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Exploring Methods of Signal Processing for Keywords Spotting in Hearing Devices

Cypress Payne[1], Jhyv Philor[2], Tadesse Ghirmai[3], Kaibao Nie[3]
[1] Seattle Pacific University, [2] University of Florida, [3] University of Washington Bothell

INTRODUCTION

Problem: Changing settings in hearing aids and cochlear implants can be inconvenient by hand. Using keywords spotting (KWS) allows parameter adjustment to be done by voice.

Current feature extraction methods for KWS:

- Bark spectrum, Mel spectrum, Mel frequency cepstral coefficients (MFCC)

Current deep learning techniques for KWS:

- Recurrent Neural Network (RNN), Convolutional Neural Networks (CNN) , Long-short term Memory (LSTM) [1]

Proposed Method: Applying amplitude modulation on an audio signal to extract information to train a CNN for keywords spotting. Amplitude modulation is vital for speech recognition because at certain frequencies useful speech information can be extracted [2] [3].

We compared the accuracy of a CNN using amplitude modulated signals with different bands versus Mel spectrum-based signal processing.

METHODS

Google speech dataset

- 65000 different utterances of words were split into training, validation, and testing sets [4].
- 11 keywords, consisting of “up”, “down”, and “one” through “nine” were selected for volume control

Preprocessing

- An audio feature extractor in MATLAB was used to convert each audio signal into a Mel spectrogram.
- Amplitude modulation was obtained by passing the signal through multiple contiguous bandpass filters and performing a Hilbert Transform to extract temporal envelopes (Figure 1).

Neural Network

- A CNN with 3 hidden layers was setup in MATLAB (Figure 1).

EXTRACTION

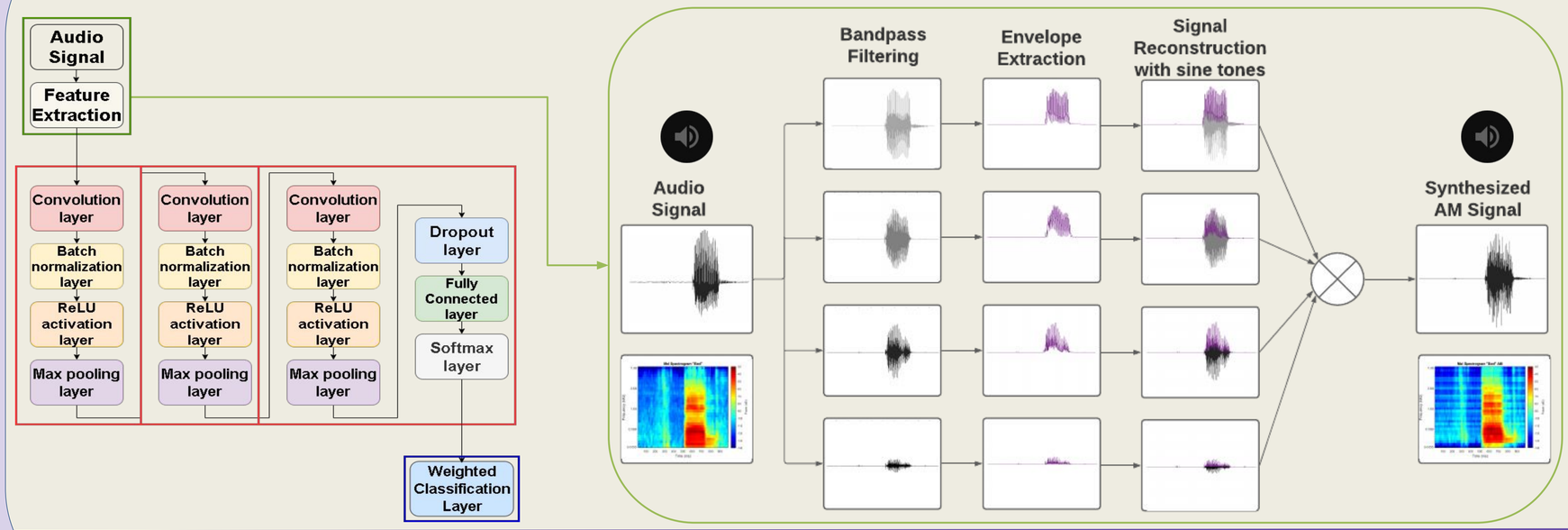


Figure 1: The left of the diagram outlines the entire convolutional neural network, with input, hidden layers, and output. The right displays the feature extraction algorithm that performs amplitude modulation on the signal before it is fed to the neural network.

