

# Speech to Intent Mapping System For Low Resourced Languages

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## DECLARATION

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## ABSTRACT

Today we can find many use cases for content-based speech classification. These include speech topic identification and speech command recognition. Among these, speech command-based user interfaces are becoming popular since they allow humans to interact with digital devices using natural language. Such interfaces are capable of identifying the intent of the given query.

Automatic Speech Recognition (ASR) sits underneath all of these applications to convert speech into textual format. However, creating an ASR system for a language is a resource-consuming task. Even though there are more than 6000 languages in the world, all of these speech-related applications are limited to the most well-known languages such as English, because of the high data requirement of ASR. There is some past research that looked into classifying speech while addressing the data scarcity. However, all of these methods have their limitations.

This study presents a direct speech intent identification method for low-resource languages with the use of a transfer learning mechanism. It makes use of three different audio-based feature generation techniques that can represent semantic information presented in the speech. They are unsupervised acoustic unit features, character and phoneme features. The proposed method is evaluated using Sinhala and Tamil language datasets in the banking domain. Among these, phoneme based features that can be extracted from Automatic Speech Recognizers (ASRs) yield the best results in intent identification. The experiment results show that this method can have more than 80% accuracy for a 0.5-hour limited speech dataset in both languages.

**Keywords:** Speech Intent Identification, Spoken Language Understanding, Low-Resource Languages.

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## LIST OF ABBREVIATIONS

AM	Acoustic Model
AMDTK	Acoustic Model Discovery Toolkit
ANN	Artificial Neural Network
ASR	Automatic Speech Recognition/Recognizer
CNN	Convolutional Neural Networks
CTC	Connectionist Temporal Classification
DBN	Dynamic Bayesian Network
DNN	Deep Neural Network
FNN	Feed-forward Neural Networks
GMM	Gaussian Mixture Models
GPU	Graphics Processing Unit
HLT	Human Language Technologies
HMM	Hidden Markov Model
LM	Language Model
LSTM	Long Short Term Memory
LVCSR	Large Vocabulary Continuous Speech Recognition/Recognizer
MFCC	Mel Frequency Cepstral Coefficients
NLU	Natural Language Understanding
RNN	Recurrent Neural Network
SVM	Support Vector Machine
WER	Word Error Rate

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