Advancing African-Accented English Speech Recognition: Epistemic Uncertainty-Driven Data Selection for Generalizable ASR Models

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Abstract

Accents play a pivotal role in shaping human communication, enhancing our ability to convey and comprehend messages with clarity and cultural nuance. While there has been significant progress in Automatic Speech Recognition (ASR), African-accented English ASR has been understudied due to a lack of training datasets, which are often expensive to create and demand colossal human labor. By combining several active learning paradigms and the core-set approach, we propose a new multi-round adaptation process that utilizes epistemic uncertainty to automate annotation, thereby significantly reducing associated costs and human labor. This novel method streamlines data annotation and strategically selects data samples that contribute most to model uncertainty, thereby enhancing training efficiency. We define a new U-WER metric to track model adaptation to hard accents. We evaluate our approach across several domains, datasets, and high-performing speech models. Our results show that our approach leads to a 27% WER relative average improvement while requiring, on average, 45% less data than established baselines. Our approach also improves out-of-distribution generalization for very low-resource accents, demonstrating its viability for building generalizable ASR models in the context of accented African ASR. We open-source the code here.

1 Introduction

Automatic Speech Recognition (ASR) is an active research area that powers voice assistant systems (VASs) like Siri and Cortana, enhancing daily communication (Kodish-Wachs et al., 2018; Finley et al., 2018; Zapata and Kirkedal, 2015). Despite this progress, no current VASs include African languages, which account for about 31% of the world languages, and their unique accents ((Eberhard et al., 2019; Tsvetkov, 2017)). This gap highlights the need for ASR systems that can effectively handle the linguistic diversity and complexity of African languages, particularly in critical applications such as healthcare. Due to the lack of representations of these languages and accents in training data, existing ASR systems often perform inadequately, even mispronouncing African names ((Olatunji et al., 2023a)).

To address these challenges, our work focuses on adapting pre-trained speech models to transcribe African-accented English more accurately, characterized by unique intonations and pronunciations (Benzeghiba et al., 2007; Hinsvark et al., 2021). We use **epistemic uncertainty (EU)** (Kendall and Gal, 2017) to guide the adaptation process by identifying gaps in model knowledge and prioritizing data for the model to learn from next. This is particularly beneficial in scenarios where data annotation is costly or time-consuming, as often seen in the African context (Badenhorst and De Wet, 2019, 2017; Barnard et al., 2009; Yemmene and Besacier, 2019; DiChristofano et al., 2022; Dossou et al., 2022; Dossou and Emezue, 2021). EU also improves robustness and encourages exploration to mitigate inductive bias from underrepresented accents. Common approaches to compute EU include Monte Carlo Dropout (MC-Dropout) (Gal and Ghahramani, 2016) and Deep Ensembles (Lakshminarayanan et al., 2017), with the latter being more effective but computationally expensive. Due to resource constraints, we utilize MC-Dropout, which necessitates that models incorporate dropout components during pretraining.

We employ **Active Learning (AL)** techniques further to enhance the efficiency and effectiveness of model adaptation. AL leverages epistemic uncertainty to select the most informative data points from an unlabeled dataset for labeling, thereby improving model performance with fewer training instances. Common types of AL include Deep Bayesian Active Learning (DBAL) (Gal et al., 2017; Houlsby et al., 2011) and Adversarial Active Learning (AAL) (Ducoffe and Precioso, 2018). AAL selects examples likely to be misclassified by the current model, refining it iteratively by challenging it with complex cases to enhance robustness. The core-set approach (CSA) (Sener and Savarese, 2017) is also related, as it selects a subset of the training data to ensure that a model trained on this subset performs comparably to one trained on the entire dataset, thereby addressing scalability and efficiency. A critical component of AL is the **acquisition function (AF)**, which determines the most informative samples from an unlabeled dataset for labeling. Key AFs include uncertainty sampling (US) (Liu and Li, 2023), Bayesian Active Learning by Disagreement (BALD) (Gal et al., 2017), and BatchBALD (Kirsch et al., 2019). US targets data points with the highest model uncertainty. BALD maximizes the mutual information between model parameters and predictions. BatchBALD is an extension of BALD that selects multiple samples simultaneously but may choose redundant points. US is the least computationally expensive, making it ideal for efficient data labeling.

In this work, we leverage and combine DBAL, AAL, US, and CSA in the following way (in order): First, we integrate the CSA by leveraging smaller training subsets ($\sim 45\%$ smaller than the entire available training sets). Second, we utilize DBAL with MC-Dropout to apply dropout during both training and inference, thereby estimating the Bayesian posterior distribution. This allows us to practically and efficiently estimate EU in the models used (Gal et al., 2017) (see section 3.2 for more details). Third, we use the estimated EU and integrate the idea of AAL using the US acquisition function.

We evaluate our approach across **several domains** (general, clinical, general+clinical aka *both*), **several datasets** (AfriSpeech-200 (Olatunji et al., 2023b)), SautiDB (Afonja et al., 2021b), MedicalSpeech, CommonVoices English Accented Dataset (Ardila et al., 2019), and **several high-performing speech models** (Wav2Vec2-XLSR-53 (Conneau et al., 2020), HuBERT-Large (Hsu et al., 2021), WavLM-Large (Chen et al., 2022), and NVIDIA Conformer-CTC Large (en-US) (Gulati et al., 2020). **Our results show a 27% Word Error Rate (WER) relative average improvement while requiring 45% less data than established baselines.** We also adapt the standard WER to create an Uncertainty WER (U-WER) metric to track model adaptation to African accents.

The impact of our approach is substantial. It develops more robust, generalizable, and cost-efficient African-accented English ASR models, reducing dependency on large labeled datasets and enabling deployment in various real-world scenarios. Our results demonstrate improved generalization for out-of-distribution (OOD) cases, particularly for accents with limited resources, addressing specific challenges in African-accented automatic speech recognition (ASR). Additionally, by focusing on equitable representation in ASR training, our methodology promotes fairness in AI, ensuring technology serves users across diverse linguistic backgrounds without bias (Selbst et al., 2019; Mitchell et al., 2019; Mehrabi et al., 2021). Our contributions are listed as follows:

- we combine DBAL, AAL, CSA, and EU to propose a novel way to adapt several high-performing pretrained speech models to build efficient African-accented English ASR models,
- we evaluate our approach across several speech domains (clinical, general, *both*), and African-accented speech datasets AfriSpeech-200 (Olatunji et al., 2023b), SautiDB (Afonja et al., 2021b), MedicalSpeech, and CommonVoices English Accented Dataset (Ardila et al., 2019), while providing domain and accent-specific analyses,
- we define a new and simple metric called U-WER that allows us to measure and track how the variance of the model, across hard accents, changes over the adaptation process,
- we show that our approach improves the relative average WER performance by 27% while significantly reducing the required amount of labeled data (by $\sim$45%),
- we show, based on additional AL experiments, that our approach is also efficient in real-world settings where there are no gold transcriptions.

2 Background and Related Works

2.1 Challenges for African-accented ASR

State-of-the-art (SOTA) ASR technologies, powered by deep learning and neural network architectures like transformers, achieve high accuracy with Standard American English and major European languages. However, they often fail with African accents due to high variability in pronunciation and lack of quality speech data (Koenecke et al., 2020; Das et al., 2021). This results in racial bias, poor performance, and potential social exclusion as speakers might alter their speech to be understood (Koenecke et al., 2020; Koenecke, 2021; Chiu et al., 2018; Mengesha et al., 2021). Enhancing Automatic Speech Recognition (ASR) for African languages is crucial for achieving equitable voice recognition, particularly in healthcare, education, and customer service. Solutions should focus on diversifying training datasets and developing robust modeling techniques tailored to the unique characteristics of these languages.

2.2 Active Learning

AL aims to reduce the number of labeled training examples by automatically processing unlabeled examples and selecting the most informative ones, considering a given cost function, for a human to label. It is particularly effective when labeled data is scarce or expensive, optimizing the learning process by focusing on samples that most improve the model performance and generalization (Settles, 2009; Gal et al., 2017). Several works have demonstrated its effectiveness and efficiency. An AL setup involves an unlabeled dataset $\mathcal{D}_{\text{pool}} = \{\mathbf{x}_i\}_{i=1}^{n_{\text{pool}}}$, a labeled training set $\mathcal{D}_{\text{train}} = \{\mathbf{x}_i, \mathrm{y}_i\}_{i=1}^{n_{\text{train}}}$, and a predictive model with likelihood $p_w(y|x)$ parameterized by $w \sim p(W|\mathcal{D}_{\text{train}})$ (W are the parameters of the model). The setup assumes the presence of an oracle to provide predictions y for all $x_i \in \mathcal{D}_{\text{pool}}$. After training, a batch of data $\{\mathbf{x}_i^*\}_{i=1}^{b}$ is selected from $\mathcal{D}_{\text{pool}}$ based on its EU.

