

INTRODUCTION

Given the similarities between speaker recognition and musical instrument recognition, we adapt speaker recognition algorithms to the task of learning meaningful instrumental timbre representations.

- Introduced a group of trainable filters initialized with Mel and MIDI filter bank to address the mismatch between speech and musical instrument sound.
- The modified speaker recognition model was capable of generating discriminative embeddings for instrument and instrument-family, performing well in both **closed-set** and **open-set** scenarios.
- Conducted extensive experiments to characterize the encoded information in learned timbre embeddings.

METHODS

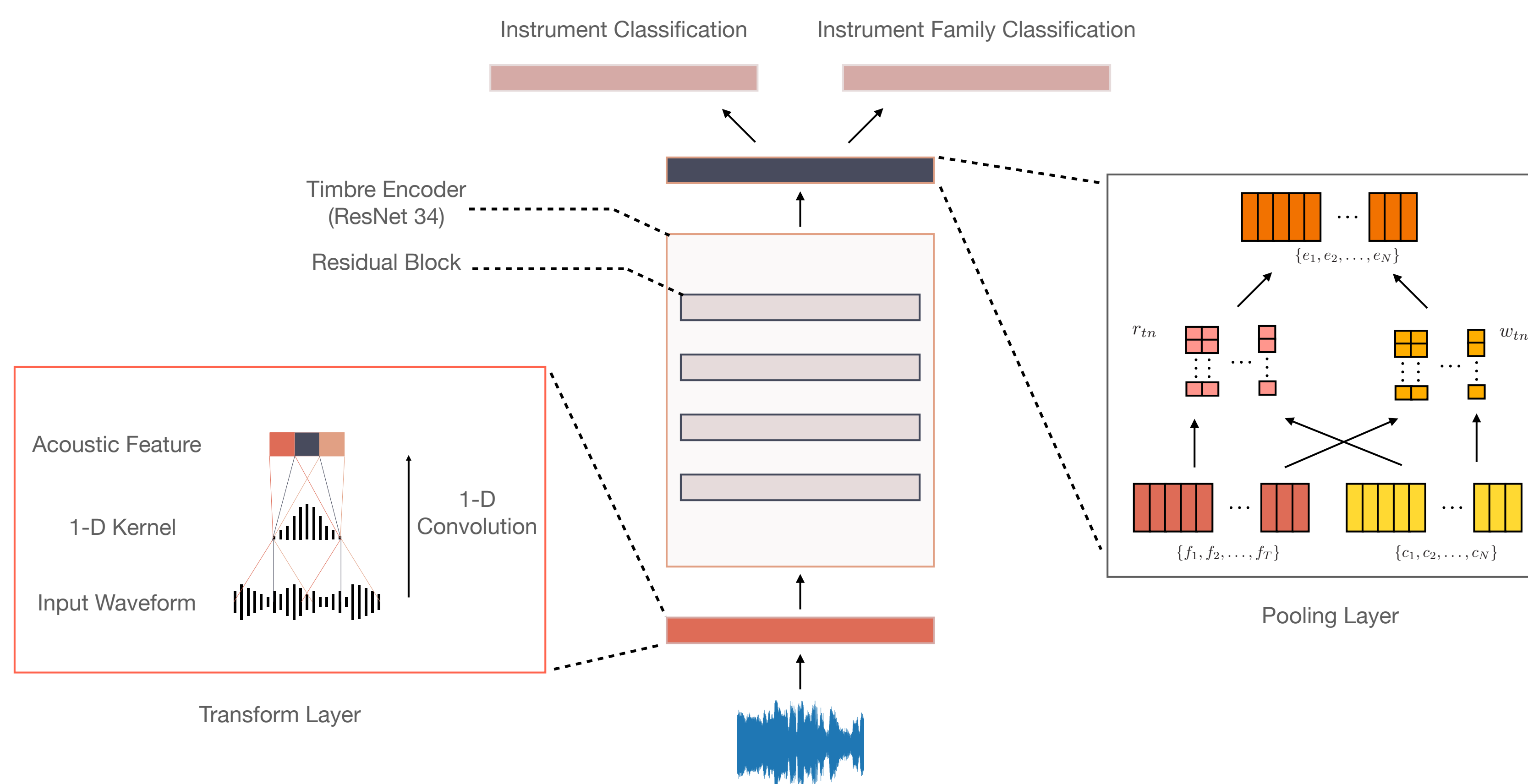


Figure 1: Architecture of proposed musical instrument recognition model inspired by speaker recognition

- Transform Layer based on SincNet[1]
- Encoder based on ResNet [2] and LDE [3]
- Dual outputs based on Angular-Softmax [4]
- MIDI filter bank initialization

RESULT I: RECOGNITION

- Two Recognition Scenarios: instrument verification, instrument-family identification.
- Database: NSynth Dataset [8] (individual notes from 1,006 instruments)
- Training Strategy: data augmentation, Angular-Softmax.

