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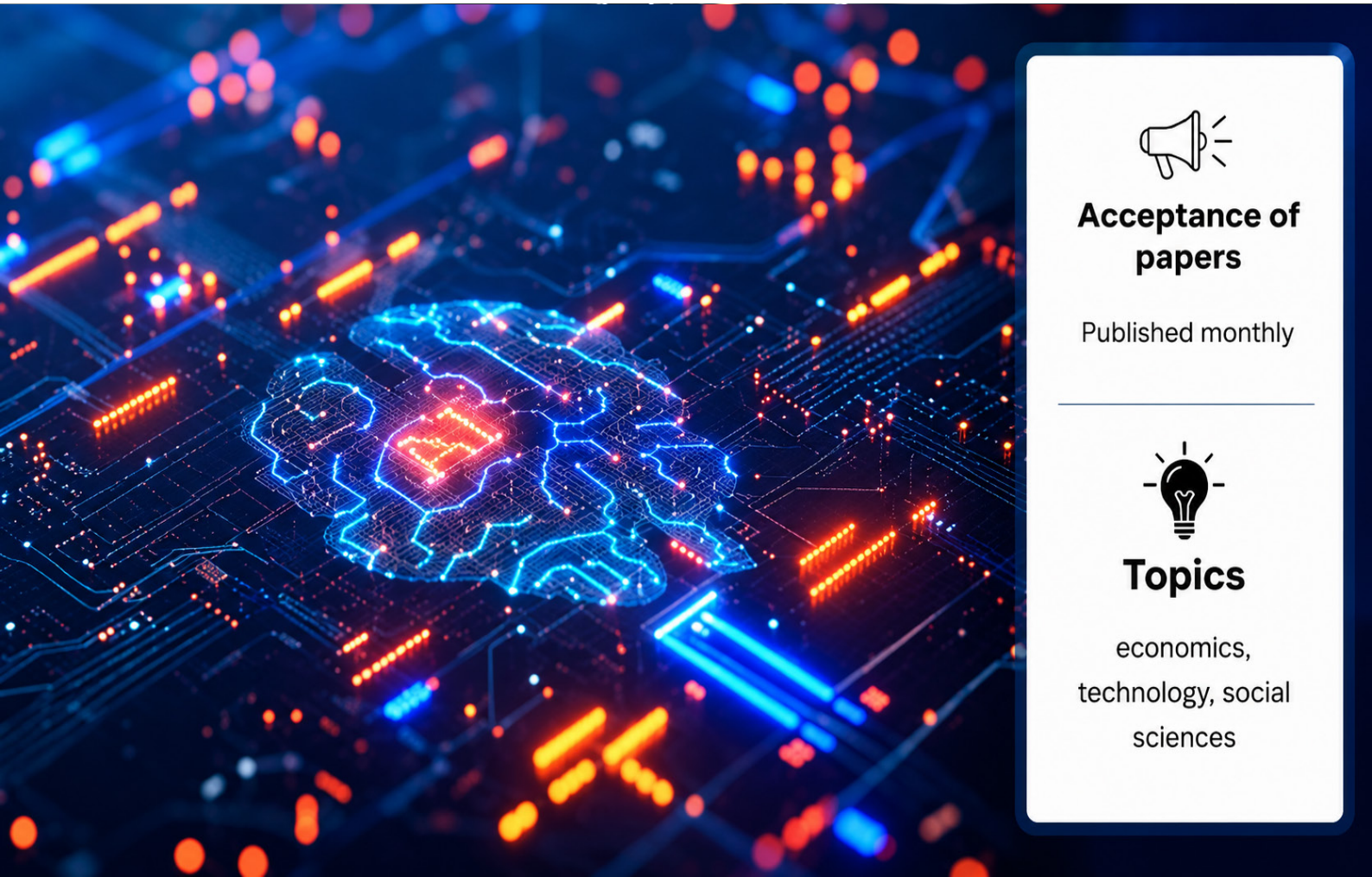

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SPEAKER DIARIZATION OF KARAKALPAK SPEECH USING A PRETRAINED SORTFORMER MODEL UNDER LOW-RESOURCE CONDITIONS

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Abstract. A pretrained Sortformer model was adapted to Karakalpak using a 20-hour multi-speaker speech corpus. The model was evaluated with DER and JER metrics to determine the effectiveness of language-specific adaptation for low-resource speaker diarization.