In (Hakkani-Tür et al., 2002), AL was applied to a toy dataset of *How May I Help You* recordings. Confidence scores were estimated for each word and used to compute the overall confidence score for the audio sample. This approach achieved competitive results using 27% less data compared to the baseline. In (Riccardi and Hakkani-Tur, 2005), the authors estimated confidence scores for each utterance using an online algorithm with the lattice output of a speech recognizer. The utterance scores were filtered through an informativeness function to select an optimal subset of training samples, reducing the labeled data needed for a given WER by over 60%. Nallasamy et al. (2012) experimented with AL for accent adaptation in speech recognition. They adapted a source recognizer to the target accent by selecting a small, matched subset of utterances from a large, untranscribed, multi-accented corpus for human transcription. They employed a cross-entropy-based relevance measure in conjunction with uncertainty-based sampling. However, their experiments on Arabic and English accents showed worse performance compared to baselines while using more hours of recordings.

3 Datasets and Methodology

3.1 Datasets

We used the AfriSpeech-200 dataset (Olatunji et al., 2023b), a 200-hour African-accented English speech corpus for clinical and general ASR. This dataset comprises over 120 African accents from five language families: Afro-Asiatic, Indo-European, Khoe-Kwadi (Hainum), Niger-Congo, and Nilo-Saharan, representing the diversity of African regional languages. It was crowd-sourced from over 2000 African speakers from 13 anglophone countries in sub-Saharan Africa and the US (see Table 1).

To demonstrate the dataset-agnostic nature of our approach, we also explored three additional datasets: (1) **SautiDB** (Afonja et al., 2021a), Nigerian accent recordings with 919 audio samples at a 48kHz sampling rate, totaling 59 minutes; (2) **MedicalSpeech**[1], containing 6,661 audio utterances of common medical symptoms, totaling 8 hours; and (3) **CommonVoices English Accented Dataset**, a subset of English Common Voice (version 10) (Ardila et al., 2019), excluding western accents to focus on low-resource settings.

[1] https://www.kaggle.com/datasets/paultimothymooney/medical-speech-transcription-and-intent

Table 1: AfriSpeech-200 Dataset statistics

AfriSpeech Dataset Statistics	
Total duration	200.91 hrs
Total clips	67,577
Unique Speakers	2,463
Average Audio duration	10.7 seconds
Speaker Gender Ratios - # Clip %	
Female	57.11%
Male	42.41%
Other/Unknown	0.48%
Speaker Age Groups - # Clips	
<18yrs	1,264 (1.88%)
19-25	36,728 (54.58%)
26-40	18,366 (27.29%)
41-55	10,374 (15.42%)
>56yrs	563 (0.84%)
Clip Domain - # Clips	
Clinical	41,765 (61.80%)
General	25,812 (38.20%)

3.2 Methodology

In our approach, to compute EU for a given input $x \in \mathcal{D}_{\text{pool}}$, we perform MC-Dropout to obtain multiple stochastic forward passes through a finetuned ASR model g with likelihood $p_{w \sim p(\mathbf{W}|\mathcal{D}^*_{\text{train}})}(y|x)$ where $\mathbf{W}$ is the weights of g. Let f be a function that computes the WER between the predicted and the target transcripts. Let T be the number of stochastic forward passes. For each pass t, we apply dropout, obtain the output transcript, and compute the WER:

$$f_t = f(y, \hat{y}_t); \hat{y}_t = g(\mathbf{W}, \tilde{x}_t); \tilde{x}_t = x \cdot \mathbf{M}_t$$

where $\mathbf{M}_t$ is a binary mask matrix sampled independently for each pass. $\mathrm{EU}(x|g,T)$ can then be estimated from the T stochastic forward passes as follows:

$$\mathrm{EU}(x|g,T) = \sigma(f) = \sqrt{\frac{1}{T}\sum_{t=1}^{T} f_t^2 - \left(\frac{1}{T}\sum_{t=1}^{T} f_t\right)^2} \tag{1}$$

Table 2: Dataset splits showing speakers, number of clips, and speech duration in Train/Dev/Test splits.

AfriSpeech-200 Dataset Splits				
Item	**Train ($\mathcal{D}^*_{\text{train}}$)**	**Dev**	**Test**	**AL Top-k**
# Speakers	1466	247	750	✗
# Hours	173.4	8.74	18.77	✗
# Accents	71	45	108	✗
Avg secs/speaker	425.81	127.32	90.08	✗
clips/speaker	39.56	13.08	8.46	✗
speakers/accent	20.65	5.49	6.94	✗
secs/accent	8791.96	698.82	625.55	✗
# general domain	21682 (*6504)	1407	2723	2000
# clinical domain	36318 (*10895)	1824	3623	3500
# *both* domain	58000 (*17400)	3221	6346	6500

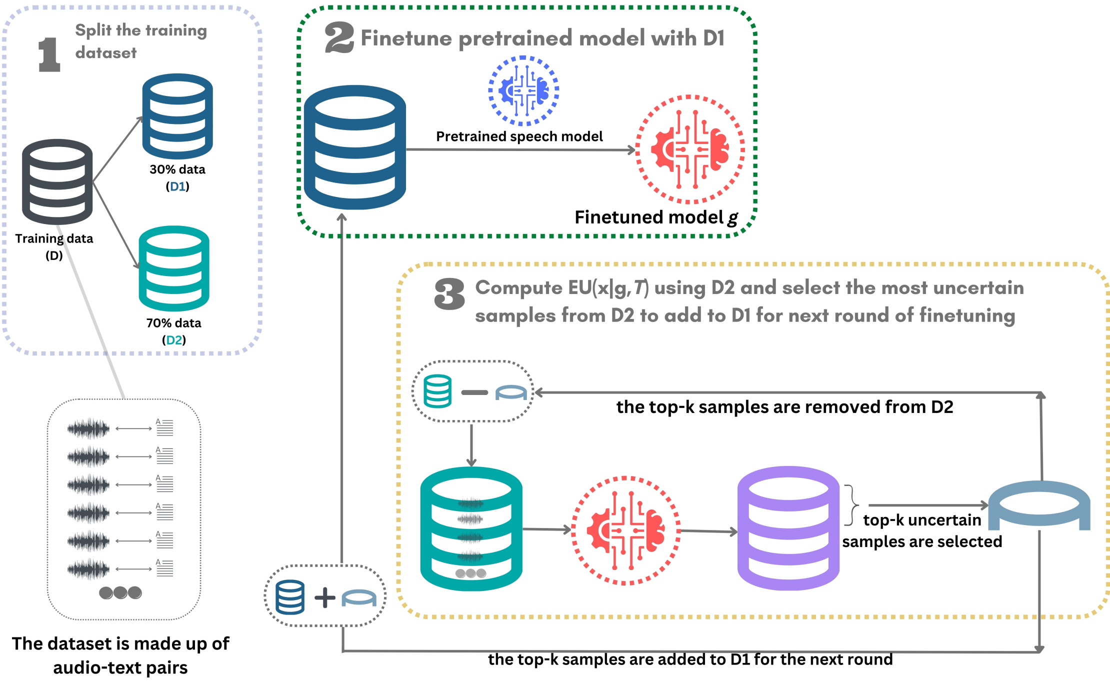


Figure 1: Our adaptation pipeline involves several phases. Initially, the dataset is split into a training set ($D1 = \mathcal{D}^*_{\text{train}}$, 30%) and a pool dataset ($D2 = \mathcal{D}_{\text{pool}}$, 70%). In the iterative process between phases 2 and 3, $D1$ is used to finetune a pretrained model. The top-k samples are selected using defined strategies and added to $D1$ for the next round. For more details on the uncertainty selection strategy, see section 3.2.

Algorithm 1 Selection of the best-generated transcript in Active Learning for an input Sample x

```
we generate the predictions ŷ_1, .., ŷ_T corresponding to each stochastic forward pass (T=10 in our experiments)
we define a list variable called wer_list and a dictionary variable called wer_target_dict, respectively tracking all pairwise WERs and the average pairwise WER of each target prediction
for ∀ i,j ∈ {1, ..., T} do
    → ŷ_i is set as target transcription
    → target_wer = list()
    for for j ≠ i do
        w = WER(ŷ_j, ŷ_i)
        wer_list.append(w)
        target_wer.append(w)
    end for
    wer_ŷi = mean(target_wer)
    wer_target_dict[ŷ_i] ← wer_ŷi
end for
ŷ_best = ŷ_i, such that wer_target_dict[ŷ_i] = min(wer_target_dict.values())
return (p_best, std(wer_list))
```

The use of MC-Dropout requires models to have dropout components during training. This exclusion applies to some models, such as Whisper (Radford et al., 2022), which we still fine-tuned and evaluated as a baseline. We utilize four state-of-the-art pre-trained models: Wav2Vec2-XLSR-53, HuBERT-Large, WavLM-Large, and NVIDIA Conformer-CTC Large (en-US), referred to as Wav2Vec, HuBERT, WavLM, and Nemo, respectively.

