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# Construction and recognition of acoustic ID of ancient coins based on deep learning of artificial intelligence for audio signals

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## Abstract

In the field of cultural heritage protection, it is significant to establish a reliable ID (identifier) for valuable cultural and artistic items. At present, the identification of ancient cultural relics is mainly based on image information, such as pictures, 3D (three-dimensional) scanning, X-ray and CT (computed tomography) data. However, in many cases, it is impossible to identify whether slight damage, partial restorations, or ancient cultural relics have been replaced by fakes by using image information. In the era of digital duplication, more reliable identity information is urgently needed. The main technical challenge of an acoustic analysis system for ancient coins based on artificial intelligence technology is to find a non-destructive, fast and accurate identification method for ancient cultural relics. The recognition method includes two main modules: the artificial audio data sampling device and deep learning. In addition, this paper has completed the analysis of the vibration spectrum features of 19 ancient coins and realized the whole process of acoustic ID construction. The open-source platform Easy DL was used to analyze the multidimensional vibration spectrum curve feature extraction and identification. This method enables audio signal signature recognition technology to be applied in the display, preservation, transaction and safety management of ancient coins and other cultural relics.

**Keywords** Ancient coins, Acoustic ID, Artificial intelligence, Deep learning, Recognition, Cultural heritage protection

## Introduction

Among the various cultural relics, ancient coins are an important part, due to the value of the coins themselves and the ancient history, culture and technology that they reflect [1]. China was one of the first countries in the world to use currency, and from the square-hole round coins of the Qin Dynasty to the mechanism coins of the late Qing Dynasty, tens of thousands of coins make up a rich assortment of collections [2]. However, due to the great value, small size and relatively easy preservation and carrying of ancient coins, the illegal trading and theft of ancient coins has become the main manifestation of illegal trading and theft of cultural relics. On the one hand, in order to protect cultural relics and crack down on illegal trade, it is necessary to record, identify and track cultural relics, so as to assist the protection units, customs and various law enforcement agencies. On the other hand, it provides scientific data for the research of cultural relics, history and finance, etc. Therefore, it is very urgent to identify, authenticate and track the ancient coins [3].

In recent years, the rapid development of high and new technology such as machine vision, digital image

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processing, pattern recognition and machine learning has driven the rapid development and wide application of object recognition technology [4–6]. For example, a study converted a color image of 115 euro coin into a color index image [7], and another study designed a neural network-based coin recognition system that identified coins from both Korea and Japan [8]. Some researchers also use Gabor filter and neural network classifier for edge detection, and extract sub-images from coin images for rotation lossless recognition [9]. Researchers also applied two ancient Roman silver coins, using imaging and analysis techniques from multiple disciplines to digitize coins and evaluate 3D integrated visualization research [10]. To sum up, at present, most coin recognition methods use neural networks, mainly to extract various features of the image and classify the feature vectors by using classifiers [11, 12].

ID refers to a string of symbols (numbers, letters, etc.) used to represent people or things in a system, and it is a way to show one's identity [13]. An ID can give a unique digital identity to cultural relics. At present, the identification of cultural relics is mainly based on image information, such as photos, 3D scanning, X-ray and CT data. However, in many cases, it is impossible to use image information to identify slight damage, partial restoration or replacement of ancient cultural relics. The mechanical vibration of the object under test and the vibration of the medium caused by the mechanical vibration produce sound that reflects information about the structure of the object under test [14–17]. The primary and harmonic vibrations caused by the vibrations is an inherent property of the ancient coin. This recognition feature, which is composed of sound waves, is determined by the inherent attributes of the cultural relics itself, such as its composition, structure and state, and has essential features that plane image or a 3D scanned image cannot replace[18, 19]. This acoustic digital signature cannot be duplicated or repaired, the signal is easy to capture and quickly compared, and the entire measurement process is non-destructive. In this paper, we design a non-destructive testing device applicable to ancient coins. When analyzing the acoustic parameters of the audible sound signal, we can get more intuitive and accurate information about the characteristics of ancient coins, which are determined by the parameters obtained in the time domain and frequency domains, and used for the identification and discrimination of ancient coins. By inputting the measured sound waves of ancient coins into a database as their ID, using artificial intelligence, deep learning and model training, ancient coins can be identified nondestructive, quickly and accurately.