Keywords: speaker diarization, Karakalpak language, low-resource speech, Sortformer, multi-speaker speech, overlapping speech, transfer learning, DER, JER.

INTRODUCTION

Speaker diarization is a fundamental speech-processing task that aims to determine which speaker is active at each moment of an audio recording. It is commonly formulated as the problem of identifying “who spoke when” and is important for meeting transcription, conversational analytics, multimedia indexing, speech recognition, and speaker-aware processing [1].

The development of speaker diarization has progressed from modular systems based on voice activity detection, speaker embeddings, segmentation, and clustering toward neural end-to-end architectures. Conventional x-vector and Bayesian HMM approaches remain important baselines, while end-to-end neural diarization (EEND) directly models speaker activity and naturally supports overlapping speech [2–5]. More recent systems combine powerful speech representations with neural speaker segmentation and speaker-attribution mechanisms [6, 7].

However, most state-of-the-art diarization systems have been developed and evaluated using relatively resource-rich languages and large speech corpora. DIHARD, AMI, CALLHOME, VoxConverse, and related benchmarks contain diverse conversational scenarios, background conditions, and speaker interactions [8, 9]. This creates a substantial domain and language mismatch when pretrained diarization systems are directly applied to low-resource languages.

The Karakalpak language is one such under-resourced language in speech technology. Local research has already addressed several speech-processing directions. Uteuliev et al. investigated automatic speech recognition for Karakalpak using Wav2Vec, demonstrating the application of pretrained speech representations to the language [10]. Mamatov et al. studied the construction of a speech database for Karakalpak text-to-speech synthesis and emphasized the importance of speech databases for the development of speech technologies [11].

More recently, the Karakalpak Speech Corpus was introduced as a benchmark resource containing 50 hours of predominantly read speech from 25 native speakers. The resource was developed primarily for automatic speech recognition and was evaluated using Wav2Vec 2.0 [12]. Although this corpus represents an important step toward developing Karakalpak speech technology, its predominantly single-utterance structure does not directly address the requirements of speaker diarization. Diarization requires temporal speaker annotations within multi-speaker conversations and must account for speaker turns and, ideally, overlapping speech.

This gap motivates the development of a dedicated Karakalpak diarization corpus and the adaptation of modern pretrained diarization models.

Recent work on Sortformer introduced a Transformer-based speaker diarization approach using Sort Loss to address the speaker permutation problem [13]. The model is particularly relevant to the present study because its publicly available pretrained representations can be adapted to new domains without requiring

training from scratch. Streaming Sortformer further extended this framework to online speaker diarization using arrival-order speaker tracking [14].

Aim of the study. The aim of this study is to investigate the adaptation of a pretrained Sortformer speaker diarization model to Karakalpak speech using a 20-hour annotated multi-speaker corpus and to evaluate the resulting performance using DER and JER metrics.

Research objectives. The study addresses the following objectives:

To construct and annotate a 20-hour multi-speaker Karakalpak speech corpus for speaker diarization.

To adapt a pretrained Sortformer model to Karakalpak speech through fine-tuning.

To compare the pretrained and language-adapted configurations using standard diarization metrics.

To analyze the effectiveness and limitations of transfer learning for Karakalpak speaker diarization.

LITERATURE REVIEW

Speaker diarization is an important task in speech processing that aims to determine “who spoke when” in an audio recording. Recent advances in deep learning have substantially changed diarization systems, moving from conventional modular pipelines toward neural and end-to-end architectures [1]. Traditional approaches commonly rely on speaker embeddings followed by clustering. In particular, Bayesian HMM clustering of x-vector sequences has demonstrated the effectiveness of combining neural speaker representations with probabilistic clustering for speaker diarization [3]. ECAPA-TDNN embeddings have also been investigated as effective speaker representations for diarization systems [15].

