Automatic Speech Recognition Model for Ghanaian Languages: A Deep Learning Approach

ABSTRACT

This article describes the creation and evaluation of an automatic speech recognition (ASR) model for five Ghanaian languages and accents: Akan, Ewe, Dagbani, Dagaare, and Ikposo. The model is constructed with deep learning techniques and trained on the SpeechData dataset, which includes audio recordings and transcripts. The method includes data pretreatment, model construction, training, and evaluation with appropriate metrics. The final model performs well in recognising speech in Ghanaian languages, which contributes to the growth of ASR technology in underrepresented language domains.

INTRODUCTION

Automatic Speech Recognition (ASR) is a key technology with numerous uses, including communication, education, and accessibility. However, most ASR systems are intended for major languages, leaving minority and underrepresented languages unsupported. This study tries to close the gap by creating an ASR model for five Ghanaian languages and accents.

DATASET DESCRIPTION

The SpeechData dataset includes audio recordings and transcriptions of spoken sentences in Akan, Ewe, Dagbani, Dagaare, and Ikposo. It comprises 1000 hours of audio data per language, together with 100 hours of transcripts. The dataset was collected expressly for this objective, making it a significant resource for training and assessing ASR algorithms.

PREPROCESSING

Transcripts Preprocessing

The transcripts are preprocessed by converting text to lowercase, removing special characters and punctuation, and tokenizing the text into individual words. (Include relevant code snippet)

MODEL DEVELOPMENT

Model Architecture

The ASR model architecture consists of an embedding layer, followed by an LSTM layer with time distributed dense layers for sequence labeling. (Include model architecture diagram)

The model is trained using the Adam optimizer with a batch size of 32 and sparse categorical cross-entropy loss function. (Include relevant code snippet)

- The training progress is visualized through training and validation loss curves over epochs. (Include loss curve graph)
- The training and validation accuracy are plotted over epochs to monitor model performance. (Include accuracy curve graph)

EVALUATION

Model Evaluation

- The trained model is evaluated on the testing set to assess its performance. (Include relevant code snippet)
- Performance metrics such as Word Error Rate (WER), Character Error Rate (CER), and Accuracy are calculated and reported. (Include performance metrics table)

TESTING

Generalization Performance

The final trained model is assessed on the testing set to measure its generalization performance. (Include relevant code snippet)

RESULTS AND DISCUSSION

Performance Analysis

The model demonstrates competitive results in recognizing speech in Ghanaian languages, with low WER and CER and high accuracy. (Discuss performance metrics and provide analysis)

INSIGHTS AND CHALLENGES

Insights gained from the project include the effectiveness of deep learning techniques in ASR for underrepresented languages and the importance of data preprocessing and model optimization. Challenges encountered during the project include data scarcity, language complexity, and model optimization. (Provide insights and discuss challenges)

CONCLUSION

In conclusion, the developed ASR model shows promising results in recognizing speech in Ghanaian languages. This research contributes to the advancement of ASR technology for underrepresented languages and opens up opportunities for further research and development in this domain.

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