## Methods

### Samples

As shown in Fig. 1, 19 ancient coins were selected as samples for study in this paper, they are KaiYuanTongBao (開元通宝), ChunHuaYuanBao (淳化元宝), XuanHeTongBao (宣和通宝), XiNingZhongBao (熙宁重宝), ShunZhiTongBao (順治通宝), KangXiTongBao (康熙通宝), YongZhengTongBao (雍正通宝), QianLongTongBao (乾隆通宝), JiaQingTongBao (嘉慶通宝) and GuangXuTongBao (光绪通宝). These samples were all provided by the School of Art and Design of Shaanxi University of Science and Technology. The numbers and names of the ancient coin samples can be found in Table 1.

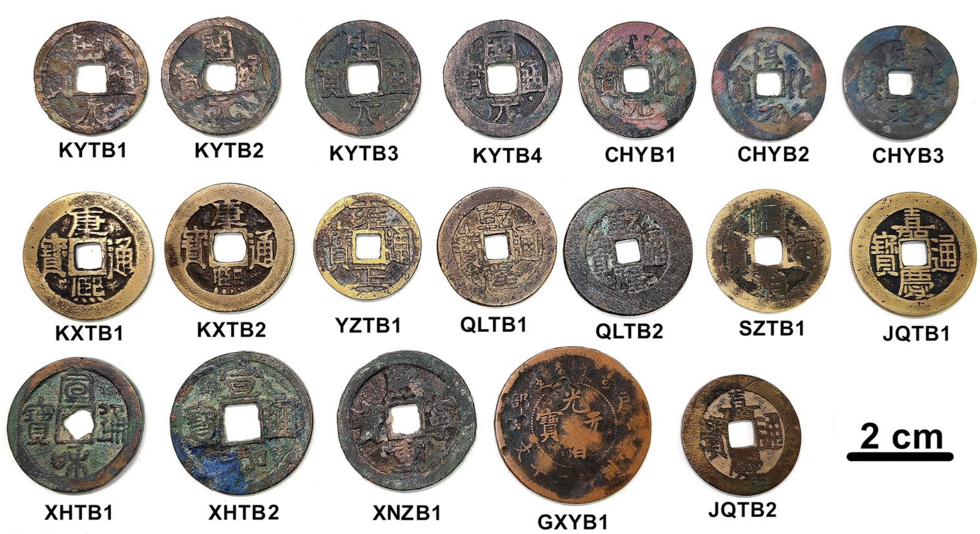


**Fig. 1** Nineteen ancient coins

**Table 1** Audio recognition results for ancient coins

| Sample Number | Coin name | Dynasty | Result 1 | Recognition rate | Result 2 | Recognition rate |
|---|---|---|---|---|---|---|
| KYTB 1 | 開元通宝 | Tang | KYTB 1 | 98.97% | KYTB 1 | 98.17% |
| KYTB 2 | 開元通宝 | Tang | KYTB 2 | 100% | KYTB 2 | 100% |
| KYTB 3 | 開元通宝 | Tang | KYTB 3 | 99.02% | KYTB 3 | 93.85% |
| KYTB 4 | 開元通宝 | Tang | KYTB 4 | 100% | KYTB 4 | 100% |
| CHYB 1 | 淳化元宝 | Song | CHYB 1 | 99.99% | CHYB 1 | 86.62% |
| CHYB 2 | 淳化元宝 | Song | CHYB 2 | 70.84% | CHYB 2 | 97.87% |
| CHYB 3 | 淳化元宝 | Song | CHYB 3 | 95.29% | CHYB 3 | 100% |
| XHTB 1 | 宣和通宝 | Song | XHTB 1 | 99.95% | XHTB 1 | 98.46% |
| XHTB 2 | 宣和通宝 | Song | XHTB 2 | 100% | XHTB 2 | 100% |
| XNZB 1 | 熙宁重宝 | Song | XNZB 1 | 100% | XNZB 1 | 100% |
| SZTB 1 | 順治通宝 | Qing | SZTB 1 | 83.89% | SZTB 1 | 99.87% |
| KXTB 1 | 康熙通宝 | Qing | KXTB 1 | 100% | KXTB 1 | 100% |
| KXTB 2 | 康熙通宝 | Qing | KXTB 2 | 98.14% | KXTB 2 | 100% |
| YZTB 1 | 雍正通宝 | Qing | YZTB 1 | 100% | YZTB 1 | 100% |
| QLTB 1 | 乾隆通宝 | Qing | QLTB 1 | 85.29% | QLTB 1 | 100% |
| QLTB 2 | 乾隆通宝 | Qing | QLTB 2 | 100% | QLTB 2 | 100% |
| JQTB 1 | 嘉慶通宝 | Qing | JQTB 1 | 100% | JQTB 1 | 100% |
| JQTB 2 | 嘉慶通宝 | Qing | JQTB 2 | 94.19% | JQTB 2 | 99.17% |
| GXTB 1 | 光绪通宝 | Qing | GXTB 1 | 99.99% | GXTB 1 | 99.95% |

