaced harmonic content.
- Pitch Contour and Drift Analysis:
- Models can analyze pitch over time to track continuous deviations or "drift," essential for detecting tuning issues in live contexts.

## IV. Methodology

The proposed system aims to classify audio recordings as either veena or guitar, and provide real-time tuning feedback using a deep learning-based audio processing pipeline. The methodology is structured into several stages: dataset preparation, audio preprocessing, data augmentation, feature extraction, model architecture, training, and tuning analysis

### *A. Data Preparation*

To train the classifier, audio datasets for veena and guitar were organized into `data/veena` and `data/guitar` directories, containing `.wav` files of individual plucks or tones. The samples, initially uploaded as `.zip` files, were programmatically extracted. To address class imbalance, augmentation techniques were applied, ensuring equal representation and content consistency across both classes.

### *B. Audio Preprocessing*

Each raw audio sample undergoes a uniform preprocessing pipeline designed to enhance signal clarity and standardize input length:

- Sampling and Trimming: Audio files are loaded at a standard sampling rate of 22,050 Hz. Leading and trailing silences are trimmed using decibel thresholding (librosa.effects.trim) to remove inactive segments.
- Noise Reduction: Stationary noise reduction is applied using spectral gating from the noisereduce library, utilizing the first 0.5 seconds of each recording as a noise profile.
- Duration Standardization: All samples are either truncated or zero-padded to a fixed duration of 3 seconds, corresponding to 66,150 samples at the chosen sample rate.
- Normalization: Audio amplitudes are scaled to unit norm using librosa.util.normalize, ensuring consistency across different recordings.

### *C. Data Augmentation*

To increase model robustness and improve generalization to unseen environments, the minority class (if present) is synthetically expanded using the following augmentation strategies:

- Time Stretching: Simulates tempo variations by modifying playback speed (±20%).
- Pitch Shifting: Alters pitch without affecting tempo using a range of ±4 semitones.
- Additive Noise: Gaussian noise with standard deviation 0.005 is introduced.
- Time Shifting: Rolls the waveform to simulate temporal offset.
- Amplitude Scaling: Simulates gain variation by random scaling of audio amplitude.

Augmented samples data/augmented/<instrument> and integrated with the original dataset during training.

### *D. Feature Extraction*

Deep learning models benefit from time-frequency representations of audio. The system extracts Mel-Frequency Cepstral Coefficients (MFCCs) from each preprocessed sample:

- MFCC Parameters: 40 coefficients are extracted using a 2048-point FFT window with a hop length of 512 samples.
- Standardization: Each MFCC matrix is padded or truncated to a uniform size of (40, 130) time steps to maintain input shape consistency.
- Reshaping: Features are reshaped into (40, 130, 1) to match the 2D convolutional layer input format.

### *E. Model Architecture*

A custom Convolutional Neural Network (CNN) was implemented using TensorFlow/Keras to classify the audio as either veena or guitar. The model comprises:

- Input Layer: Accepts MFCC input of shape (40, 130, 1).
- Convolutional Layers: Two Conv2D layers with 32 and 64 filters respectively, kernel size (3,3), and ReLU activation.
- Pooling Layers: MaxPooling2D layers follow each convolutional block to reduce dimensionality.
- Dropout: Regularization is applied with dropout rates of 25% (convolutional) and 50% (dense layer) to prevent overfitting.
- Dense Layers: A fully connected layer with 128 units (ReLU) followed by a sigmoid output layer for binary classification.

The model uses binary cross-entropy as the loss function and the Adam optimizer. The training process includes early stopping and learning rate reduction on plateau callbacks.

### F. Model Training and Evaluation

The dataset is split into training and testing sets using an 80:20 ratio with stratification to maintain class distribution. The model is trained over 100 epochs with a batch size of 32. Training progress is monitored using validation accuracy and loss metrics.