Table 1: Instrument verification and instrument-family identification results on NSynth database.

Systems	EER	Micro F1
Melspec-aug-asm	3.186	77.00
wav-transMel-aug-asm	3.424	77.34
wav-transMIDI-aug-asm	3.737	77.76
LEAF [5]		72.0
Baseline in [6]		73.78
Best in [6]		74.73

REFERENCES

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RESULT II: GENERALIZATION

- Task: generalize the model trained on NSynth to RWC dataset [9] (45 categories).
- Training Strategy: training from the scratch, training based on pre-trained model.
- Results: pre-trained parameters from NSynth help the model to converge faster and achieve higher accuracy on RWC.

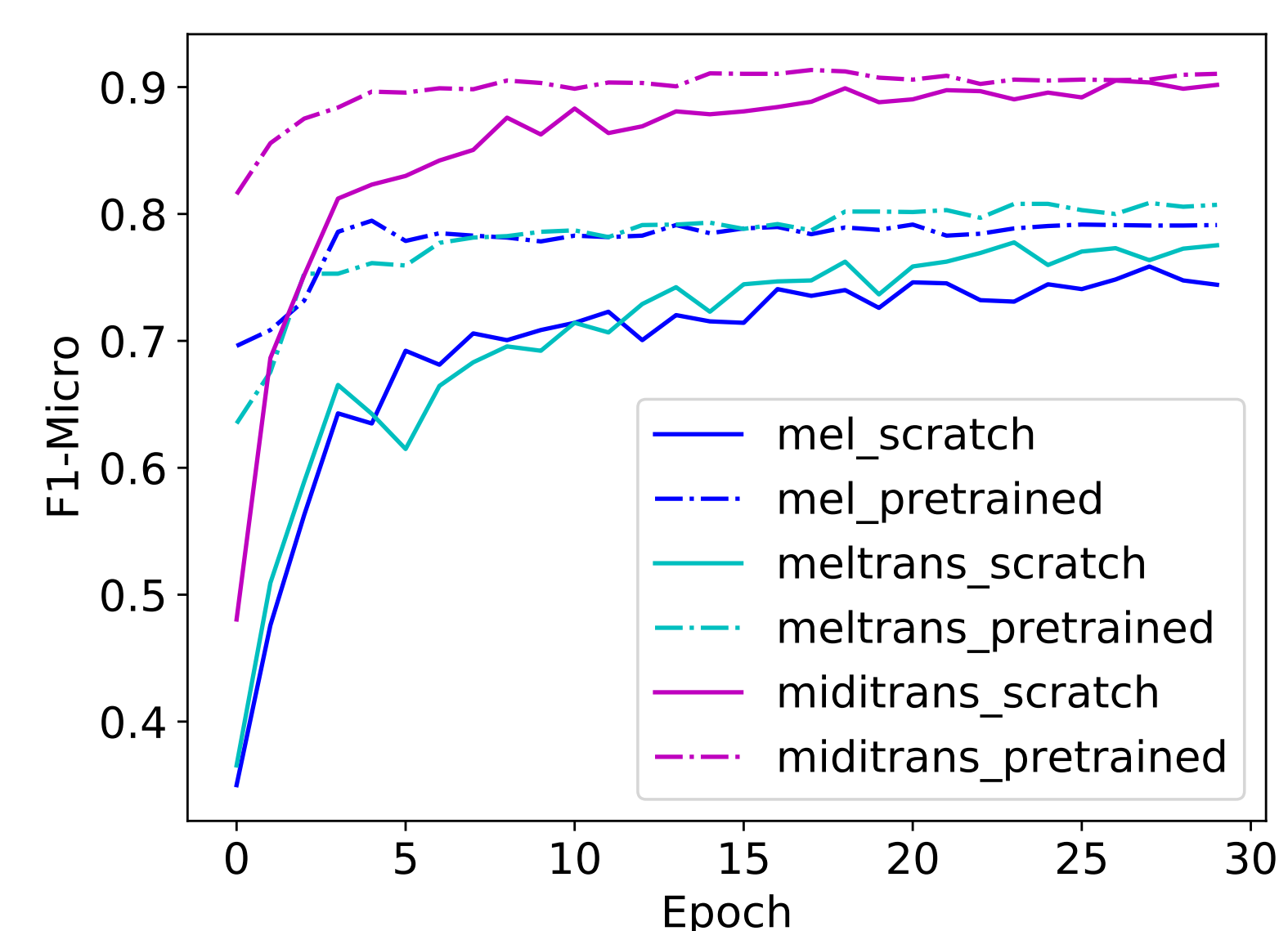


Figure 2: F1-Scores on RWC dataset. Solid lines indicate training from scratch, and dashed lines indicate fine-tuning from pre-trained model.