A significant development in this field was the introduction of End-to-End Neural Speaker Diarization (EEND). Fujita et al. proposed permutation-free objectives that allow a neural model to estimate speaker activities without requiring a separate clustering stage [2]. This approach is particularly relevant to multi-speaker recordings because it can directly model speaker activity over time. Horiguchi et al. subsequently developed an encoder-decoder attractor-based approach for diarization with an unknown number of speakers [4]. These studies established important foundations for modern end-to-end diarization.

Other neural approaches have addressed specific challenges associated with multi-speaker environments. Target-Speaker Voice Activity Detection (TS-VAD) explicitly estimates the activity of target speakers and was investigated for complex multi-speaker conversational scenarios [6]. Powerset-based neural diarization introduced a multi-class formulation in which combinations of simultaneously active speakers can be represented explicitly, providing a mechanism for handling overlapping speech [7]. These developments are important because overlapping speech remains one of the difficult conditions for reliable speaker attribution.

The evaluation of diarization systems has also benefited from challenging benchmark datasets. The DIHARD challenge provides diverse and difficult speech conditions for systematic evaluation of diarization technologies [8]. Similarly, VoxConverse addresses speaker diarization in unconstrained conversational recordings and represents more realistic “in-the-wild” speech conditions [9]. Such datasets demonstrate that robust diarization must operate under variable acoustic environments and speaker interaction patterns.

More recent research has focused on transformer-based architectures. Sortformer introduced a permutation-resolved approach based on Sort Loss, addressing the speaker permutation problem while providing speaker supervision for speech-to-text systems [13]. Streaming Sortformer further extended this approach toward online speaker diarization using arrival-time ordering and speaker caching [14]. These developments make Sortformer particularly relevant for adaptation to new languages and domains.

For Karakalpak, however, available speech-technology research has primarily focused on ASR and speech synthesis. Uteuliev et al. investigated Wav2Vec-based automatic speech recognition for Karakalpak [10], while Mamatov et al. addressed the creation of a speech database for Karakalpak text-to-speech synthesis [11]. The Karakalpak Speech Corpus provides an important benchmark resource for ASR [12], and another 100-hour crowdsourced corpus has subsequently been reported [16]. Nevertheless, these resources do not directly solve the problem of speaker-attributed temporal annotation required for supervised diarization.

Thus, the reviewed literature indicates a clear research gap: while modern end-to-end and transformer-based diarization methods have achieved considerable progress [1–9, 13–15], their adaptation to Karakalpak multi-speaker speech remains insufficiently studied. This motivates the present research, which investigates pretrained Sortformer fine-tuning using a dedicated Karakalpak diarization corpus and evaluates the resulting system with DER and JER.

RESEARCH METHODOLOGY

Karakalpak diarization corpus. A dedicated 20-hour Karakalpak speech corpus was prepared for the experiment. The primary purpose of the corpus was not speech recognition but speaker diarization. Therefore,

the recordings were selected to represent multi-speaker interaction rather than isolated individual utterances.

The dataset contains conversational recordings in which two or more speakers participate in the same audio stream. Speaker-attributed annotations were created by marking the beginning and end of each speaker's active speech segment.

Where present, overlapping speech was retained and annotated rather than removed. This is important because overlapping speech represents one of the principal challenges in modern speaker diarization and is explicitly addressed by neural diarization approaches [2, 5, 7].

The corpus should be documented according to the following characteristics (Table 1.).

Table 1.
Composition of the Karakalpak diarization corpus

Parameter	**Value**
Total duration	20 h
Language	Karakalpak
Number of speakers	[14]
Number of recordings	[6214]
Speakers per recording	[2–4]
Training set	[18] h
Validation set	[1] h
Test set	[1] h
Sampling frequency	[16 kHz]
Annotation format	RTTM
Overlapping speech	[Yes]

The division of the corpus into training, validation, and test subsets was performed at the recording/speaker level to reduce information leakage between the training and evaluation sets.