RESULTS

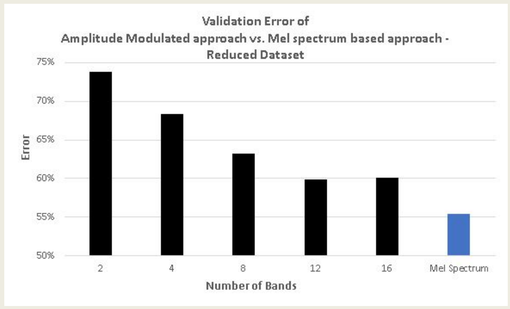
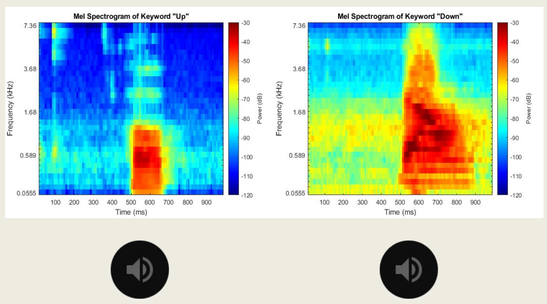


Fig. 2: Accuracy of AM signals with different numbers of bands compared to Mel spectrum accuracy using a reduced dataset



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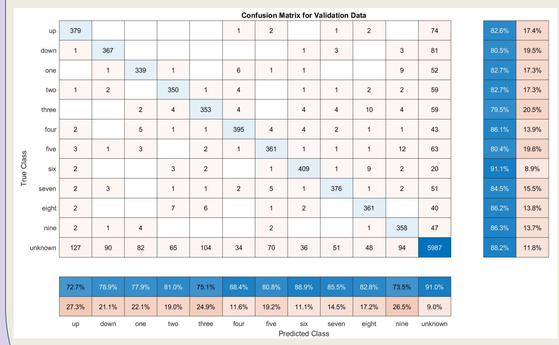

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Validation Error: 13.6105%

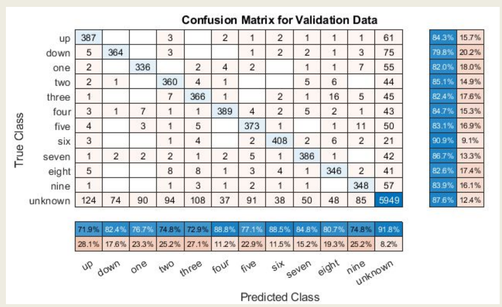

Fig. 5: Confusion matrix of a CNN trained with the full dataset of Mel spectrograms of both original and amplitude modulated signals identifying keywords from the validation set
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CONCLUSIONS

- It is feasible to perform keywords spotting using a convolutional neural network for volume adjustments of hearing devices.
- Mel-based spectral information is vital to train a neural network for keywords spotting, but combining this with amplitude information is a viable method
- Results are consistent with previous studies which show that with 8 or more bands, amplitude modulated audio can be recognized by human subjects.
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REFERENCES

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ACKNOWLEDGEMENTS

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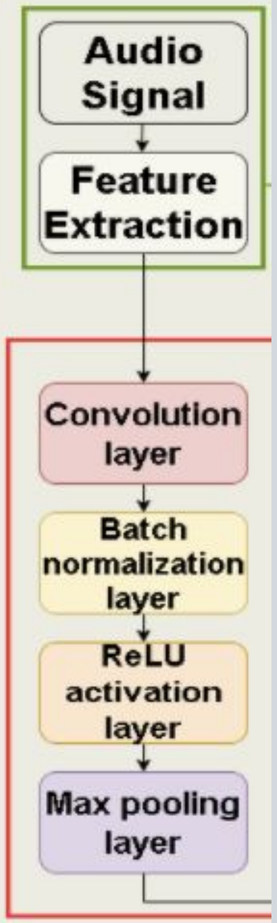