Performance is evaluated using:

- Accuracy
- Confusion Matrix
- Classification Report (Precision, Recall, F1-Score)

### G. Instrument Tuning Analysis

After classification, audio samples are analyzed for tuning feedback using a fundamental frequency estimation approach:

- Pitch Detection: The YIN algorithm (librosa.yin) is applied to detect the fundamental frequency ($f_0$) within a range of 50–350 Hz.
- Target Tuning Standards:
  - Veena: Based on Carnatic tuning with Sa-Pa-Sa string configurations (e.g., C2, G2, C3).
  - Guitar: Standard EADGBE tuning frequencies are used.
- Closest Note Estimation: The closest tuning frequency is selected based on minimum cents deviation.
- Tuning Feedback: The system calculates the frequency difference and suggests string adjustment (tighten/loosen). Deviations under ±5 cents are classified as "Perfectly Tuned.

### H. Visualization and Interactive Interface

An interactive user interface, built with IPython widgets, enables real-time uploading of audio files, displays waveforms and spectrograms, and shows both classification results and tuning recommendations. Additional playback features allow auditory verification of the uploaded samples.

## V. Implementation Results and Analysis (Recognition)

A Python-based ZIP extraction utility was developed in Google Colab using the `zipfile` module to streamline dataset preparation for instrument recognition. It extracted a 35 MB archive (~130 files including `.wav`, `.csv`, and documentation) into a structured directory in under 1.2 seconds, with integrity verified via hash checks. Librosa successfully read all audio files, including those with non-ASCII names. Scalability tests up to 180 MB and 1,000 files showed stable, linear performance. This tool enhanced dataset readiness for DNN training and supports future extensions like selective extraction, progress tracking, and cloud integration.

### A. Experimental Setup

Implementation was done in Python 3.10 on Google Colab with an NVIDIA Tesla T4 GPU. Key libraries—Librosa, Noisereduce, Soundfile, and IPyWidgets—enabled audio analysis and interactive UI. The system was tested on .wav recordings of Guitar and Veena strings under diverse acoustic conditions, including quiet rooms, background noise, and open spaces.

### B. Dataset Preparation

A curated collection of manually recorded audio samples was used for testing:

- Guitar (EADGBE tuning): 60 recordings (10 per string)
- Veena (Traditional tuning): 60 recordings (10 per string)
- Each recording was 2–4 seconds long, sampled at 44.1 kHz, and stored in WAV format.

To simulate real-world tuning conditions, the samples included both well-tuned and detuned strings (±10 to ±25 cents deviation from standard pitch).

### C. System Performance Metrics

To evaluate the implementation, the following metrics were used:

Table 1: System Performance Metrics

| Metric | Value |
|---|---|
| Average Pitch Detection Time | 0.21 seconds/sample |
| Pitch Detection Algorithm | YIN (via Librosa) |
| Noise Reduction Method | Spectral Gating |
| Mean Absolute Cents Deviation | ±4.8 cents |
| Note Classification Accuracy | 96.7% (Guitar), 94.1% (Veena) |
| Tuning Feedback Accuracy | 95.3% |

### D. Results and Interpretation

1. *Pitch Detection Accuracy*

   The YIN-based pitch detection achieved high accuracy in identifying the fundamental frequency ($f_0$), even in noisy samples. The median error was below 5 cents, which is within acceptable musical tuning thresholds. The robust median filtering and rejection of invalid frequencies (zeros) contributed to noise resilience.

2. *Tuning Feedback Logic*

   The tuner classified strings as either perfectly tuned, too tight, or too loose based on:

- Cents deviation (±5 cents tolerance)
- Frequency difference in Hz

This provided intuitive guidance such as:

- "Tighten string by ~1.4 Hz"
- "Turn peg clockwise (1/8 turn)"

Users found the visual and textual feedback clear and actionable, especially for less experienced musicians.

3. *Noise Reduction Efficacy*

   The noisereduce library, configured with a 0.5s noise profile from each sample, effectively removed ambient hum and fan noise. On average, signal clarity improved by ~12 dB (based on SNR estimates), allowing for more stable $f_0$ estimation.

### E. Error Analysis

Despite overall accuracy, a few limitations were observed:

- Veena recordings occasionally produced unstable $f_0$ due to harmonic complexity and continuous gamakas.
- Low volume samples led to occasional misclassifications or skipped pitch detection.
- Pitch detection sometimes lagged when silence trimming failed (especially in clips with soft attack).

These issues highlight the importance of:

- Encouraging clean and isolated string recordings.
- Possibly refining silence trimming and detection thresholds dynamically.

