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KAZAKH SPEECH AND RECOGNITION METHODS: ERROR ANALYSIS AND IMPROVEMENT PROSPECTS

Abstract: This study offers a detailed evaluation of automatic speech recognition (ASR) systems for the Kazakh, examining their performance in recognizing the phonetic and linguistic features unique to the language. The Kazakh language presents specific challenges for ASR due to its complex phonology, vowel harmony, and the presence of multiple regional dialects. To address these challenges, a comparative analysis of three leading ASR systems were conducted—Kaldi, Mozilla DeepSpeech, and Google Speech-to-Text API—using a dataset of 101 recordings of spoken the Kazakh text. This study focuses on the systems' word error rates (WER), identifying common misrecognitions, especially with the Kazakh-specific phonemes like "қ," "ң," and "ү." Kaldi and Mozilla DeepSpeech exhibited high WERs, particularly struggling with Kazakh's vowel harmony and consonant distinctions, while Google Speech-to-Text achieved of the lowest WER among the three. However, none of the systems demonstrated accuracy levels sufficient for practical applications, as errors in recognizing Kazakh's agglutinative morphology and case endings remained pervasive. To improve these outcomes, a series of enhancements are proposed, including adapting acoustic models to better reflect Kazakh's phonetic and morphological traits, integrating dialect-specific data, and employing machine learning methods such as transfer learning and hybrid models. Additional steps include refining data preprocessing and increasing dataset diversity to capture Kazakh's linguistic nuances more accurately. By addressing these limitations, the ASR systems can better handle complex sentence structures and regional speech variations. This research thus provides a foundation for advancing Kazakh ASR technologies and contributes insights that are vital for developing inclusive, effective ASR systems capable of supporting linguistically diverse users.

Keywords*:* The Kazakh speech recognition, Automatic speech recognition (ASR), Kaldi, Mozilla DeepSpeech, Google Speech-to-Text API, Speech recognition errors, Phonetic analysis, Acoustic model adaptation, Linguistic features, the Kazakh language processing

Introduction

In recent years, Automatic Speech Recognition (ASR) has become an integral part of data processing technologies used in various applications, such as virtual assistants, transcription systems, and real-time translation tools. However, most modern speech recognition systems are primarily focused on widely spoken languages like English, Chinese, and Spanish, while under-resourced languages, such as Kazakh, remain underrepresented and insufficiently supported [1]. This presents significant challenges for Kazakh-speaking users, as models trained

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on other languages fail to capture the unique phonetic and grammatical features of the Kazakh language, leading to a higher error rate in speech recognition.

One of the critical issues is the complex phonological system of the Kazakh language, which includes characteristics such as vowel harmony and distinctive consonants that are difficult to accurately recognize with existing algorithms. Furthermore, regional dialects and accents introduce additional challenges, making it even more difficult to develop accurate ASR systems for Kazakh [2].

This study aims to identify the primary recognition errors encountered by current ASR systems when processing Kazakh speech. By conducting a comparative analysis of three widely-used algorithms – Kaldi, Mozilla DeepSpeech, and Google Speech-to-Text API – it is aimed to assess their performance on Kazakh language datasets [3],[4]. The findings will allow to propose solutions to improve existing models and optimize ASR systems for better performance in Kazakh, contributing to more accurate speech processing technologies tailored to under-resourced languages.

This study is highly relevant due to the increasing demand for speech recognition technologies that support under-resourced languages like Kazakh. While significant progress has been made in automatic speech recognition (ASR) for widely spoken languages, existing systems struggle with the unique phonetic and grammatical features of Kazakh, leading to lower accuracy [5].

As the state language of Kazakhstan, Kazakh is spoken by millions, yet its digital language technologies remain underdeveloped. With the growing use of Kazakh in education, media, and public services, there is an urgent need for reliable ASR systems tailored to this language.

This research aims to fill this gap by assessing the performance of current ASR algorithms and proposing improvements. The findings will contribute to developing more accurate speech recognition systems for Kazakh and other under-resourced languages.

Several studies have explored automatic speech recognition (ASR) systems for under-resourced languages like Kazakh, though progress remains limited compared to widely spoken languages. Below is a summary of key research findings and ASR system performances relevant to Kazakh and similar languages [6].

Table 1. Comparative Analysis of Speech Recognition Algorithms for Kazakh Language: Evaluation Based on Word Error Rate

Study/Source	Language	Algorithm	WER (Word Error Rate)	Dataset Size
Baevski et al., 2020 (Facebook AI)	Kazakh	wav2vec 2.0	23.7%	~10 hours of speech
Yessenbayev et al., 2021	Kazakh	Google Speech-to-Text API	34.5%	~50 hours of speech
Kudaibergenov et al., 2022	Kyrgyz (similar)	Kaldi	27.6%	~20 hours of speech
Google Research, 2021	Multilingual	Google Multilingual Model	21.9% (Kazakh)	>100 hours (Kazakh)

Summary of Approaches:

1. wav2vec 2.0: A neural network-based approach that has shown promising results for low-resource languages. In tests on Kazakh, it achieved a WER of 23.7% using a relatively small dataset(Table 1)[7].

2. Google Speech-to-Text API: Widely used in commercial applications, but less accurate for Kazakh with a WER of 34.5%. The study by Yessenbayev et al. highlighted that Google's model performs better with larger datasets but struggles with phonetic nuances.

3. Kaldi: Popular in academia for speech recognition, Kaldi's performance for related languages, such as Kyrgyz, suggests it could be adapted for Kazakh. Kudaibergenov et al. achieved a WER of 27.6%.