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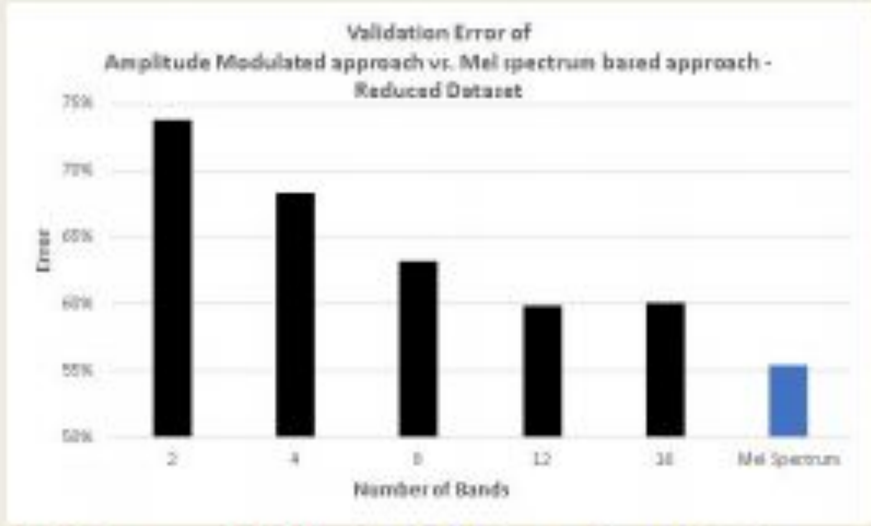

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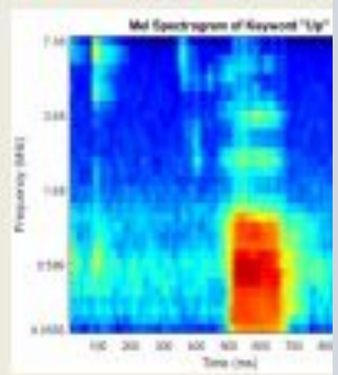

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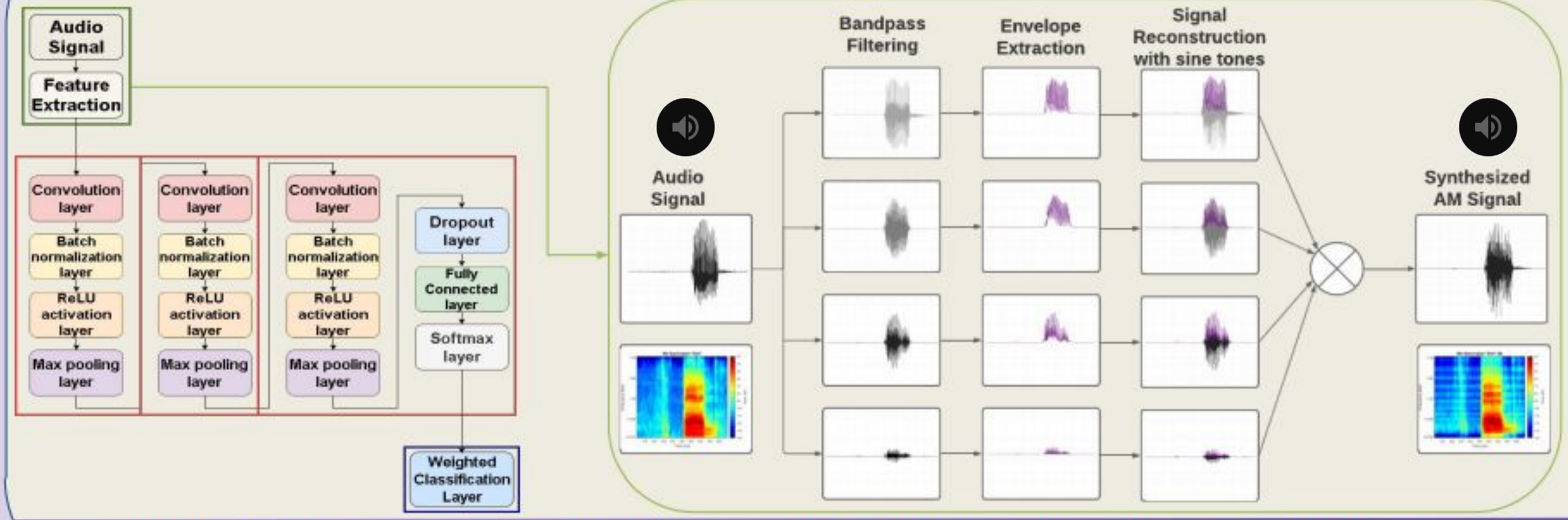