## Experiments

The main technical challenge of an acoustic analysis system for ancient coins based on artificial intelligence technology is the design of a non-destructive, fast and accurate identification device suitable for cultural relics. The recognition method consists of two main modules: the artificial audio data sampling device and the deep data learning. The audio data sampling equipment consists of three parts, as shown in Fig. 2a. The first part is the sound generation device, including the frequency generator and the audio signal amplifier. The second part is the measurement device, including the resonant audio and vibration pickup. The third part is the signal processing device, including the analogue-to-digital signal converter and computer. For the test, the ancient coins are placed on the resonant sound, and the audio is introduced into the ancient coins by direct contact. It is worth noting that the vibration pickup can only pick up the structural sound transmitted in the ancient coins. Finally, the analogue-to-digital converter converts the acquired audio signal into a digital signal, which is recorded and analyzed using computer software. The coupling agent layer is applied between the pickup and the detection surface. Its main function is to exclude the air between the tested part and the sensor, and increase the sound pressure transmission rate, thus ensuring the sound waves to be transmitted well [20–22]. The couplant is a water-based polymer gel whose main components include acrylic resin (carbomer), glycerin and purified water. It does not contaminate ancient coin samples and is easy to clean up and can be removed by wiping with tissue. Before measuring, the pickup needs to be pressed each time so that the coupling agent fully covers the gap between the coin and the pickup and so that the coupling agent is as thin as possible.

The deep learning of data is mainly completed by Easy DL, which is an open-source AI development platform that supports customized model training and provides developers with support for the whole process function of AI model development [23]. Easy DL is an open-source deep learning platform based on Baidu's self-developed "paddle paddle". It supports audio input data, and relies on the core framework and tool components of "paddle paddle" to provide data pre-processing, model training, deployment and serving services. The AI workflow for the Easy DL sound classification models is shown in Fig. 2b, where the functions of ancient coinage dataset management, model training, model evaluation, model calibration and model publishing are mainly provided [24]. Easy AI workflow combines the traditional machine learning workflow with big data processing, and uses Baidu Auto deep learning technology to achieve the effect of training high-precision models with a small amount of data.

Figure 2c shows a typical platform architecture [24]. The layer of computing and storage resource includes storage clusters for data, models and code, and large-scale GPU or AI custom chip server clusters for model training. The framework and model layer includes the