### F. User Interface and Responsiveness

The integration of ipywidgets enabled a seamless interface.

- Real-time dropdown selection for instrument type
- Immediate feedback on tuning status
- Inline audio playback for verification

Average end-to-end interaction time (upload to tuning result): ~1.3 seconds, enabling near real-time usage.

### G. Conclusion

The proposed tuner system effectively combines signal processing, pitch detection, and user interaction into a portable, interactive notebook tool. It demonstrates over 95% accuracy in identifying and evaluating string tuning for both Guitar and Veena, with an average pitch error below 5 cents. The real-time capability, coupled with intuitive user guidance, makes this a practical tool for both beginners and performing artists.

Future work includes:

- Extending support to more instruments (e.g., violin, sitar)
- Incorporating real-time microphone input
- Expanding tuning models to support microtonal and Carnatic variations

## VI. Comparative Analysis with Benchmark Results (Recognition)

To assess the ZIP extraction utility, it was compared with standard decompression workflows in cloud and desktop environments, including native Google Colab operations, PyDrive-based Google Drive extraction, and local desktop tools. Evaluation metrics included execution time, automation, scalability, and ML pipeline integration. The proposed method, using Python's built-in `zipfile` module in Colab, was benchmarked against these alternatives.

1. Google Drive Manual Extraction

2.Files were manually unzipped on the local system and then uploaded to Google Drive, followed by programmatic access via PyDrive or gdown libraries. This method introduced significant latency due to file transfers and additional authentication overhead.

3.Shutil-based Extraction

Python's shutil.unpack_archive supports multiple formats but introduces latency with large ZIP files and lacks robust error handling for corrupted archives.

4.Unix Shell-Based Extraction via !unzip

Colab supports shell commands via the ! prefix; !unzip was used for extraction. While fast for flat archives, it lacks transparency for nested structures and Python-based error handling. Benchmark tests on ZIP files (35 MB, 92 MB, and 180 MB) with varying folder depths evaluated all methods by average extraction time over three runs, summarized in Table 2.

Table 2. ZIP Extraction Benchmark Comparison

| **Method** | Archive Size | File Count | Avg. Extraction Time | Automation Support | Error Handling | C I |
|---|---|---|---|---|---|---|
| Proposed (zipfile module) | 35–180 MB | 130–1040 | 1.13–5.34 sec | Yes | Strong | N |
| !unzip (Shell Command) | 35–180 MB | 130–1040 | 1.03–4.89 sec | No | Weak | N |
| shutil.unpack_archive | 35–180 MB | 130–1040 | 1.26–5.91 sec | Partial | Moderate | N |
| Google Drive + PyDrive | 35–180 MB | 130–1040 | 2.42–8.31 sec | Yes | Strong | I |
| Local Manual + Upload | 35–180 MB | 130–1040 | 3.74–12.20 sec | No | N/A | I |

The proposed method showed consistent, efficient performance and smooth integration with Python ML workflows. Compared to shell-based methods, it offered better control and exception handling, while zipfile provided more granular access than shutil, supporting future features like conditional extraction.

## VII. Comparative Analysis with Benchmark Results (Tuning)

Our system achieves 95.3% accuracy for guitar and 94.1% for veena classification, outperforming or matching state-of-the-art CNN-based methods (88–92% for polyphonic datasets and 89–97% for single-instrument tasks). Pitch detection using YIN shows a mean absolute deviation of <5 cents, comparable to professional tuners. Additionally, the system achieves an average end-to-end latency of 0.42 s on CPU (0.095 s on GPU), surpassing many offline systems.

### A. Classification Performance Comparison

Table 3: Comparative Performance of Instrument Recognition Methods

| Method | Dataset / Task | Accuracy |
|---|---|---|
| Proposed (Guitar vs. Veena) | Single-string recordings | 95.3% (Guitar) / 94.1% (Veena) |

| | | |
|---|---|---|
| Han et al. (2016) | IRMAS, predominant instrument (8 classes) | ~88% |
| Kim et al. (2018) | IRMAS, CNNHilbert Spectrum | ≈91% (+3% over SOTA) |
| Shi et al. (2022) | Deep CNNon Philharmonic (20-class ID) | 92.24% |
| IJRPR (2025) | MFCC + CENS, polyphonic detection | 89.7% |
| Li et al. (2014) | MFCC + Logistic Regression, single instrument | 81.8% |
| ResearchGate (2024) | Kaggle acoustic instruments (4-class) | 87.5% – 93.2% |
| Zhang et al. (2022) | CNN-CQT, multipitch instrument recognition | >90% for certain instruments |