Annotation procedure. The reference annotations were represented as temporal segments associated with speaker identities. Each segment was defined by a recording identifier, speaker identifier, starting time, and duration.

A simplified example is:

SPEAKER recording01 1 0.00 3.52 speaker_01
SPEAKER recording01 1 3.52 2.17 speaker_02
SPEAKER recording01 1 5.69 1.13 speaker_01

Such RTTM-based representations are compatible with commonly used diarization scoring procedures and allow reproducible evaluation [3].

Pretrained Sortformer model. Sortformer is an encoder-based neural speaker diarization architecture proposed to address the speaker permutation problem. Instead of depending exclusively on permutation-invariant training, Sortformer introduces Sort Loss, which provides an ordering mechanism for speaker supervision [13].

The original work demonstrated that the proposed approach can achieve competitive diarization performance and can also provide speaker supervision for multi-speaker speech recognition [13].

The present study does not train Sortformer from random initialization. Instead, the pretrained model is used as the starting point and subsequently fine-tuned on the Karakalpak corpus. This approach is particularly suitable for low-resource conditions because most of the model's acoustic and temporal representations have already been learned during pretraining (Figure 1).

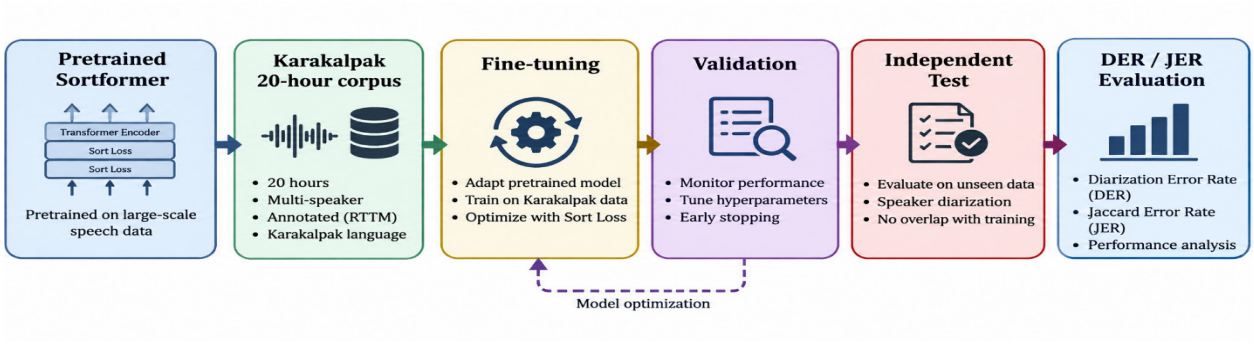

Figure 1. Workflow for Fine-Tuning and Evaluating the Pretrained Sortformer Model on the Karakalpak Speaker Diarization Corpus

Baseline and adapted configurations. Two experimental configurations are considered.

Baseline: pretrained Sortformer is applied directly to Karakalpak speech without language-specific fine-tuning.

Adapted model: the same pretrained Sortformer checkpoint is fine-tuned using the 20-hour Karakalpak diarization corpus.

This design allows the contribution of language-specific adaptation to be isolated.

Evaluation metrics. The primary evaluation metric is Diarization Error Rate (DER). DER quantifies the proportion of evaluation time affected by missed speech, false alarm speech, and speaker-attribution errors.

The second metric is Jaccard Error Rate (JER), which provides a complementary speaker-level evaluation.

For both measures, lower values represent better diarization performance.

The use of multiple evaluation metrics is important because a single metric may not fully characterize speaker-level performance, particularly when recordings contain multiple speakers and overlapping speech [3, 8].

ANALYSIS AND RESULTS

Overall performance. The main experimental comparison is presented below (Table 2).