RESULT III: PROBING THE ENCODED INFORMATION

- Task: probing the encoded information in the timbre embeddings obtained from the proposed model in a similar way to [7].
- Models: a series of shallow classifiers.

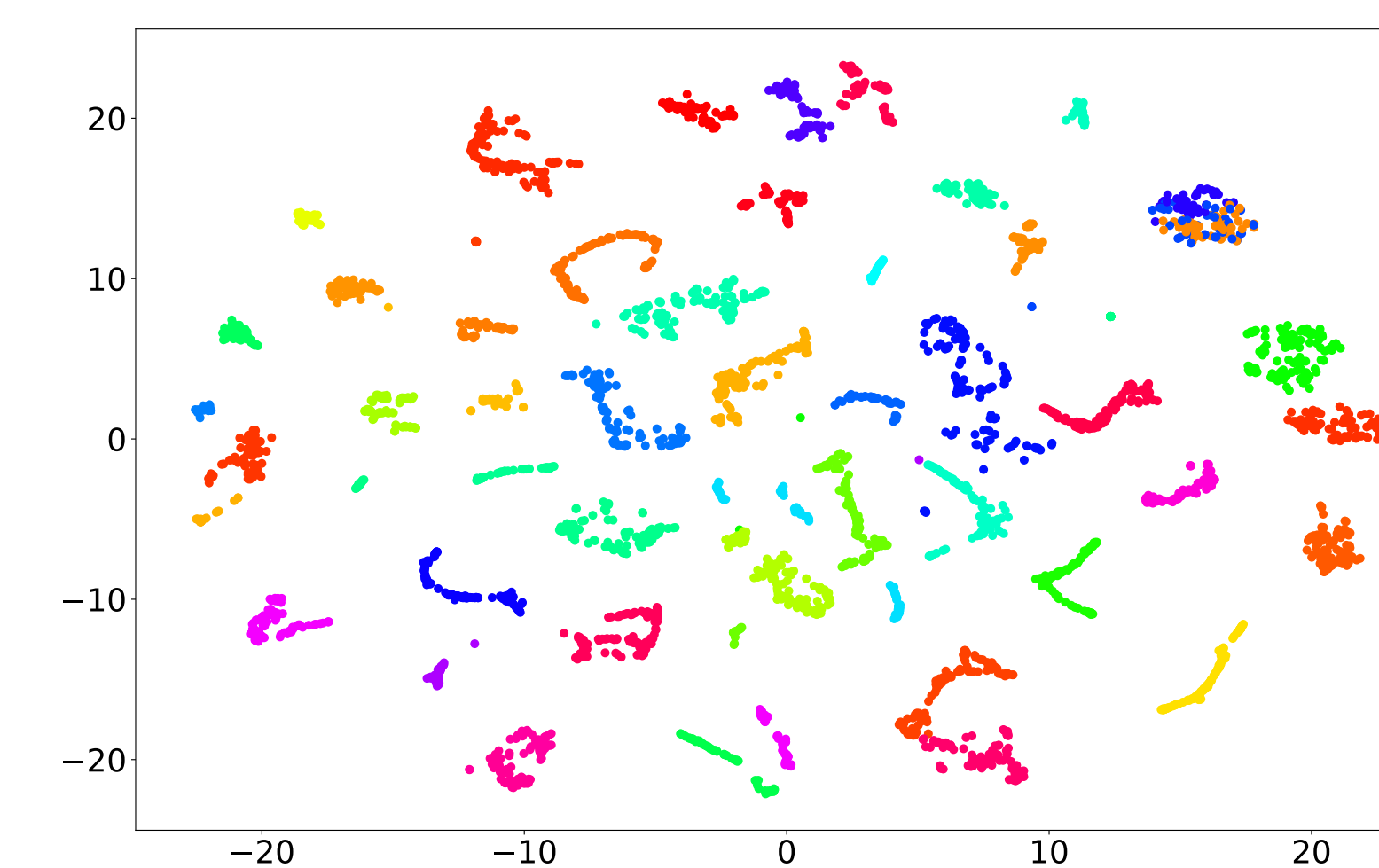


Figure 3: T-SNE visualization of embeddings extracted from wav-transMel-aug-asm.