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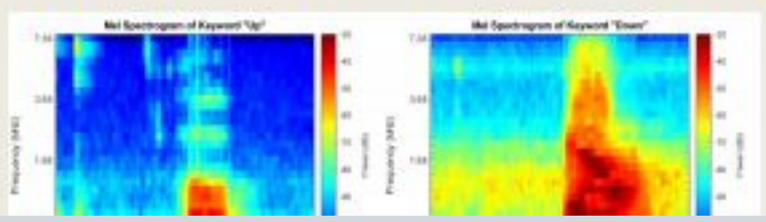

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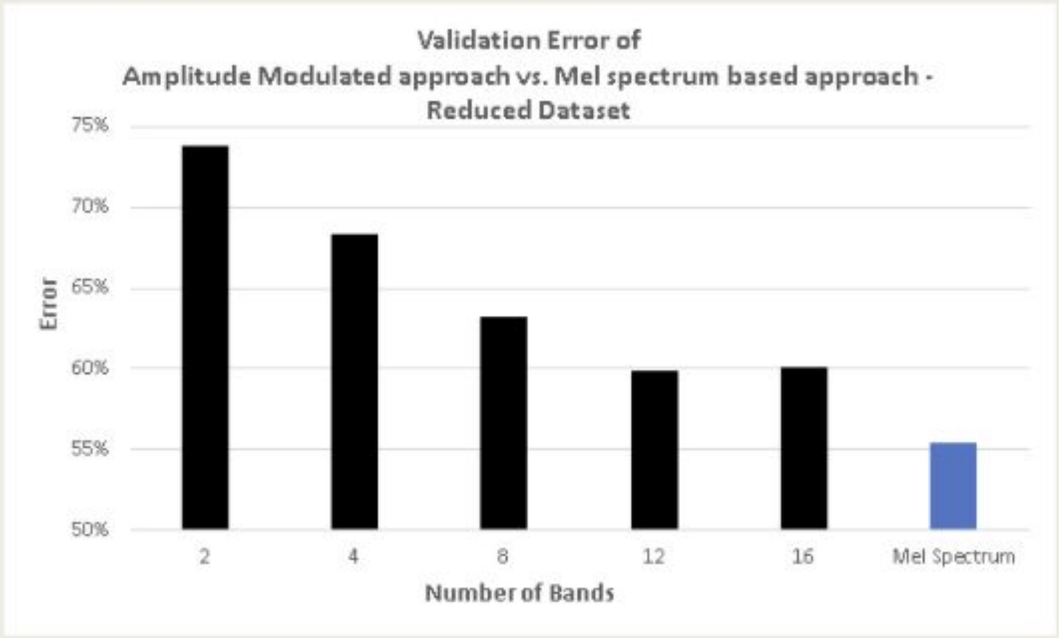

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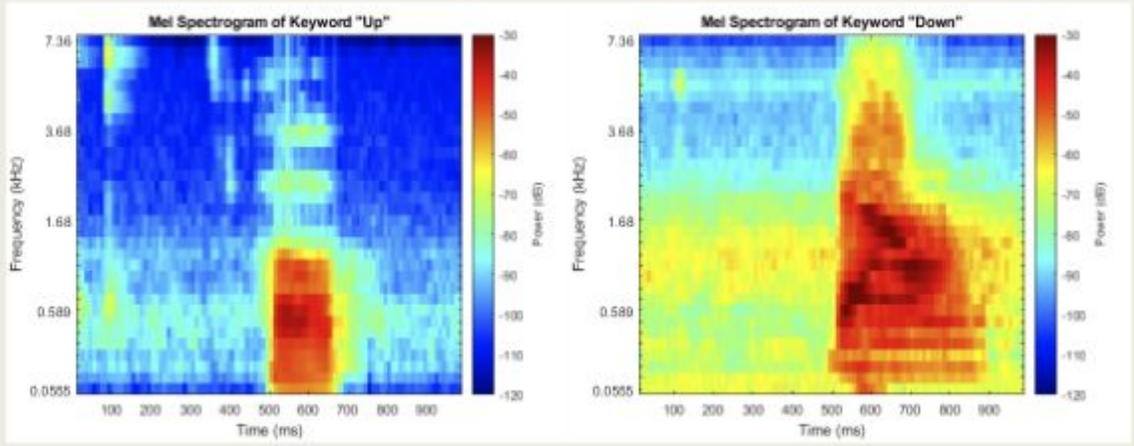