3.2.1 Uncertainty WER

To handle diverse accents, we aim to reduce the EU of the models across hard accents after each adaptation round. We define a metric called *U-WER* to track this. To compute U-WER(a) where a is a hard accent, we condition EU on a:

$$\text{EU}(x|g, T, a) = \sigma(f_a) = \sqrt{\frac{1}{T}\sum_{t=1}^{T} f^2_{t,a} - \left(\frac{1}{T}\sum_{t=1}^{T} f_{t,a}\right)^2} \tag{2}$$

where x_a is the audio sample with accent a and

$$f_{t,a} = f(y_a, \hat{y}_{t,a}); \hat{y}_{t,a} = g(\mathbf{W}, \tilde{x}_{t,a}); \tilde{x}_{t,a} = x_a \cdot \mathbf{M}_t$$

Ideally, U-WER→0. The rationale behind U-WER is that as beneficial data points are acquired, U-WER should decrease or remain constant, indicating increased robustness, knowledge, and performance, which is crucial for generalization. During AL, U-WER is computed using pairwise WER scores among predicted transcriptions, not gold transcriptions (see section 3.3). To select the best-generated transcript for unlabeled speech x, we follow Algorithm 1.

Algorithm 2 Adaptation Round using Epistemic Uncertainty-based Selection

Require: Pretrained Model $\mathcal{M}$, Training Dataset $\mathcal{D}^*_{\text{train}}$, Validation Dataset $\mathcal{D}_{Val}$, and Pool Dataset $\mathcal{D}_{\text{pool}}$
$\mathcal{N} \leftarrow 3$ ▷ Number of Adaptation Rounds
$T \leftarrow 10$ ▷ Number of Stochastic Forward Passes
for $k \leftarrow 1$ to $\mathcal{N}$ **do**
    $g \leftarrow$ Finetune $\mathcal{M}$ on $\mathcal{D}^*_{\text{train}}$ using $\mathcal{D}_{Val}$
    $\mathcal{EUL} \leftarrow \{\}$ ▷ List of Uncertainty Scores
    for x in $\mathcal{D}_{\text{pool}}$ **do** ▷ x is an audio sample
        $\text{EU}_x \leftarrow \text{EU}(x|g, T)$ ▷ Epistemic Uncertainty of x
        $\mathcal{EUL} \leftarrow \mathcal{EUL} \cup \{(x, \text{EU}_x)\}$
    end for
    $topk \leftarrow \{x_1, ..., x_k\}$ ▷ Samples with highest $\mathcal{EU}$
    $\mathcal{D}^*_{\text{train}} \leftarrow \mathcal{D}^*_{\text{train}} \cup topk$
    $\mathcal{D}_{\text{pool}} \leftarrow \mathcal{D}_{\text{pool}} \setminus topk$
end for

3.3 Experimental Design

To work within our framework, we define the following selection strategies:

- **random**: Randomly selects audio samples from $\mathcal{D}_{\text{pool}}$.
- **EU-Most**: Selects the most uncertain audio samples from $\mathcal{D}_{\text{pool}}$ to add to $\mathcal{D}_{\text{train}}$.
- **AL-EU-Most**: Combines AL with the **EU-Most** strategy to finetune the pretrained model.

We also define **standard fine-tuning (SFT)** as baseline using all available data for finetuning. In SFT, $\mathcal{D}_{\text{pool}}$ is empty. While running the defined strategies in our framework, we **impose data constraints, not exceeding 60-65% of the initial dataset after all adaptation rounds.** $\mathcal{D}^*_{\text{train}}$ is 30% of $\mathcal{D}_{\text{train}}$, and $\mathcal{D}_{\text{pool}}$ is 70% of $\mathcal{D}_{\text{train}}$. This simulates realistic scenarios where not all data might be available, testing the approach's robustness and efficiency under constraints. The number of samples in $\mathcal{D}_{\text{train}}$ and $\mathcal{D}_{\text{pool}}$ is based on available training examples for each domain (see Tables 2, 4, and Appendix A.1).

Our EU-based pipeline is shown in Figure 1 and Algorithm 2. In each adaptation round, we use a finetuned model and a selection strategy to choose samples from $\mathcal{D}_{\text{pool}}$ to add to $\mathcal{D}^*_{\text{train}}$. During AL experiments, we consider samples from $\mathcal{D}_{\text{pool}}$ as unlabeled: (1) using MC-Dropout, we obtain $n = 10$ different input representations per audio sample to get n different transcripts; (2) we then learn to select the best-generated transcription as the target transcription according to Algorithm 1.

Our experiments aim to answer the following research questions:

1. how does the pretrained ASR model adapt to a set of African accents across adaptation rounds and domains?
2. which selection strategy (**EU-most** or **random**) works better, and for which domain(s)?
3. which domain(s) help the model perform better, and how does the model perform (in terms of uncertainty) across the domain(s)?
4. what is the impact of EU-based selection on the model's efficiency in low-resource data scenarios?
5. is uncertainty-based selection, model, and dataset agnostic?

U-WER will answer question 4. To answer question 5, we evaluated our approach with three additional pretrained models (Nemo, WavLM, and Hubert) and across three external datasets (SautiDB, CommonVoices English Accented Dataset, and MedicalSpeech). For consistency and better visualization, we considered the top-10 (in terms of frequency) accents across three adaptation rounds and both selection strategies to answer questions 1-4. For very low-resource settings, we considered the five accents with the least recording hours.

For our experiments, we utilized six RTX 8000 GPUs and four A100 GPUs. Training and evaluation were conducted over a period of one month. Our models have approximately 311 million trainable parameters. Each audio sample was normalized and processed at a 16 kHz sample rate. We used default parameters from the HuggingFace library for each pretrained model.

4 Results and Discussion

To assess the performance improvement for each domain, we compute the relative average improvement

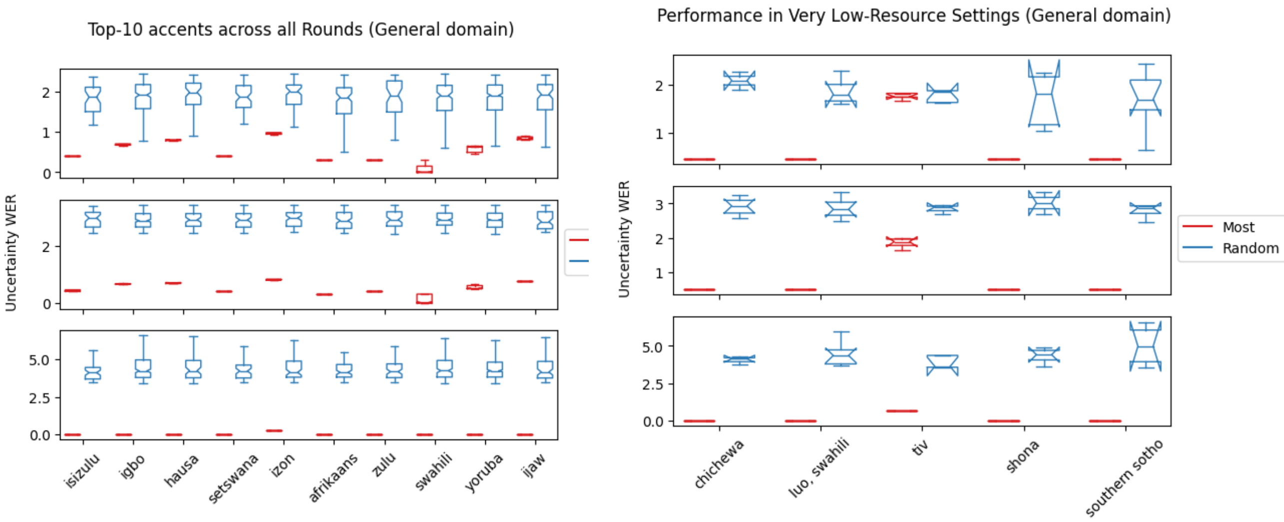
$$\text{RIA}_{wer,d} = \left(\frac{b^d_{wer} - s^d_{wer}}{b^d_{wer}} \right) \times 100\%$$

where b^d_{wer} and s^d_{wer} are the average WER respectively of the baseline, and the best selection strategy, in a domain $d \in \{general, clinical, both\}$. A higher percentage reflects a higher improvement in our approach.