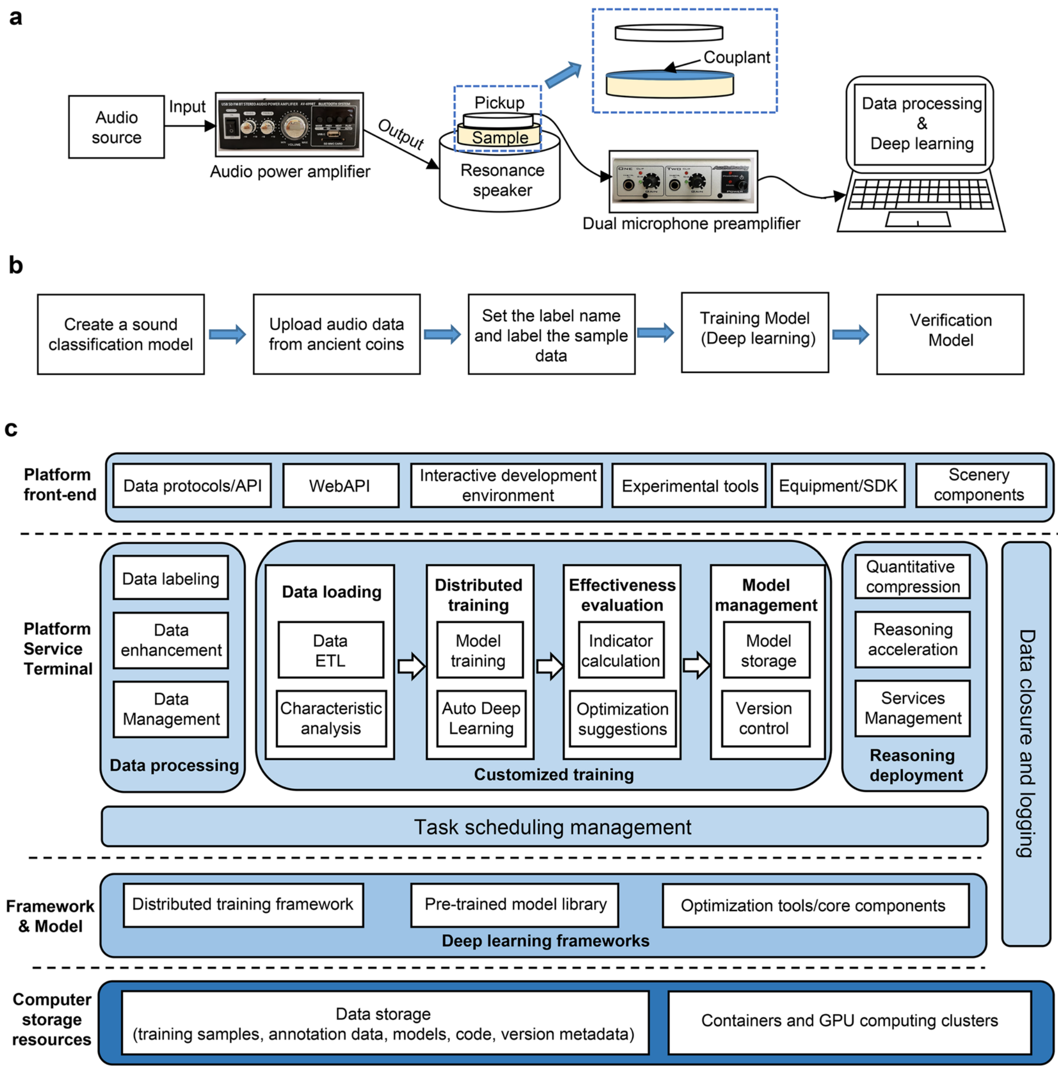


**Fig. 2** Acoustic measurement devices and identification models for ancient coins: **a** acoustic measurement devices, **b** AI workflow for the Easy DL sound classification models, and **c** a typical platform architecture of Easy DL platform

core deep learning framework, distributed training APIs for the platform, prefabricated models based on large-scale data training, and model performance optimization tool components. The platform realizes data processing, customized training and reasoning deployment, and generally realizes the continuous iterative optimization of model effects through the call of data closure. The top layer is the front-end of the platform that interacts with users, including scene components that adapt to different scenes. Improving the accuracy of the execution judgment models also requires the training of big data. This also needs to consider the differences of actual cultural relics, the specific application requirements, and the actual loadable sound sources and pickup processes.

## Results and discussion

We tested each of the 19 samples 100 times using a 1 kHz source, each test lasting six seconds, with each audio having greater than 270,000 data sampling points. An acoustic classification model of ancient coins is established on the Easy DL. The measured 1900 audio data are uploaded into the model, and 1900 audio data are labeled, and then the model is trained. During model training, the model learns deeply from these 1900 audios. When the training was complete, we measured each of the 19 samples twice, for a total of 38 test audios. These test audios were put into a training model for calibration, and recognition results 1 and result 2 were obtained for each coin, as shown in Table 1. It can be seen that the recognition rate of the model is high, the correct recognition rate is 100%, and a recognition matching degree is between 70.84% and 100%. The matching rate of samples KYTB 2, KYTB 4, CHYB 3, XHTB 2, XNZB 1, KXTB 1, KXTB 2, YZTB 1, QLTB 1, QLTB 2 and JQTB 1 reached 100%.

