Musical instruments recognition is widely used in music information retrieval. Most previous musical instruments recognition datasets focus on western musical instruments, making it difficult for researchers to study and evaluate the area of traditional Chinese musical instrument recognition. This paper addresses this by collecting a traditional Chinese music dataset, named ChMusic, for training models and performance evaluation. The dataset includes 11 traditional Chinese musical instruments and 55 traditional Chinese music excerpts. An evaluation standard is proposed based on ChMusic dataset, allowing researchers to compare their results following the same rules, making different research results comparable.

Additional Keywords and Phrases: Chinese instruments, music dataset, Chinese music, machine learning, evaluation of musical instrument recognition

1 INTRODUCTION

Musical instruments recognition is an important and fascinating application for music information retrieval (MIR). Deep learning is a powerful tool for image processing [1, 2, 3], video processing [4, 5, 6], natural language processing [7, 8, 9], speech processing [10, 11, 12] and music processing [13, 12, 15] applications, and has demonstrated better performance compared with previous approaches. However, deep learning-based approaches rely on proper datasets to train models and evaluate performance.

Though there are already several musical instruments recognition datasets, most of these datasets only cover western musical instruments. For example, the Good-sounds dataset [16] contains 12 musical instruments consisting of flute, cello, clarinet, trumpet, violin, sax alto, sax tenor, sax baritone, sax soprano, oboe, piccolo, and bass. Another musical instruments recognition dataset called [17] includes 20 musical instruments consisting of accordion, banjo, bass, cello, clarinet, cymbals, drums, flute, guitar, mallet percussion, mandolin, organ, piano, saxophone, synthesizer, trombone, trumpet, ukulele, violin, and voice. Very few attention has been made to other cultures’ musical instruments recognition. Even for the very limited researches based on Chinese musical instruments recognition [18, 19], the datasets used for research are not publicly available. Without an open access Chinese musical instruments dataset, another critical problem is that researchers cannot evaluate their model performance by a same standard, so results reported from their papers are not comparable.

To deal with the problems mentioned above, a traditional Chinese music dataset, named ChMusic, is proposed to help train Chinese musical instruments recognition models and conduct performance evaluation. The major contributions of this paper are:

1) Propose a traditional Chinese music dataset for Chinese traditional instrument recognition, named ChMusic.
2) Come up with an evaluation standard to conduct Chinese traditional instrument recognition on ChMusic dataset.
3) Propose baseline approach for Chinese traditional instrument recognition on ChMusic dataset, code for this baseline is https://github.com/HaoranWeiUTD/ChMusic

The rest of the paper is organized as follows: Section 2 covers details of ChMusic dataset. Then, the corresponding evaluation standard to conduct Chinese traditional instrument recognition on ChMusic dataset are described in Section 3. Baseline for Musical Instrument Recognition on ChMusic Dataset is proposed in Section 4. Finally, the paper is concluded in Section 5.

2 CHMUSIC DATASET

ChMusic is a traditional Chinese music dataset for training model and performance evaluation of musical instrument recognition. This dataset covers 11 musical instruments, consisting of Erhu, Pipa, Sanxian, Dizi, Suona, Zhuiqin, Zhongruan, Liuqin, Guzheng, Yangqin, and Sheng, the indicating numbers and images are shown on Figure 1 respectively.

Each musical instrument has 5 traditional Chinese music excerpts, so there are 55 traditional Chinese music excerpts in this dataset. The name of each music excerpt and the corresponding musical instrument is shown on Table 1. Each music excerpt only played by one musical instrument in this dataset.
Each music excerpt is saved as a .wav file. The name of these files follows the format of “x.y.wav”, “x” indicates the instrument number, ranging from 1 to 11, and “y” indicates the music number for each instrument, ranging from 1 to 5. These files are recorded by dual channel, and has sampling rate of 44100 Hz. The duration of these music excerpts are between 25 to 280 seconds. This ChMusic dataset can be download from Baidu Wangpan by link: pan.baidu.com/s/13e-6GnVJmC3tcwJtxed3-g with passwords: xk23, or from google drive: drive.google.com/file/d/1rfbXpkYEUw5h_CZJtC7eyYemeFMzij/view?usp=sharing