Table 3 shows the results of our experiments, indicating that our uncertainty-based selection approach significantly outperforms the baselines across **all models, domains, and datasets: general (27.00%), clinical (15.51%), and *both* (26.56%)**. Our approach also surpasses Whisper-Medium ((Olatunji et al., 2023b; Radford et al., 2023)), demonstrating the importance of epistemic uncertainty in ASR for low-resource languages. The **EU-Most** selection strategy proves to be the most effective across all domains due to the model's exposure to highly uncertain samples, enhancing robustness and performance. However, performance disparities between the general and clinical domains

Table 3: We utilized Wav2Vec to conduct initial experiments across various domains and strategies, aiming to identify the optimal selection strategy. Models marked with ** are used to demonstrate that our algorithm is model agnostic, utilizing the **EU-Most** selection strategy, which has been proven to be the most effective. Our AL experiments also use this strategy. Wav2Vec, using the **random** strategy, scored 0.1111, 0.3571, and 0.1666 for the general, clinical, and *both* domains, respectively. We omit **random** results to enhance readability.

Model	General			Clinical			*Both*		
	Baseline	EU-Most	AL-EU-Most	Baseline	EU-Most	AL-EU-Most	Baseline	EU-Most	AL-EU-Most
Wav2vec	0.2360 (Olatunji et al., 2023b)	**0.1011**	0.1059	0.3080 (Olatunji et al., 2023b)	**0.2457**	0.2545	0.2950 (Olatunji et al., 2023b)	**0.1266**	**0.1309**
**Hubert	**0.1743**	0.1901	0.1887	0.2907	**0.2594**	0.2709	**0.2365**	0.2453	0.2586
**WavLM	0.1635	**0.1576**	0.1764	0.3076	**0.2313**	0.2537	0.2047	**0.1897**	0.1976
**Nemo	0.2824	**0.1765**	0.1815	0.2600	**0.2492**	0.2526	0.3765	**0.2576**	0.2610
Average Performance	0.2141	**0.1563**	0.1631	0.2916	**0.2464**	0.2579	0.2782	**0.2043**	0.2120
Whisper-Medium	0.2806	-	-	0.3443	-	-	0.3116	-	-



(a) (b)

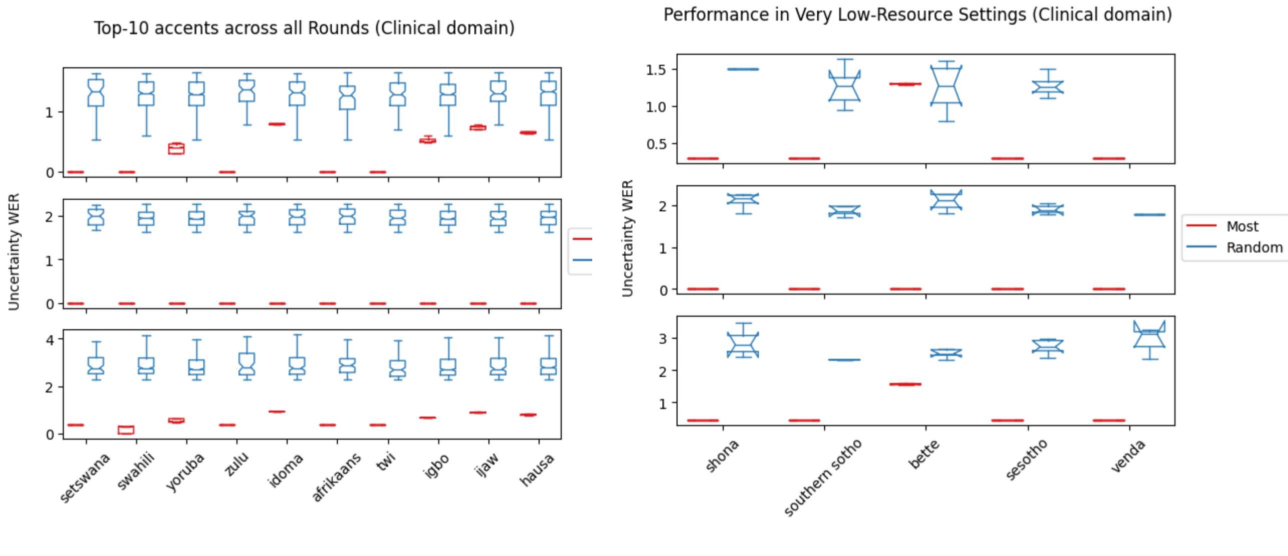
Figure 2: WER Performance on Accents from General Domain

Table 4: WER Evaluation Results on External Datasets, with $\alpha \in [0.60, 0.65]$ as described in Section 3.1 and on Figure 1. We observe an improvement in WER using our approach across all datasets, indicating that our algorithm is dataset-agnostic.

Dataset	Split and Size for our approach				Finetuning Epochs	Baseline	EU-Most
	$\mathcal{D}^*_{\text{train}}$	$\mathcal{D}_{\text{pool}}$	Top-k	Test		($\mathcal{D}_{\text{train}}$)	($\mathcal{D}^*_{\text{train}} + \alpha\mathcal{D}_{\text{pool}}$)
SautiDB (Afonja et al., 2021a)	234	547	92	138	50	0.50	**0.12**
MedicalSpeech	1598	3730	1333	622	5	0.30	**0.28**
CommonVoices English Accented Dataset (v10.0) (Ardila et al., 2019)	26614	62100	10350	232	5	0.50	**0.22**
Average	✗	✗	✗	✗	✗	0.43	**0.20**

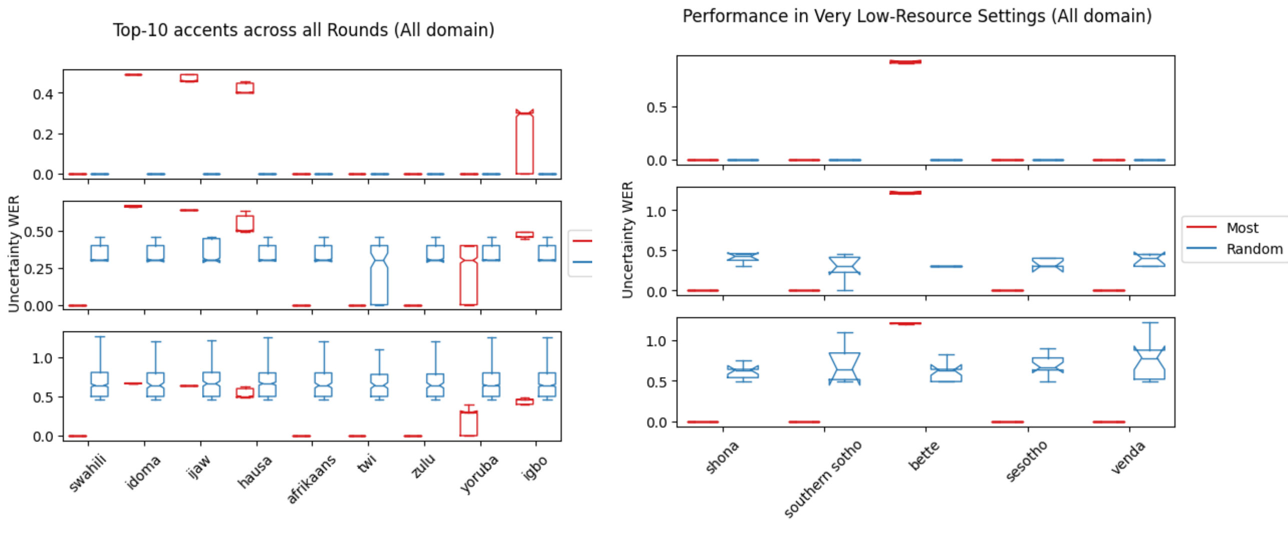
are noted, likely due to the complexity of the clinical sample. These findings confirm **EU-Most** as the superior selection strategy, as detailed in the results and illustrated in Figures 2, 3, and 4. This answers question 2.