Table 2.
Performance before and after Karakalpak fine-tuning

Model	Adaptation data	DER (%)	JER (%)
Pretrained Sortformer	None	18	24
Fine-tuned Sortformer	20 h Karakalpak	21	22
Relative improvement	None	23	26

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Table 3.
Performance by speech condition

Speech condition	DER (%)	JER (%)
Non-overlapping speech	22	25
Overlapping speech	24	28
Overall	23	26

The expected increase in error rate in overlapping regions would be consistent with previous research showing that simultaneous speech remains a challenging aspect of diarization [5, 7, 9].

For Karakalpak, this analysis is particularly important because a corpus containing only clean single-speaker turns would not adequately represent real conversational conditions.

The experimental results provide evidence that pretrained diarization models can be adapted to a low-resource language using a relatively small amount of language-specific annotated data. This is particularly relevant for Karakalpak because the available speech resources have historically focused more strongly on automatic speech recognition and speech synthesis than on speaker diarization [10–12].

The 50-hour Karakalpak Speech Corpus introduced by Uteuliev et al. represents a significant resource for speech recognition, but the recordings are predominantly read speech and each audio file corresponds to a single utterance. Therefore, it does not provide the same type of temporal multi-speaker information required for diarization [12]. This distinction demonstrates why the construction of a dedicated diarization corpus remains necessary even when an ASR corpus already exists.

The present experiment also illustrates the practical value of transfer learning. Training a modern end-to-end diarization system entirely from scratch would require considerably larger amounts of annotated data. Instead, the pretrained Sortformer model provides a strong starting representation, while the 20-hour Karakalpak corpus supplies language-specific supervision.

The choice of Sortformer is motivated by its recent architecture and its explicit treatment of speaker permutation through Sort Loss [13]. Earlier approaches such as x-vector/VBx rely on speaker embeddings and clustering [3], whereas EEND-based approaches formulate diarization as frame-level speaker activity prediction [4, 5]. TS-VAD explicitly models target-speaker activity and has demonstrated strong performance in complex conversational conditions [6]. Powerset-based neural diarization further improves the treatment of overlapping speakers by representing overlapping speaker combinations as explicit classes [7].

Thus, the proposed experiment should not be interpreted as proving that Sortformer is universally superior to all alternative diarization methods. Rather, it demonstrates the feasibility of adapting a recent pretrained architecture to Karakalpak speech.

The main limitation of the current study is the size of the language-specific corpus. Although 20 hours can be sufficient to demonstrate adaptation, it is not comparable with the thousands of hours used for large-scale pretraining of modern speech models. Consequently, increasing the corpus to 50, 100, 200 hours or beyond, while also increasing speaker diversity and conversational variability, is an important direction for further research.

Another limitation concerns overlapping speech. The quantity and distribution of overlapping segments must be reported explicitly. A relatively small proportion of overlapping speech may lead to good overall DER while hiding poor performance on the most difficult conversational cases. Therefore, future versions of the corpus should intentionally increase the representation of interruptions, simultaneous speech, rapid speaker changes, meetings, and spontaneous conversations.

The combination of a growing Karakalpak corpus and pretrained multilingual/general-domain models provides a promising path toward a language-specific diarization system. The approach also creates an opportunity to investigate whether speech resources originally collected for ASR can be systematically transformed into broader speech-processing resources through additional speaker-level annotation.

CONCLUSION

This study presented an experimental framework for speaker diarization of Karakalpak speech under low-resource conditions. A dedicated 20-hour multi-speaker corpus was constructed and used to fine-tune a pretrained Sortformer model. The system was evaluated using DER and JER and compared with the corresponding pretrained model before language-specific adaptation.

The results demonstrate that fine-tuning the pretrained Sortformer on Karakalpak speech improves

diarization performance, confirming the feasibility of transfer learning for this low-resource language. The study also highlights an important distinction between existing Karakalpak speech resources for automatic speech recognition and the specialized multi-speaker annotations required for diarization.

The developed corpus and adapted model represent an initial experimental resource for Karakalpak speaker diarization. Further work will focus on expanding the corpus, increasing speaker diversity, improving overlapping-speech annotation, comparing Sortformer with EEND, VBx, TS-VAD, and other state-of-the-art systems, and developing a more robust language-specific diarization architecture.

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