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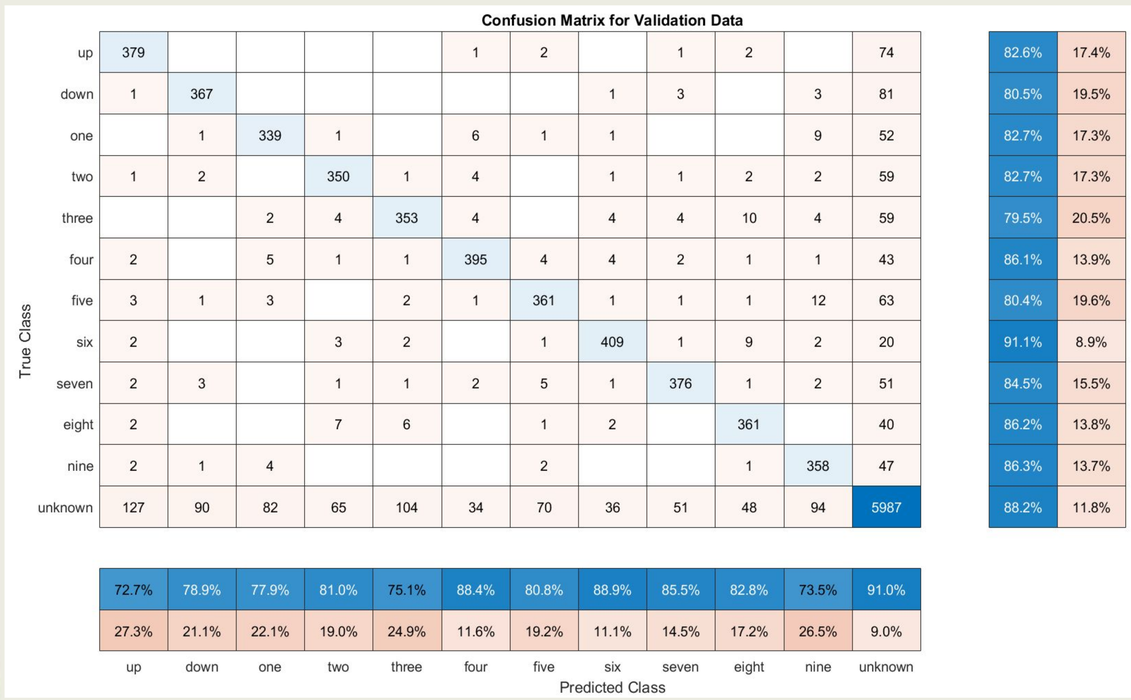