To identify the best learning signals within a diverse dataset characterized by various accents, speaker traits, genders, and ages, we analyzed the top-k uncertain accents using the **EU-Most** selection strategy. Our findings, illustrated in Figures 2, 3, and 4, show that the top-10 accents (most represented in recording hours) remained consistently challenging across all rounds of analysis (refer to Figures 2, 3, 4 and Tables 6, 7, and 8). These accents, characterized by high linguistic richness and variability, facilitate model learning and im-



(a) (b)

Figure 3: WER Performance on Accents from Clinical Domain



(a) (b)

Figure 4: WER Performance on Accents from Clinical+General (*Both*) Domain

prove performance over time. We positively answer questions 1 and 3, confirming that the model adapts effectively to the beneficial accents from all domains. This demonstrates that the model adapts qualitatively and quantitatively well to the beneficial accents and benefits from all domains. Figures 2 (b), 3 (b), and 4 (b) also affirm positive outcomes for question 4, showing consistent improvement or stable performance on low-resource accents. This highlights the relevance of our approach in addressing the challenges associated with the limited resource availability typical of many African languages and dialects.

To demonstrate the agnostic aspect of our approach, we evaluated it using three additional pretrained models (Hubert, WavLM, and Nemo) and three datasets containing accented speech in general and clinical domains, employing only the **EU-Most** selection strategy. The results, shown in Tables 3 and 4, indicate that our uncertainty-based adaptation approach consistently outperforms baselines. This confirms that our approach applies to any model architecture and dataset, allowing us to answer question 5 positively.

5 Conclusion

We combined several AL paradigms, the CSA, and the EU to create a novel multi-round adaptation process for high-performing pretrained speech models, aiming to build efficient African-accented English ASR models. We introduced the U-WER metric to track model adaptation to intricate accents. Our experiments demonstrated a remarkable 27% WER ratio improvement while reducing the data required for effective training by approximately 45% compared to existing baselines. This reflects the efficiency and potential of our approach to lower the barriers to ASR technologies in underserved regions significantly. Our method enhances model robustness and generalization across various domains, datasets, and accents, which are crucial for scalable ASR systems. This also helps mitigate bias in ASR technologies, promoting more inclusive and fair AI applications.

6 Limitations

In discussing trade-offs (Section 4), we noted that while our approach enhances performance, particularly with linguistically rich accents, a stopping criterion is essential for complex domains like the **clinical** one to balance adaptation rounds with the pool size. With better resources, we would consider implementing Deep Ensembles ((Lakshminarayanan et al., 2017)) as an alternative to our current MC-Dropout method for estimating epistemic uncertainty and leveraging other acquisition functions (such as BALD, BatchBALD) highlighted in this work.

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References

Tejumade Afonja, Clinton Mbataku, Ademola Malomo, Olumide Okubadejo, Lawrence Francis, Munachiso Nwadike, and Iroro Orife. 2021a. Sautidb: Nigerian accent dataset collection.

Tejumade Afonja, Oladimeji Mudele, Iroro Orife, Kenechi Dukor, Lawrence Francis, Duru Goodness, Oluwafemi Azeez, Ademola Malomo, and Clinton Mbataku. 2021b. Learning nigerian accent embeddings from speech: preliminary results based on sautidb-naija corpus. *arXiv preprint arXiv:2112.06199*.

Rosana Ardila, Megan Branson, Kelly Davis, Michael Henretty, Michael Kohler, Josh Meyer, Reuben Morais, Lindsay Saunders, Francis M Tyers, and Gregor Weber. 2019. Common voice: A massively-multilingual speech corpus. *arXiv preprint arXiv:1912.06670*.

Jaco Badenhorst and Febe De Wet. 2017. The limitations of data perturbation for asr of learner data in under-resourced languages. In *2017 Pattern Recognition Association of South Africa and Robotics and Mechatronics (PRASA-RobMech)*, pages 44–49. IEEE.

Jaco Badenhorst and Febe De Wet. 2019. The usefulness of imperfect speech data for asr development in low-resource languages. *Information*, 10(9):268.

Etienne Barnard, Marelie Davel, and Charl Van Heerden. 2009. Asr corpus design for resource-scarce languages. ISCA.

M. Benzeghiba, R. De Mori, O. Deroo, S. Dupont, T. Erbes, D. Jouvet, L. Fissore, P. Laface, A. Mertins, C. Ris, R. Rose, V. Tyagi, and C. Wellekens. 2007. Automatic speech recognition and speech variability: A review. *Speech Communication*, 49(10):763–786. Intrinsic Speech Variations.

Sanyuan Chen, Chengyi Wang, Zhengyang Chen, Yu Wu, Shujie Liu, Zhuo Chen, Jinyu Li, Naoyuki Kanda, Takuya Yoshioka, Xiong Xiao, et al. 2022. Wavlm: Large-scale self-supervised pre-training for full stack speech processing. *IEEE Journal of Selected Topics in Signal Processing*, 16(6):1505–1518.

Chung-Cheng Chiu, Anshuman Tripathi, Katherine Chou, Chris Co, Navdeep Jaitly, Diana Jaunzeikare, Anjuli Kannan, Patrick Nguyen, Hasim Sak, Ananth Sankar, Justin Tansuwan, Nathan Wan, Yonghui Wu, and Xuedong Zhang. 2018. Speech Recognition for Medical Conversations. In *Proc. Interspeech 2018*, pages 2972–2976.

Alexis Conneau, Alexei Baevski, Ronan Collobert, Abdel rahman Mohamed, and Michael Auli. 2020. Unsupervised cross-lingual representation learning for speech recognition. *INTERSPEECH*.

Nilaksh Das, Sravan Bodapati, Monica Sunkara, Sundararajan Srinivasan, and Duen Horng Chau. 2021. Best of both worlds: Robust accented speech recognition with adversarial transfer learning. *arXiv preprint arXiv:2103.05834*.

Alex DiChristofano, Henry Shuster, Shefali Chandra, and Neal Patwari. 2022. Performance disparities between accents in automatic speech recognition. *arXiv preprint arXiv:2208.01157*.

Bonaventure FP Dossou and Chris C Emezue. 2021. Okwugb\'e: End-to-end speech recognition for fon and igbo. *arXiv preprint arXiv:2103.07762*.

Bonaventure FP Dossou, Atnafu Lambebo Tonja, Oreen Yousuf, Salomey Osei, Abigail Oppong, Iyanuoluwa Shode, Oluwabusayo Olufunke Awoyomi, and Chris Chinenye Emezue. 2022. Afrolm: A self-active learning-based multilingual pretrained language model for 23 african languages. *arXiv preprint arXiv:2211.03263*.

Melanie Ducoffe and Frederic Precioso. 2018. Adversarial active learning for deep networks: a margin based approach. *arXiv preprint arXiv:1802.09841*.

David Eberhard, Gary Simons, and Chuck Fennig. 2019. *Ethnologue: Languages of the World, 22nd Edition*.

Gregory Finley, Wael Salloum, Najmeh Sadoughi, Erik Edwards, Amanda Robinson, Nico Axtmann, Michael Brenndoerfer, Mark Miller, and David Suendermann-Oeft. 2018. From dictations to clinical reports using machine translation. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 3 (Industry Papers)*, pages 121–128.

Yarin Gal and Zoubin Ghahramani. 2016. Dropout as a bayesian approximation: Representing model uncertainty in deep learning. In *international conference on machine learning*, pages 1050–1059. PMLR.

Yarin Gal, Riashat Islam, and Zoubin Ghahramani. 2017. Deep Bayesian active learning with image data. In *Proceedings of the 34th International Conference on Machine Learning*, volume 70 of *Proceedings of Machine Learning Research*, pages 1183–1192. PMLR.

Anmol Gulati, James Qin, Chung-Cheng Chiu, Niki Parmar, Yu Zhang, Jiahui Yu, Wei Han, Shibo Wang, Zhengdong Zhang, Yonghui Wu, et al. 2020. Conformer: Convolution-augmented transformer for speech recognition. *arXiv preprint arXiv:2005.08100*.

Dilek Hakkani-Tür, Giuseppe Riccardi, and Allen Gorin. 2002. Active learning for automatic speech recognition. In *2002 IEEE International Conference on Acoustics, Speech, and Signal Processing*, volume 4, pages IV–3904–IV–3907.

Arthur Hinsvark, Natalie Delworth, Miguel Del Rio, Quinten McNamara, Joshua Dong, Ryan Westerman, Michelle Huang, Joseph Palakapilly, Jennifer Drexler, Ilya Pirkin, Nishchal Bhandari, and Miguel Jette. 2021. Accented speech recognition: A survey.

Neil Houlsby, Ferenc Huszár, Zoubin Ghahramani, and Máté Lengyel. 2011. Bayesian active learning for classification and preference learning. *arXiv preprint arXiv:1112.5745*.