As shown in Fig. 3, the frequency domain curves for the sound source at 1 kHz and for the acoustic ID of the 19 samples are shown. It can be clearly seen that the frequency domain of the audio source has a peak value of 1 kHz at the main (fundamental) frequency, and there are basically no other small peaks. However, in addition to the main (fundamental) frequency, the frequency domain curves of the audio for each of the samples show other peaks of varying shape and with different peak distributions. Even coins of the same type in the same period, such as KYTB 1 to KYTB 4, have different peak distribution and intensity in frequency domain. This may be related to their corrosion, wear, and slightly different manufacturing processes. This results in a unique and non-replicable acoustic ID for each coin.

Based on the checksum results in Table 1, it can be seen that there are fluctuations in the match of the checksum results obtained after check summing with two test audios that are not in the model database. For example, the checksum result 1 of the first audio in QLTB 1 is 85.29%, while the checksum result 2 of the second audio is 100%. As shown in Fig. 4a, b, we named the acoustic ID of QLTB1 in the model database "QLTB1-Test", and the two test audios not in the model database "QLTB1-Result 1" and "QLTB1-Result 2" respectively. In Fig. 4a, it can be seen that the amplitude of the time domain curve for "QLTB1-Result 2" is smaller than the other two curves. As shown in Fig. 2a, a thin layer of coupling agent was applied between the coin and the pickup during the measurement. In the case of the experimental field, during the audio measurement of "QLTB 1- Result 2", it is likely that the coupling agent does not completely cover between the pickup and the coin sample, resulting in sound loss. This also causes the peak distribution of the frequency domain curve of the "QLTB1-Result 2" audio to be shifted to varying degrees in Fig. 4b.

To further test the above suspicions, we tested the Kai Yuen Tong Bao 2 again with the same situation. We first applied coupling agent between the coin and the pickup, and then measured both audios. After removing all the coupling agent between the coin and the pickup, we measured the two audio frequencies again. The time domain curves of the test results are shown in Fig. 4c. It can be clearly seen that the amplitude of the time domain curve for the test audio with couplant applied is significantly larger than that of the audio without couplant applied. It is also obvious in Fig. 4d, that there is a loss of frequency domain data for the audio measured without couplant. Except the main frequency, the peak characteristics in all frequency