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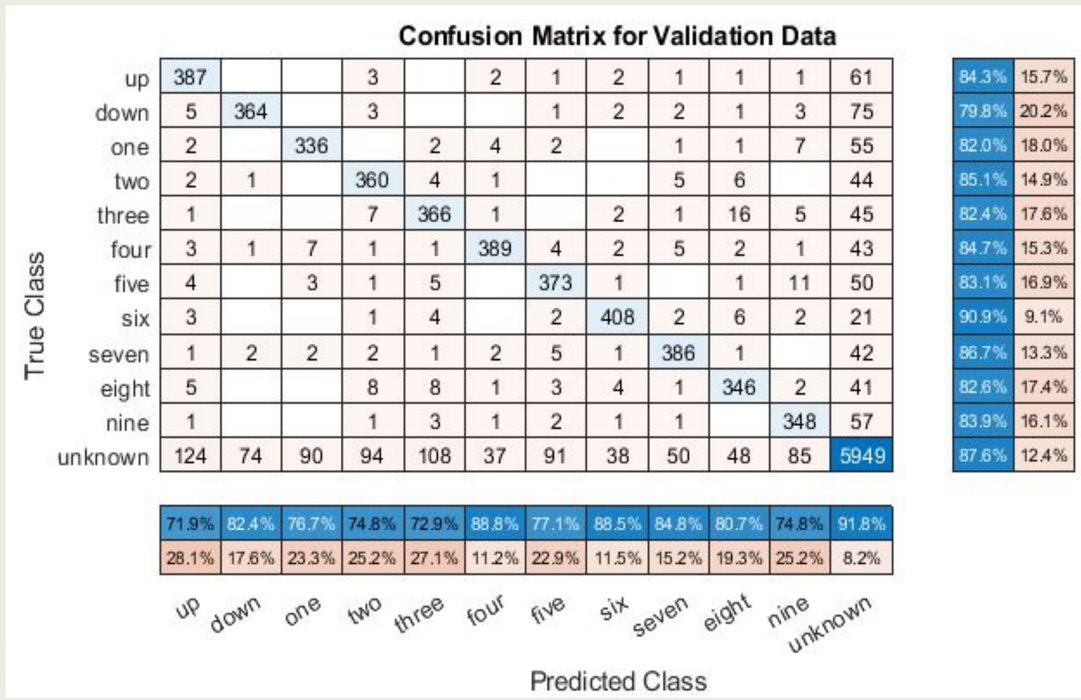

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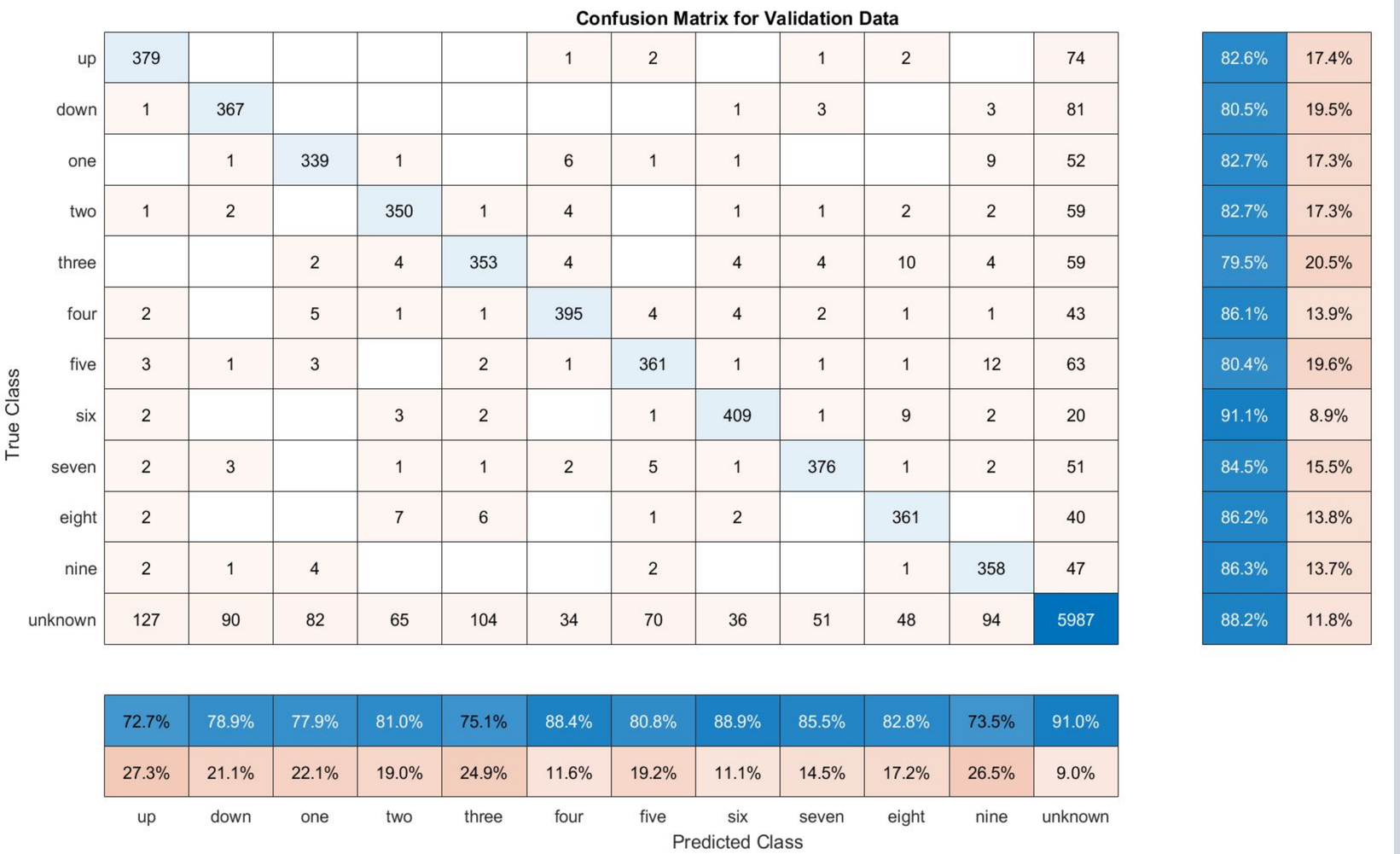