Wei-Ning Hsu, Benjamin Bolte, Yao-Hung Hubert Tsai, Kushal Lakhotia, Ruslan Salakhutdinov, and Abdelrahman Mohamed. 2021. Hubert: Self-supervised speech representation learning by masked prediction of hidden units. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 29:3451–3460.

Alex Kendall and Yarin Gal. 2017. What uncertainties do we need in bayesian deep learning for computer vision? *Advances in Neural Information Processing Systems*, 30:5574–5584.

Andreas Kirsch, Joost van Amersfoort, and Yarin Gal. 2019. *BatchBALD: efficient and diverse batch acquisition for deep Bayesian active learning*. Curran Associates Inc., Red Hook, NY, USA.

Jodi Kodish-Wachs, Emin Agassi, Patrick Kenny III, and J Marc Overhage. 2018. A systematic comparison of contemporary automatic speech recognition engines for conversational clinical speech. In *AMIA Annual Symposium Proceedings*, volume 2018, page 683. American Medical Informatics Association.

Allison Koenecke. 2021. Racial Disparities in Automated Speech Recognition. In *Proc. 2021 ISCA Symposium on Security and Privacy in Speech Communication*.

Allison Koenecke, Andrew Nam, Emily Lake, Joe Nudell, Minnie Quartey, Zion Mengesha, Connor Toups, John R Rickford, Dan Jurafsky, and

Sharad Goel. 2020. Racial disparities in automated speech recognition. *Proceedings of the National Academy of Sciences*, 117(14):7684–7689.

Balaji Lakshminarayanan, Alexander Pritzel, and Charles Blundell. 2017. Simple and scalable predictive uncertainty estimation using deep ensembles. *Advances in neural information processing systems*, 30.

Shang Liu and Xiaocheng Li. 2023. Understanding uncertainty sampling. *arXiv preprint arXiv:2307.02719*.

Ninareh Mehrabi, Fred Morstatter, Nripsuta Saxena, Kristina Lerman, and Aram Galstyan. 2021. A survey on bias and fairness in machine learning. *ACM Comput. Surv.*, 54(6).

Zion Mengesha, Courtney Heldreth, Michal Lahav, Juliana Sublewski, and Elyse Tuennerman. 2021. “i don’t think these devices are very culturally sensitive.”—impact of automated speech recognition errors on african americans. *Frontiers in Artificial Intelligence*, page 169.

Margaret Mitchell, Simone Wu, Andrew Zaldivar, Parker Barnes, Lucy Vasserman, Ben Hutchinson, Elena Spitzer, Inioluwa Deborah Raji, and Timnit Gebru. 2019. Model cards for model reporting. In *Proceedings of the Conference on Fairness, Accountability, and Transparency*, FAT* ’19, page 220–229, New York, NY, USA. Association for Computing Machinery.

Udhyakumar Nallasamy, Florian Metze, and Tanja Schultz. 2012. Active learning for accent adaptation in automatic speech recognition. In *2012 IEEE Spoken Language Technology Workshop (SLT)*, pages 360–365.

Tobi Olatunji, Tejumade Afonja, Bonaventure F. P. Dossou, Atnafu Lambebo Tonja, Chris Chinenye Emezue, Amina Mardiyyah Rufai, and Sahib Singh. 2023a. AfriNames: Most ASR Models "Butcher" African Names. In *Proc. INTERSPEECH 2023*, pages 5077–5081.

Tobi Olatunji, Tejumade Afonja, Aditya Yadavalli, Chris Chinenye Emezue, Sahib Singh, Bonaventure F. P. Dossou, Joanne Osuchukwu, Salomey Osei, Atnafu Lambebo Tonja, Naome A. Etori, and Clinton Mbataku. 2023b. Afrispeech-200: Pan-african accented speech dataset for clinical and general domain asr.

Alec Radford, Jong Wook Kim, Tao Xu, Greg Brockman, Christine McLeavey, and Ilya Sutskever. 2022. Robust speech recognition via large-scale weak supervision.

Alec Radford, Jong Wook Kim, Tao Xu, Greg Brockman, Christine McLeavey, and Ilya Sutskever. 2023. Robust speech recognition via large-scale weak supervision. In *International Conference on Machine Learning*, pages 28492–28518. PMLR.

G. Riccardi and D. Hakkani-Tur. 2005. Active learning: theory and applications to automatic speech recognition. *IEEE Transactions on Speech and Audio Processing*, 13(4):504–511.

Andrew D. Selbst, Danah Boyd, Sorelle A. Friedler, Suresh Venkatasubramanian, and Janet Vertesi. 2019. Fairness and abstraction in sociotechnical systems. In *Proceedings of the Conference on Fairness, Accountability, and Transparency*, FAT* ’19, page 59–68, New York, NY, USA. Association for Computing Machinery.

Ozan Sener and Silvio Savarese. 2017. Active learning for convolutional neural networks: A core-set approach. *arXiv preprint arXiv:1708.00489*.

Burr Settles. 2009. Active learning literature survey.

Yulia Tsvetkov. 2017. Opportunities and challenges in working with low-resource languages. In *Carnegie Mellon Univ., Language Technologies Institute*.

Patrice Yemmene and Laurent Besacier. 2019. Motivations, challenges, and perspectives for the development of an automatic speech recognition system for the under-resourced ngiemboon language. In *Proceedings of The First International Workshop on NLP Solutions for Under Resourced Languages (NSURL 2019) co-located with ICNLSP 2019-Short Papers*, pages 59–67.

Julián Zapata and Andreas Søeborg Kirkedal. 2015. Assessing the performance of automatic speech recognition systems when used by native and non-native speakers of three major languages in dictation workflows. In *Proceedings of the 20th Nordic Conference of Computational Linguistics (NODALIDA 2015)*, pages 201–210.

A Appendices

A.1 Hyper-parameters

Table 5 shows the hyper-parameter settings used in this study. The top-k value in the table is changed according to the domain used in each of the experiments. For example, when conducting experiments in the general domain, we set the value of top-k to 2k.

A.2 Country Statistics

Table 6 shows the countries' statistics across the AfriSpeech-200 dataset.

A.3 Dataset Accents Stats

Tables 7 and 8 provide a list of AfriSpeech accents along with the number of unique speakers, countries where speakers for each accent are located, duration in seconds for each accent, and their presence in the train, dev, and test splits.

Hyper-parameters	Values
attention dropout	0.1
hidden dropout	0.1
layer drop	0.1
train batch size	16
val batch size	8
number of epochs	5
learning rate	3e-4
maximum audio length	260000
maximum label length	260
minimum transcript length	10
top_k	2000, 3500, 6500
domains	general, clinical, all
active learning rounds	3
sampling mode	EU-Most, random
MC-Dropout round	10

Table 5: Hyper-parameters summary

Country	Clips	Speakers	Duration (seconds)	Duration (hrs)
Nigeria	45875	1979	512646.88	142.40
Kenya	8304	137	75195.43	20.89
South Africa	7870	223	81688.11	22.69
Ghana	2018	37	18581.13	5.16
Botswana	1391	38	14249.01	3.96
Uganda	1092	26	10420.42	2.89
Rwanda	469	9	5300.99	1.47
United States of America	219	5	1900.98	0.53
Turkey	66	1	664.01	0.18
Zimbabwe	63	3	635.11	0.18
Malawi	60	1	554.61	0.15
Tanzania	51	2	645.51	0.18
Lesotho	7	1	78.40	0.02

Table 6: Countries Statistics across the dataset

A.4 Most common accent distribution

Figures 5 and 6 show the most common accent distribution across the general domain with random and EU-Most selection strategies.

A.5 Ascending and Descending Accents

Figure 7 shows ascending and descending accents across the Top 2k *most* uncertain samples.