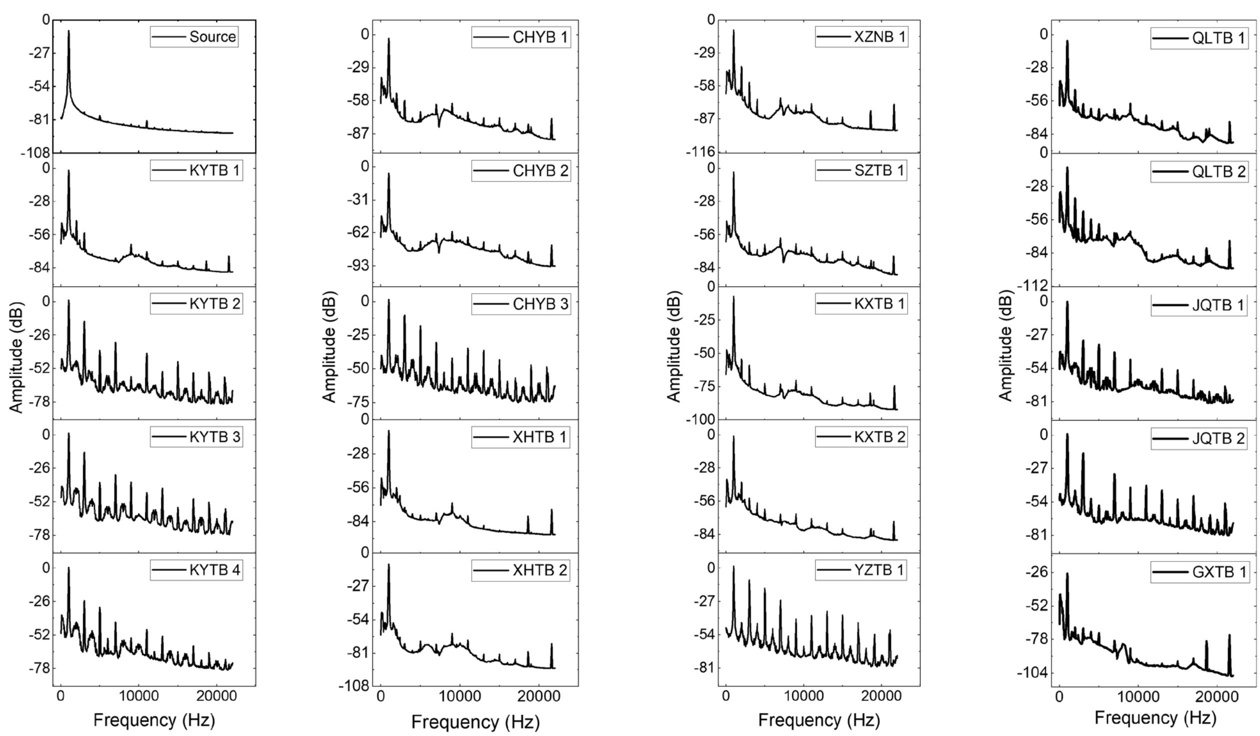


**Fig. 3** The frequency domain curves for the sound source at 1 kHz and for the acoustic ID of the 19 ancient coin samples