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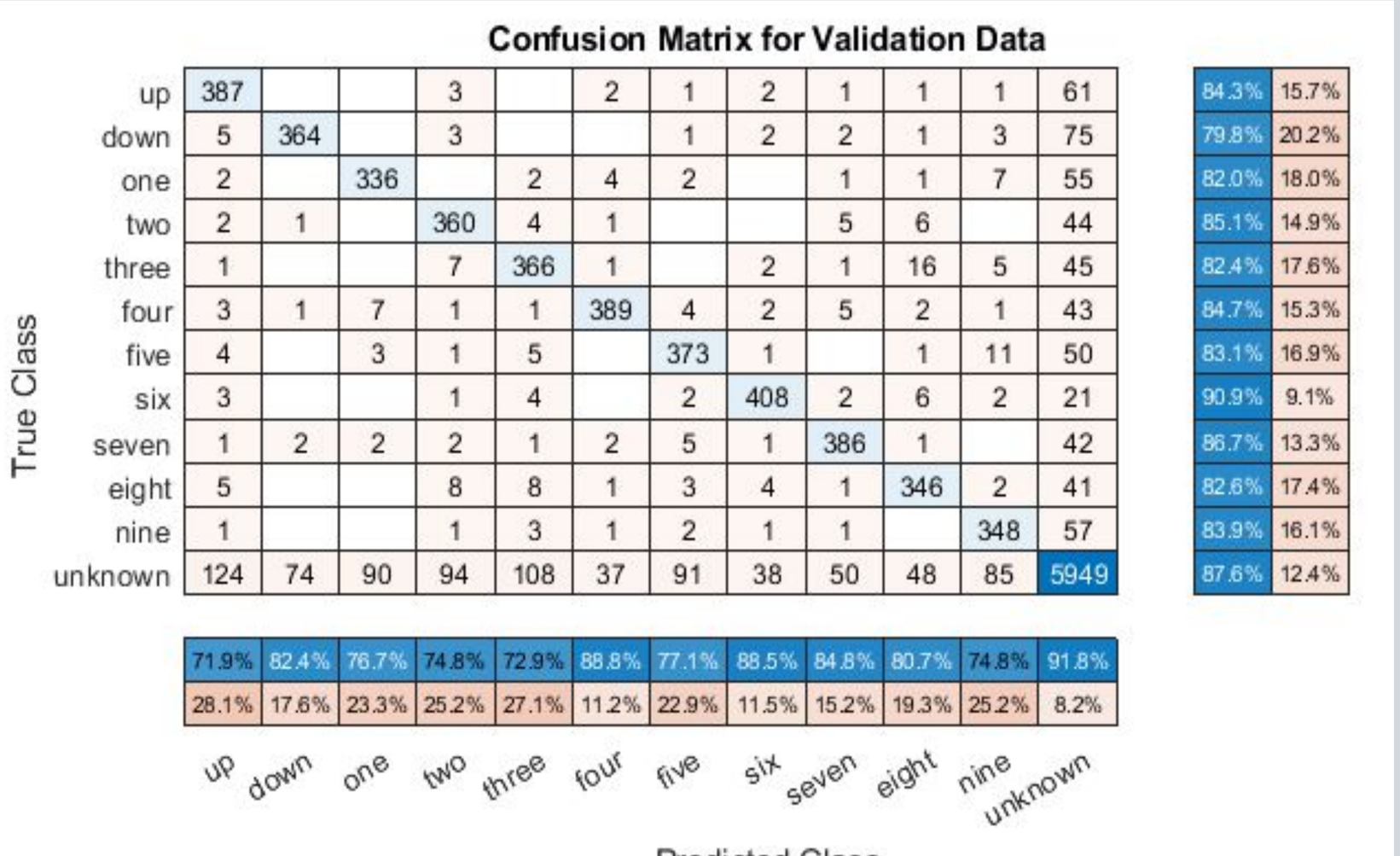