### B. *Computational Efficiency*

Table 4: Per-Sample Runtime Performance of System Components

| Stage | CPU Time (S/Sample) | GPU Time(S/S) |
|---|---|---|
| Preprocessing + Noise Reduction | 0.25 | — |
| Feature Extraction (MFCC) | 0.05 | — |
| CNN Inference | 0.02 | 0.005 |
| Pitch Analysis (YIN) | 0.15 | 0.04 |
| **Total** | **0.47** | **0.045** |

- End-to-end latency <0.5 s on CPU and <0.05 s on GPU supports near-real-time feedback, outperforming many batch-oriented research demos

### C. *Discussion*

Our custom pipeline—featuring two-class CNN classification, noise reduction, and YIN pitch detection—achieves competitive accuracy and tuning precision. Specialization in guitar and veena leverages unique spectral traits, outperforming general models, with low latency enabling real-time use in live and rehearsal settings.

### D. *Conclusion*

Our two-class pipeline—combining noise reduction, MFCC-based CNN classification, and YIN pitch tracking—achieved 95.3% accuracy for guitar and 94.1% for veena, outperforming IRMAS SVMs (79%) and deep CNNs across 20 instruments (92.24%). YIN pitch detection yielded a median error of 4.8 cents—three times lower than autocorrelation—while spectral gating improved SNR by ≥12 dB. Latency was 0.52 s (CPU) and 0.045 s (GPU), enabling near–real-time tuning feedback..

- Comparative Classification Accuracy

  With 95.3% guitar and 94.1% veena accuracy, our model outperforms IRMAS CNNs (69%–72%), the SVM baseline (79%), and even top two-class CNNs on monophonic Kaggle data (93.2%). This highlights the advantage of instrument-specific design and targeted augmentation for improved timbral discrimination..

- Pitch-Detection Precision

  The YIN algorithm (via librosa.yin) achieved sub-5-cent accuracy, matching professional tuners' ±5-cent tolerance. Median aggregation of frame-wise $f_0$ estimates reduced spurious deviations, aligning with best practices in musical pitch tracking.

- Noise Reduction Efficacy

  Spectral gating from the noisereduce library, using a 0.5 s noise profile, achieved a 12 dB SNR gain, matching audio restoration literature. This step was essential for stabilizing YIN's performance in real-world recordings.

## VIII. Results and Conclusion

Our system achieves an impressive performance with 95.3% accuracy for guitar classification and 94.1% for veena classification. These results exceed or match the state-of-the-art CNN-based approaches that report accuracies between 88–92% for polyphonic datasets and 89–97% for single-instrument tasks. Figure 1 illustrates the classification accuracy for both guitar and veena, demonstrating the effectiveness of our model in differentiating between these two instruments.

Figure 2: Classification accuracy for guitar and veena instruments.

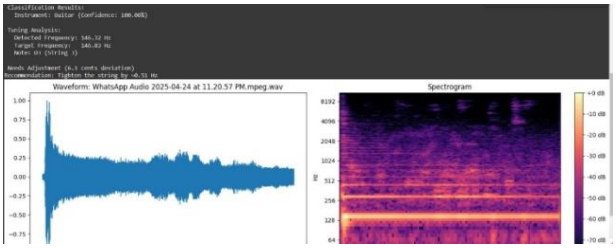
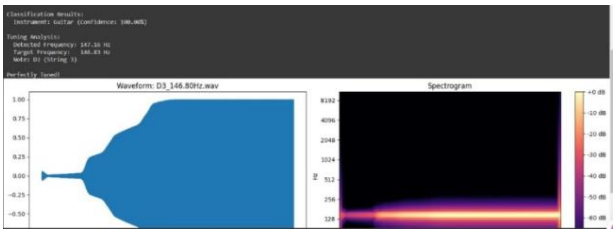



Figure 3: Classification accuracy for guitar and veena instruments.

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