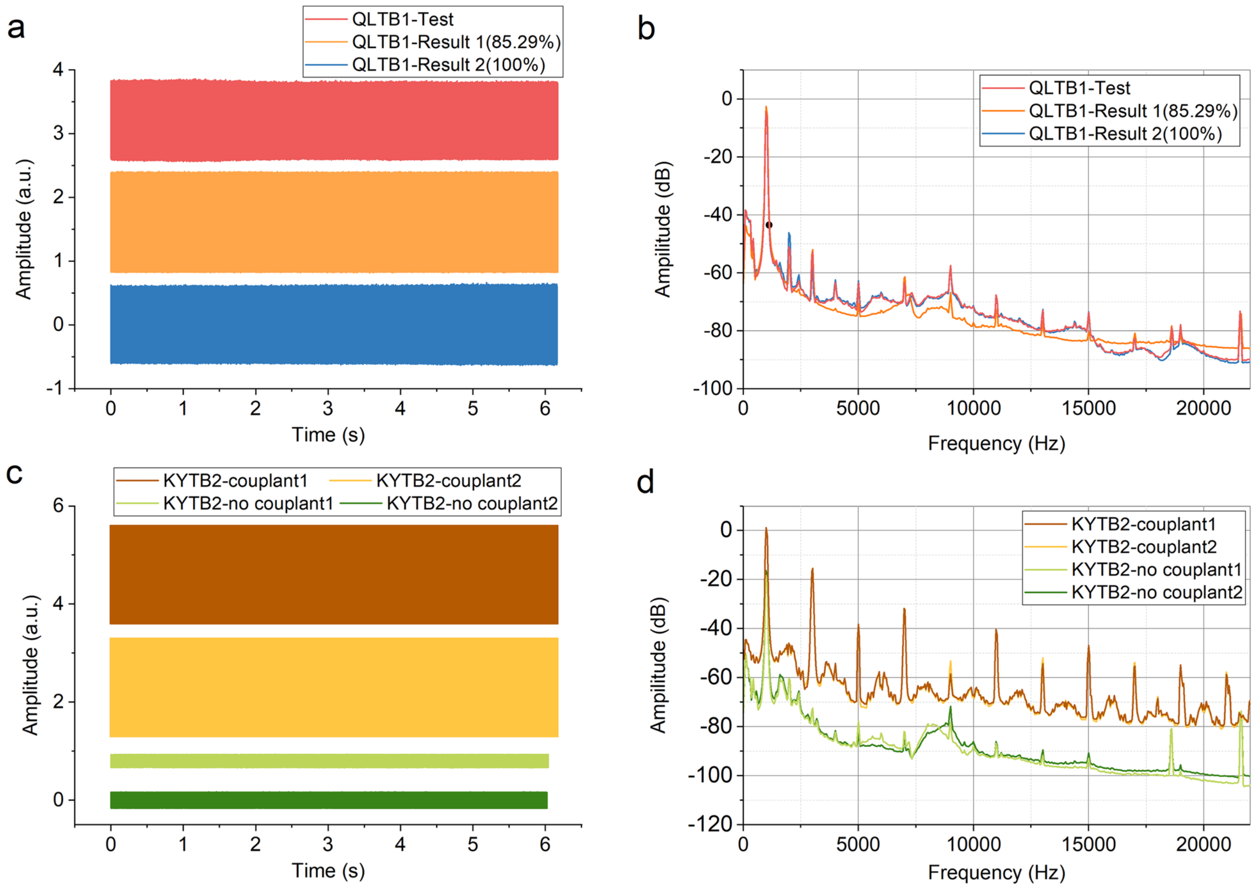


**Fig. 4** Acoustic parameter curves of ancient coin samples: **a** time domain curves for one training audio and two test audios of the QLTB1 sample, **b** frequency domain curves for one training audio and two test audios of the QLTB1 sample, **c** time domain curves for the two test audios with couplant and the two test audios without couplant for the sample KYTB2, and **d** frequency domain curves for the two test audios with couplant and the two test audios without couplant for the sample KYTB2

bands are not obvious. It can be seen that the amount of coupling agent, the consistency of test environment and conditions have influence on the test results and recognition results. In addition, in the experiment, the coupling dose used for both measurements were 1 ml, which could cover the surface of the coins without excess. According to the time-domain and frequency-domain curves of "KYTB2-couplant 1" and "KYTB2-couplant 2" in Fig. 4c and d, it can be seen that after applying coupling agent, the test results are consistent. The matching rate of the results of the two tests in Easy DL was 100%. This indicates that when the state of the coin does not change and the measurement conditions are consistent, the features of the ID of the same coin can be successfully recognized, and the matching rate is about 100%. This is of application significance to the identification of ancient coins and the identification of whether the status of ancient coins has changed.

## Conclusions

The main technical challenge of an acoustic analysis system for cultural relics based on artificial intelligence technology is to find non-destructive, rapid and accurate identification methods for cultural relics. Improving the accuracy of the model performing the judgement also requires training with big data. Improving accuracy also requires consideration of differences in actual cultural relics, special application requirements, and the consistency of test conditions during the actual loadable sound source and pick-up process, such as the usage and dosage of coupling agents.

Based on the acoustic measurement methods in this paper, it was found that acoustic parameters can give a unique and unchangeable acoustic ID to ancient coins. By designing a non-destructive detection device applicable to ancient coins and in the analysis of acoustic parameters of audible signals, we can obtain more intuitive and accurate information about the characteristics of ancient coins. Combined with artificial intelligence and deep learning, this allows the non-destructive, fast and accurate identification of ancient coins. This will not only record, identify and trace ancient coins, but also help the staff of cultural relics protection units, customs and various law enforcement agencies to do related work. In addition, the technology can also be applied to the construction of acoustic ID of ancient ceramics, ancient bronze and ancient wooden utensils in the future, allowing the audio signal feature recognition technology to provide maximum value in the display, protection, trading and security management of ancient coins and wares, meeting the needs of the majority of heritage collection enthusiasts, auction houses and museums for the identification, authentication and tracking of a wide range of cultural relics.

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**Author contributions**
Conceptualization: XW and XJ; methodology: XW and XJ; software: XJ; resources: XC; writing—original draft preparation: XJ; writing—review and editing: XJ and XW; project administration: XW and CX; funding acquisition: XW. All authors have agreed to the published version of the manuscript. All authors read and approved the final manuscript.

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**Availability of data and materials**
The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

## Declarations

**Competing interests**
The authors declare no competing interests.

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## Publisher's Note