Accent	Clips	Speakers	Duration(s)	Countries	Splits
yoruba	15407	683	161587.55	US,NG	train,test,dev
igbo	8677	374	93035.79	US,NG,ZA	train,test,dev
swahili	6320	119	55932.82	KE,TZ,ZA,UG	train,test,dev
hausa	5765	248	70878.67	NG	train,test,dev
ijaw	2499	105	33178.9	NG	train,test,dev
afrikaans	2048	33	20586.49	ZA	train,test,dev
idoma	1877	72	20463.6	NG	train,test,dev
zulu	1794	52	18216.97	ZA,TR,LS	dev,train,test
setswana	1588	39	16553.22	BW,ZA	dev,test,train
twi	1566	22	14340.12	GH	test,train,dev
isizulu	1048	48	10376.09	ZA	test,train,dev
igala	919	31	9854.72	NG	train,test
izon	838	47	9602.53	NG	train,dev,test
kiswahili	827	6	8988.26	KE	train,test
ebira	757	42	7752.94	NG	train,test,dev
luganda	722	22	6768.19	UG,BW,KE	test,dev,train
urhobo	646	32	6685.12	NG	train,dev,test
nembe	578	16	6644.72	NG	train,test,dev
ibibio	570	39	6489.29	NG	train,test,dev
pidgin	514	20	5871.57	NG	test,train,dev
luhya	508	4	4497.02	KE	train,test
kinyarwanda	469	9	5300.99	RW	train,test,dev
xhosa	392	12	4604.84	ZA	train,dev,test
tswana	387	18	4148.58	ZA,BW	train,test,dev
esan	380	13	4162.63	NG	train,test,dev
alago	363	8	3902.09	NG	train,test
tshivenda	353	5	3264.77	ZA	test,train
fulani	312	18	5084.32	NG	test,train
isoko	298	16	4236.88	NG	train,test,dev
akan (fante)	295	9	2848.54	GH	train,dev,test
ikwere	293	14	3480.43	NG	test,train,dev
sepedi	275	10	2751.68	ZA	dev,test,train
efik	269	11	2559.32	NG	test,train,dev
edo	237	12	1842.32	NG	train,test,dev
luo	234	4	2052.25	UG,KE	test,train,dev
kikuyu	229	4	1949.62	KE	train,test,dev
bekwarra	218	3	2000.46	NG	train,test
isixhosa	210	9	2100.28	ZA	train,dev,test
hausa/fulani	202	3	2213.53	NG	test,train
epie	202	6	2320.21	NG	train,test
isindebele	198	2	1759.49	ZA	train,test
venda and xitsonga	188	2	2603.75	ZA	train,test
sotho	182	4	2082.21	ZA	dev,test,train
akan	157	6	1392.47	GH	test,train
nupe	156	9	1608.24	NG	dev,train,test
anaang	153	8	1532.56	NG	test,dev
english	151	11	2445.98	NG	dev,test
afemai	142	2	1877.04	NG	train,test
shona	138	8	1419.98	ZA,ZW	test,train,dev
eggon	137	5	1833.77	NG	test
luganda and kiswahili	134	1	1356.93	UG	train
ukwuani	133	7	1269.02	NG	test
sesotho	132	10	1397.16	ZA	train,dev,test
benin	124	4	1457.48	NG	train,test
kagoma	123	1	1781.04	NG	train
nasarawa eggon	120	1	1039.99	NG	train
tiv	120	14	1084.52	NG	train,test,dev
south african english	119	2	1643.82	ZA	train,test
borana	112	1	1090.71	KE	train

Table 7: Dataset Accent Stats, Part I

Accent	Clips	Speakers	Duration(s)	Countries	Splits
swahili ,luganda ,arabic	109	1	929.46	UG	train
ogoni	109	4	1629.7	NG	train,test
mada	109	2	1786.26	NG	test
bette	106	4	930.16	NG	train,test
berom	105	4	1272.99	NG	dev,test
bini	104	4	1499.75	NG	test
ngas	102	3	1234.16	NG	train,test
etsako	101	4	1074.53	NG	train,test
okrika	100	3	1887.47	NG	train,test
venda	99	2	938.14	ZA	train,test
siswati	96	5	1367.45	ZA	dev,train,test
damara	92	1	674.43	NG	train
yoruba, hausa	89	5	928.98	NG	test
southern sotho	89	1	889.73	ZA	train
kanuri	86	7	1936.78	NG	test,dev
itsekiri	82	3	778.47	NG	test,dev
ekpeye	80	2	922.88	NG	test
mwaghavul	78	2	738.02	NG	test
bajju	72	2	758.16	NG	test
luo, swahili	71	1	616.57	KE	train
dholuo	70	1	669.07	KE	train
ekene	68	1	839.31	NG	test
jaba	65	2	540.66	NG	test
ika	65	4	576.56	NG	test,dev
angas	65	1	589.99	NG	test
ateso	63	1	624.28	UG	train
brass	62	2	900.04	NG	test
ikulu	61	1	313.2	NG	test
eleme	60	2	1207.92	NG	test
chichewa	60	1	554.61	MW	train
oklo	58	1	871.37	NG	test
meru	58	2	865.07	KE	train,test
agatu	55	1	369.11	NG	test
okirika	54	1	792.65	NG	test
igarra	54	1	562.12	NG	test
ijaw(nembe)	54	2	537.56	NG	test
khana	51	2	497.42	NG	test
ogbia	51	4	461.15	NG	test,dev
gbagyi	51	4	693.43	NG	test
portuguese	50	1	525.02	ZA	train
delta	49	2	425.76	NG	test
bassa	49	1	646.13	NG	test
etche	49	1	637.48	NG	test
kubi	46	1	495.21	NG	test
jukun	44	2	362.12	NG	test
igbo and yoruba	43	2	466.98	NG	test
urobo	43	3	573.14	NG	test
kalabari	42	5	305.49	NG	test
ibani	42	1	322.34	NG	test
obolo	37	1	204.79	NG	test
idah	34	1	533.5	NG	test
bassa-nge/nupe	31	3	267.42	NG	test,dev
yala mbembe	29	1	237.27	NG	test
eket	28	1	238.85	NG	test
afo	26	1	171.15	NG	test
ebiobo	25	1	226.27	NG	test
nyandang	25	1	230.41	NG	test
ishan	23	1	194.12	NG	test
bagi	20	1	284.54	NG	test
estako	20	1	480.78	NG	test
gerawa	13	1	342.15	NG	test

Table 8: Dataset Accent Stats, Part II

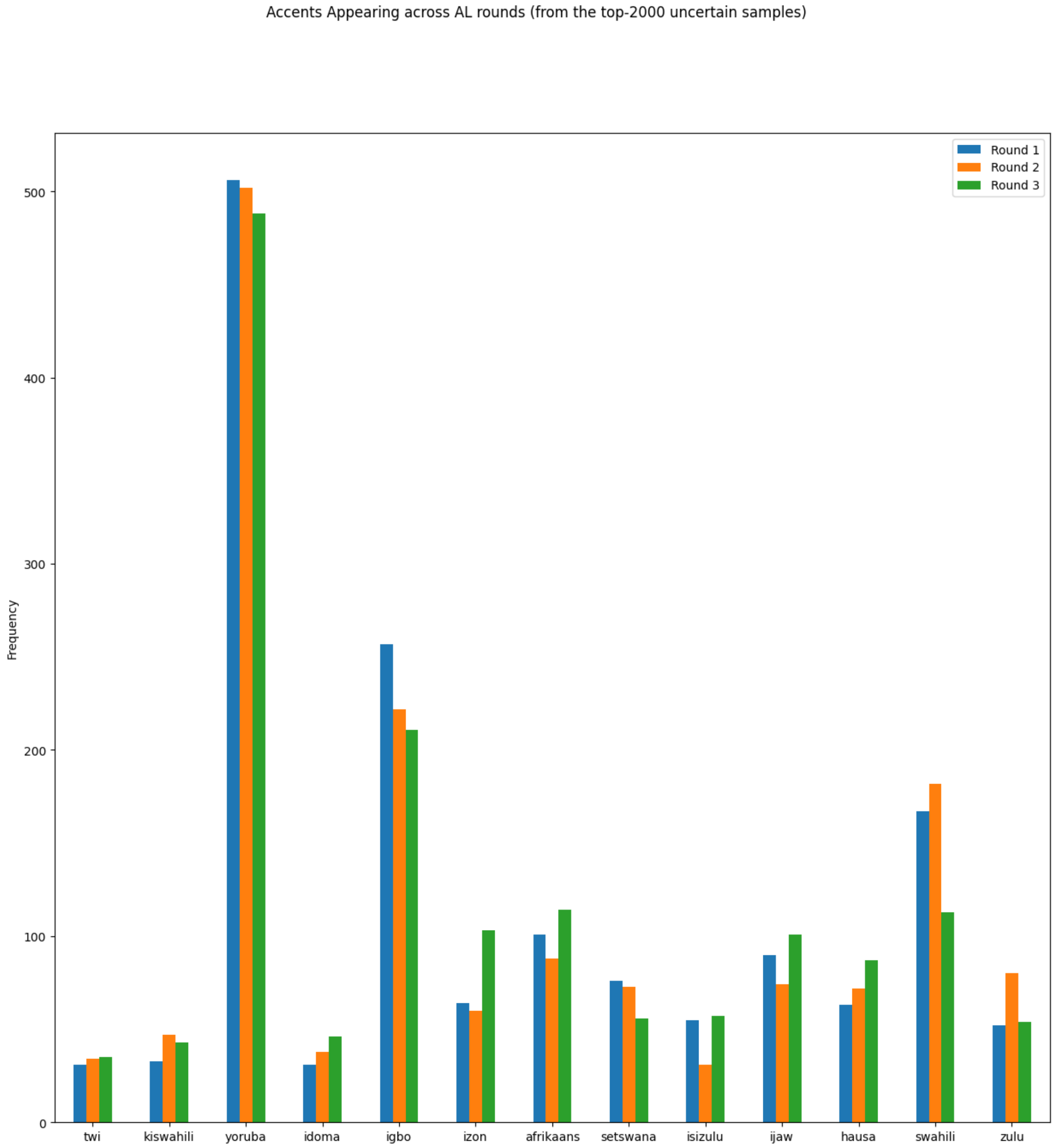

Figure 5: Most common accents distribution across the general domain with EU-Most sampling strategy.