3 EVALUATION OF MUSICAL INSTRUMENT RECOGNITION ON CHMUSIC DATASET

The diagram of musical instrument recognition can be simplified as Figure 2. Figure 2 consisting of two stages, corresponding to training stage and testing stage respectively. Training data is used for training stage to train a musical instrument recognition model. Then this model is tested by testing data during testing stage.
| Instrument Name | Music Number | Music Name |
|-----------------|--------------|------------|
| Erhu            | 1            | "Ao Bao Xiang Hui" |
|                 | 2            | "Mu Yang Gu Niang" |
|                 | 3            | "Xiao He Tang Shui" |
|                 | 4            | "Er Xing Qian Li" |
|                 | 5            | "Yu Jia Gu Niang" |
| Pipa            | 1            | "Shi Mian Mai Fu" excerpts |
|                 | 2            | "Su" excerpts |
|                 | 3            | "Zhu Fu" excerpts |
|                 | 4            | "Xian Zi Yun" excerpts |
|                 | 5            | "Ying Hua" |
| Sanxian         | 1            | "Kang Ding Qing Ge" |
|                 | 2            | "Ao Bao Xiang Hui" |
|                 | 3            | "Gan Niu Shan" |
|                 | 4            | "Mao Zhu Xi De Hua Er Ji Xin Shang" |
|                 | 5            | "Nan Ni Wan" |
| Dizi            | 1            | "Hong Mei Zan" |
|                 | 2            | "Shan Hu Song" |
|                 | 3            | "Wei Shan Hu" |
|                 | 4            | "Xiu Hong Qi" |
|                 | 5            | "Xiao Bai Yang" |
| Suona           | 1            | "Hao Han Ge" |
|                 | 2            | "She Yuan Dou Shi Xiang Yang Hua" |
|                 | 3            | "Yi Zhi Hua" |
|                 | 4            | "Huang Tu Qing" excerpts |
|                 | 5            | "Liang Zhu" excerpts |
| Zhuiqin         | 1            | "Jie Nian" excerpt 1 |
|                 | 2            | "Jie Nian" excerpt 2 |
|                 | 3            | "Hong Sao" excerpt |
|                 | 4            | "Jie Nian" excerpt 3 |
|                 | 5            | "Zi Mei Yi Jia" excerpt |
| Zhongruan       | 1            | "Yun Nan Hui Yi" excerpt 1 |
|                 | 2            | "Yun Nan Hui Yi" excerpt 2 |
|                 | 3            | "Yun Nan Hui Yi" excerpt 3 |
|                 | 4            | "Yun Nan Hui Yi" excerpt 4 |
|                 | 5            | "Yun Nan Hui Yi" excerpt 5 |
| Liuqin          | 1            | "Chun Dao Yi He" excerpt 1 |
|                 | 2            | "Yu Ge" excerpt |
|                 | 3            | "Chun Dao Yi He" excerpt 2 |
|                 | 4            | "Yu Hou Ting Yuan" excerpt |
|                 | 5            | "Jian Qi" excerpt |
| Guzheng         | 1            | "Lin Chong Ye Ben" excerpt 1 |
|                 | 2            | "Zhan Tai Feng" excerpt |
|                 | 3            | "Yu Zhou Chang Wan" |
|                 | 4            | "Lin Chong Ye Ben" excerpt 2 |
|                 | 5            | "Han Jiang Yun" |
| Yangqin         | 1            | "Zuo Zhu Fa Lian Xi Qu" |
|                 | 2            | "Fen Jie He Xian Lian Xi Qu" |
|                 | 3            | "Dan Yin Yu He Yin Jiao Ti Lian Xi Qu" |
|                 | 4            | "Lun Yin Lian Xi Qu" |
|                 | 5            | "Da Qi Luo Gu Qing Feng Shou" |
| Sheng           | 1            | "Gua Hong Deng" excerpt |
|                 | 2            | "Qin Wang Po Zhen Yue" excerpt |
|                 | 3            | "Shui Ku Yin Lai Jin Feng Huang" |
|                 | 4            | "Shan Xiang Xi Kai Feng Shou Lian" |
|                 | 5            | "Xi Ban Ya Dou Niu Wu Qu" |
The widely used features for musical instrument recognition include linear predictive cepstral coefficient (LPCC) [20] and mel-scale frequency cepstral coefficients (MFCC) [21]. The commonly used classification models include k-nearest neighbors (KNN) model [18], Gaussian mixture model (GMM) [22], support vector machine (SVM) model [23], hidden markov model (HMM) [24] and deep learning based models [25].

In ChMusic Dataset, music with number 1 to 4 of each instrument are used as training dataset, music with number 5 of each instrument are used as testing dataset. Every music is cut into 5 seconds clips without overlap, the ending part of each music which is shorter than 5 seconds is discarded. Each 5 seconds clips need to make a prediction for musical instrument classification result.

\[
Accuracy = \frac{Correct\text{ClassifiedClips}}{All\text{ClipsFromTestingData}}
\] (1)

Classification accuracy will be the evaluation metrics for musical instrument recognition on ChMusic Dataset. And confusion matrix is also recommended to present the result.

## 4 BASELINE FOR MUSICAL INSTRUMENT RECOGNITION ON CHMUSIC DATASET

Baseline for musical instrument recognition on ChMusic dataset is described in this section. Machine learning [26, 27, 28, 29, 30, 31] and deep learning [32, 33, 34, 35, 36, 37, 38, 39, 40] are useful tools to deal with classification and recognition related problems [41, 42, 43, 44, 45, 46, 47, 48, 49, 50]. Baseline approach is conducted by machine learning approach. Twenty dimensions MFCCs are extracted from each frame, and KNN is used for frame level data training and testing. As each test clip have 5 minutes in duration, a majority voting is conducted to get final classification result from frame-level results within the 5 minutes test clip.

KNN models with various K value are compared. Accuracy for KNN models with each K value are presented in Table 2 then confusion matrix for K=3, K=5, K=9 and K=15 are presented in Figure 3, Figure 4, Figure 5 and Figure 6 respectively.

| Model   | Accuracy(%) |
|---------|-------------|
| KNN (K=3) | 93.57       |
| KNN (K=5) | 93.57       |
| KNN (K=9) | 93.57       |
| KNN (K=15) | 94.15      |
Figure 3. Confusion matrix of KNN model with K=3.

Figure 4. Confusion matrix of KNN model with K=5.
5 CONCLUSION

Musical instruments recognition is an interesting application for music information retrieval. While most of previous musical instruments recognition dataset focus on western musical instruments, very few works have been conducted on the area of traditional Chinese musical instrument recognition. This paper proposes a traditional Chinese music dataset for training model and performance evaluation, named ChMusic. With this dataset, researchers can download it for free. Eleven traditional Chinese musical instruments and 55 traditional Chinese music excerpts are covered in this dataset. Then an evaluation standard is proposed based on ChMusic dataset. With this standard, researchers can compare their results following the same rule, and results from different researchers will become comparable.
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