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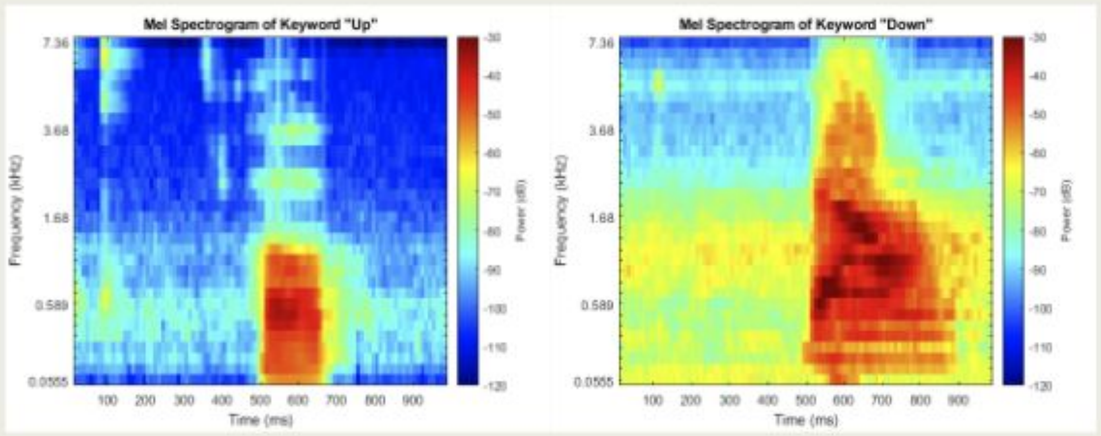

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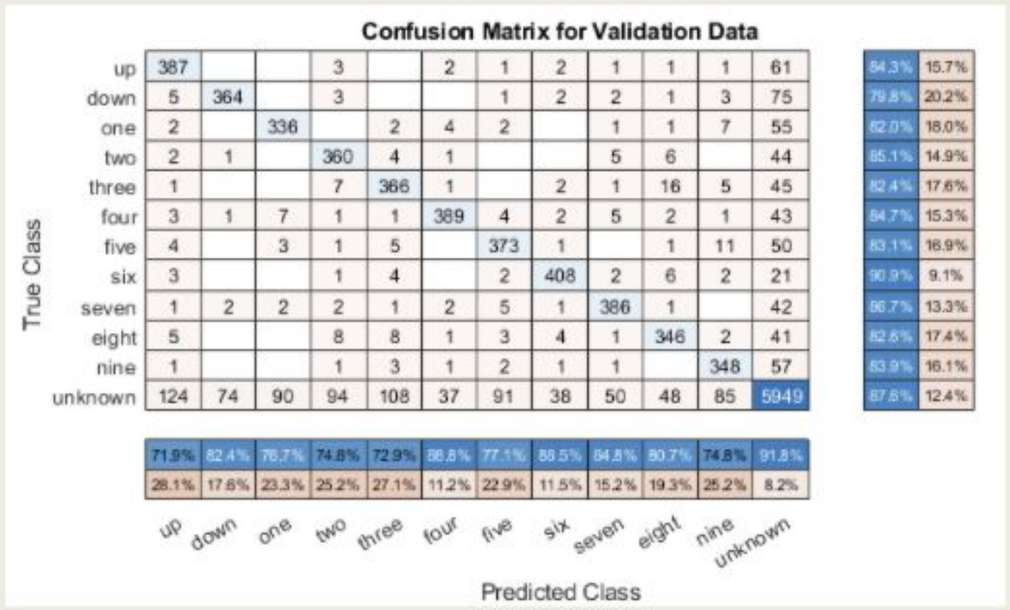

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