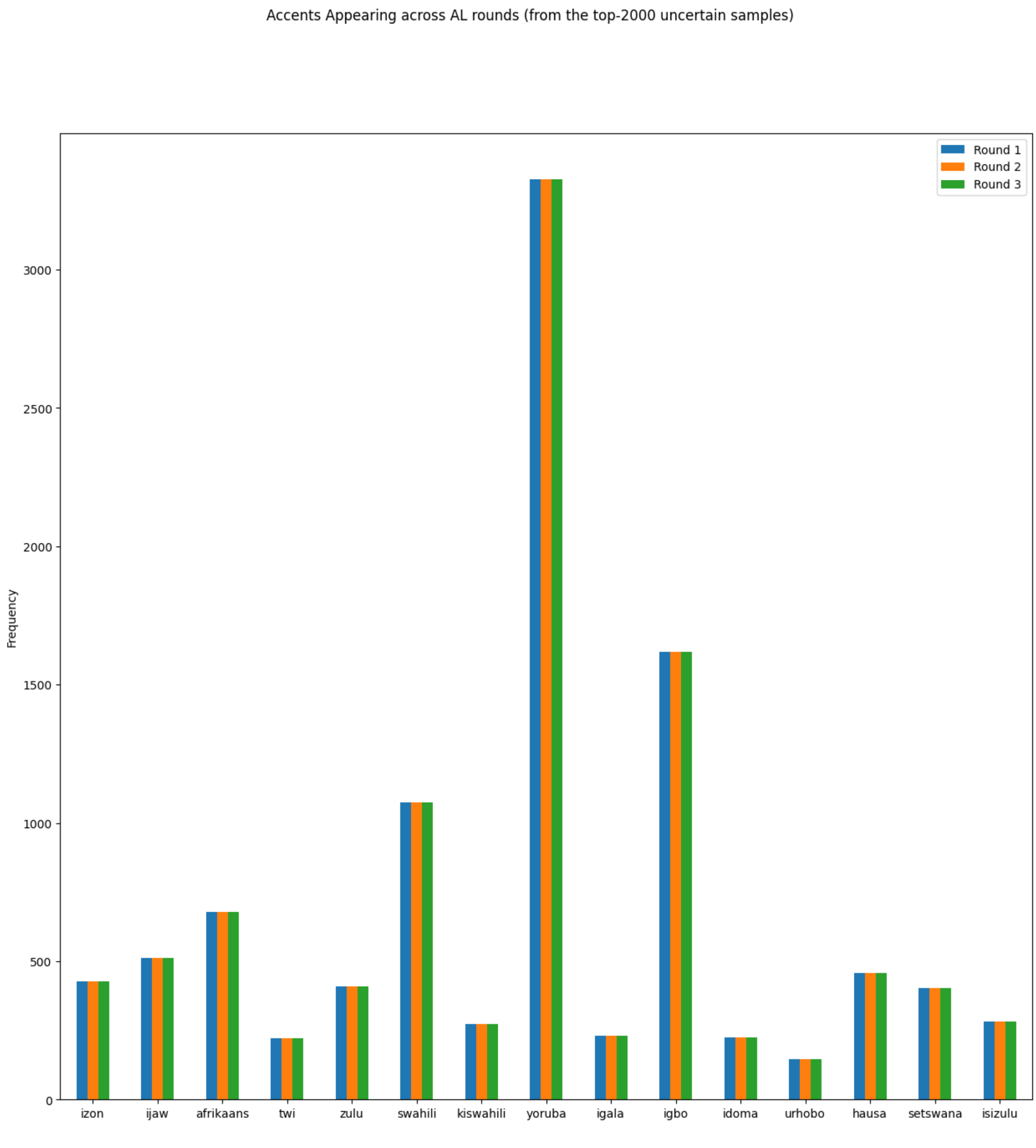

Figure 6: Most common accents distribution across the general domain with random selection strategy.

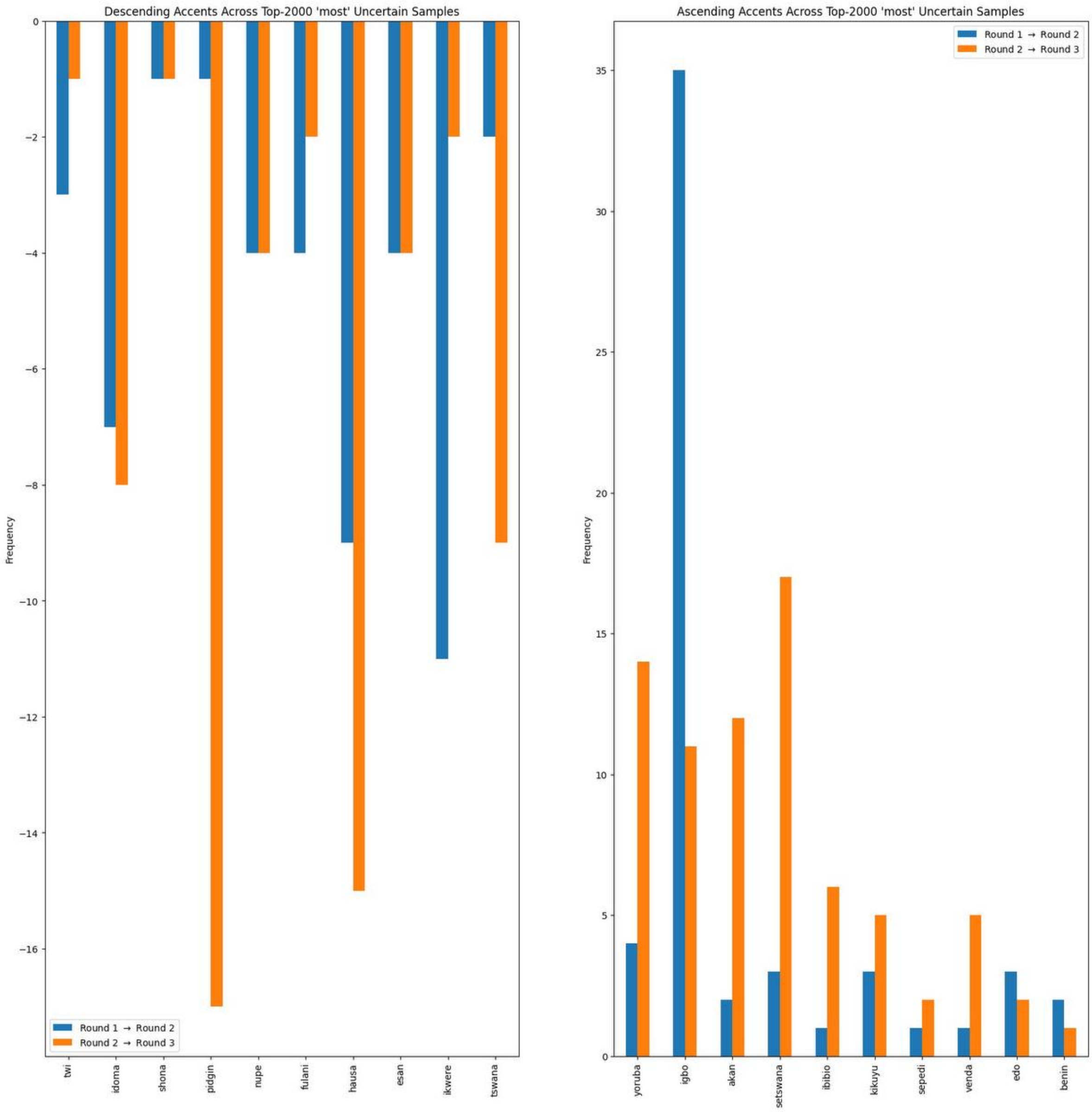

Figure 7: Ascending and descending accents across Top-2K *most* uncertain samples.