- Results: some meta information is encoded in embeddings, such as pitch, source.

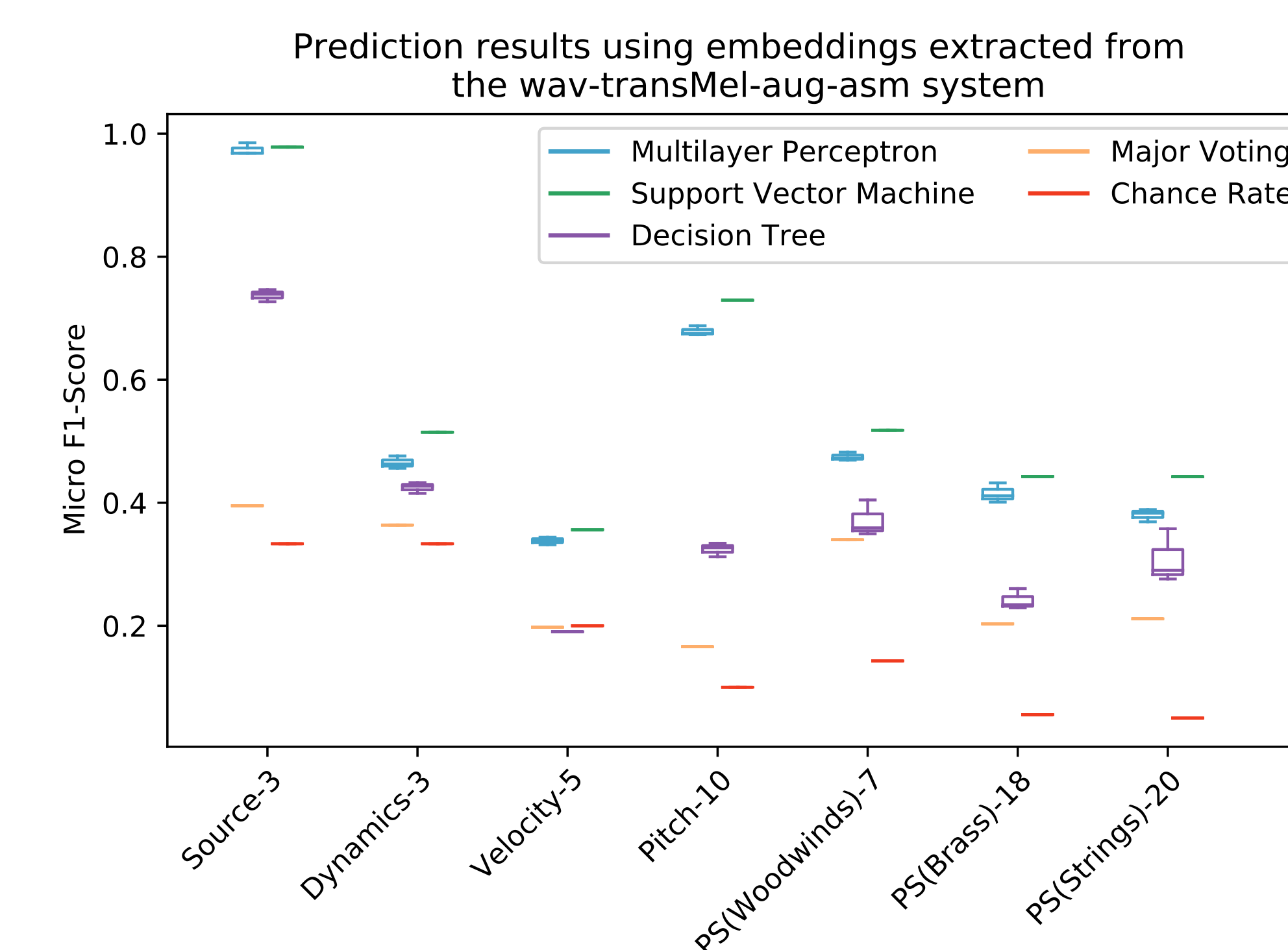


Figure 4: Prediction results.

FUTURE RESEARCH

- Construct the instrument timbre space for polyphonic musical instrument sound input
- Apply the timbre representation in multi-instrument sound synthesis