Research Gaps:

- Phonetic Adaptation: Existing algorithms show high error rates due to the lack of adaptation to Kazakh phonetics, including vowel harmony and consonant variations.
- Dataset Size: The lack of extensive labeled datasets for Kazakh speech significantly limits the performance of most ASR models [8].

The novelty of this research lies in its comprehensive analysis of Kazakh speech recognition errors across multiple state-of-the-art ASR systems, including Kaldi, Mozilla DeepSpeech, and Google Speech-to-Text API, which have not been thoroughly compared in prior studies for this language [9]. While existing works primarily focus on evaluating individual algorithms or improving specific models, the approach offers a direct, head-to-head comparison of different ASR systems on the same dataset of Kazakh speech. This allows for a more robust assessment of each system's strengths and weaknesses in handling the unique phonetic and grammatical features of Kazakh, such as vowel harmony and consonant variations.

Moreover, this study not only identifies and categorizes common recognition errors but also proposes specific improvements for enhancing the performance of these algorithms. Unlike prior research, which often addresses errors at a superficial level, the work provides detailed recommendations for adapting acoustic models and incorporating linguistic features unique to Kazakh. This targeted approach, focused on error correction and optimization, represents a significant contribution to the development of more accurate ASR systems for under-resourced languages like Kazakh [10],[11].

Methods and Materials

This section outlines the detailed methodology of the experiment conducted to evaluate the performance of various automatic speech recognition (ASR) algorithms for Kazakh speech. The experiment involved collecting a dataset of 101 voice recordings of a specific text in the Kazakh language and processing them through Kaldi, Mozilla DeepSpeech, and Google Speech-to-Text API to assess their accuracy and error patterns.

1. Data Collection

The dataset was collected in compliance with the Law of the Republic of Kazakhstan on Personal Data and its Protection. All participants provided consent for the use of their data, and the recordings were anonymized to meet legal requirements.

A total of 101 recordings were collected from participants, predominantly university students, who were asked to read aloud a predefined text in Kazakh. The text, carefully chosen for its linguistic diversity, is as follows:

«Қазақстан табиғаты әсем елдердің бірі. Оның кең далалары, биік таулары, өзен-көлдері баршаға танымал. Әрбір маусымда табиғат өзгеше көрініс береді: көктемде шөптер мен гүлдер қаулайды, жазда күн ысып, дала кең көкжиекке дейін созылады.

Қыста қар жамылған таулар ерекше сұлулыққа ие болады. Қазақстанның әр өңірі табиғи байлықтарға толы, және оларды қорғау — әрбір азаматтың міндеті.»

2. Text Selection Justification

The text was selected based on several criteria to ensure a comprehensive evaluation of ASR systems:

- Variety of Sentence Structures: The text includes both simple and complex sentences, which allows for testing the recognition accuracy of both short and long phrases. This is critical for identifying how well the algorithms handle sentence segmentation and complex syntactic structures.

- Presence of Unique Kazakh Phonemes: The text contains words with distinctive Kazakh sounds (such as "ә", "ң", and "қ"), providing an opportunity to assess how each ASR system manages the phonetic nuances of Kazakh, which are often challenging for speech recognition systems designed for other languages.
- Diverse Morphological Features: The text includes a variety of word forms (verbs, nouns, adjectives) with different affixes, enabling an examination of the algorithms' ability to handle Kazakh morphology. This is particularly important in testing how well the ASR systems process agglutinative structures typical of the Kazakh language.

3. Recording Procedure

Each participant was instructed to read the text clearly in a quiet environment, ensuring minimal background noise. The recordings were made using a standardized device to maintain consistency across the dataset. The recordings were then converted to a suitable format for processing by the selected ASR algorithms.

4. Algorithms and Processing

The recordings were processed through three different ASR systems:

- Kaldi: An open-source speech recognition toolkit widely used in academic research. Kaldi is known for its flexibility in adapting to various languages and acoustic models.
- Mozilla DeepSpeech: A neural network-based system designed to be used for speech-to-text applications. DeepSpeech was selected for its end-to-end architecture, which allows for the automatic learning of features from data.
- Google Speech-to-Text API: A commercially available ASR system, offering support for multiple languages, including Kazakh. It serves as a benchmark for comparing how a general-purpose ASR system performs with Kazakh speech [12], [13].

5. Error Analysis

After processing the recordings, the output from each algorithm was compared with the reference text. The following key metrics were used for evaluation:

- Word Error Rate (WER): The primary measure of accuracy, calculated based on the number of insertions, deletions, and substitutions in the recognized text compared to the reference.
- Phonetic Error Analysis: A detailed examination of how each ASR system handled the unique sounds of Kazakh, focusing on common misrecognitions of vowels and consonants.
- Morphological Error Patterns: Errors related to the recognition of affixes and word forms were categorized to determine how well the systems handle the agglutinative nature of Kazakh.

6. Rationale for Methodology

The chosen methodology ensures a comprehensive assessment of each ASR system's strengths and weaknesses in recognizing Kazakh speech. By using a linguistically diverse text and a varied dataset of recordings, this experiment provides insight into the specific challenges faced by speech recognition algorithms when processing an under-resourced language like Kazakh (Table 2) [14].

Table 2. Comparison of Acoustic Models, Language Models, and Features across Speech Recognition Systems

Feature	Kaldi	Mozilla DeepSpeech	Google Speech-to-Text API
Acoustic Model	GMM-HMM, DNN-HMM, TDNN (Chain models with LF-MMI)	Deep Neural Networks (RNN with LSTM, BiRNN)	Deep Neural Networks (DNN, potentially RNN)
Architecture	Modular, highly configurable, can use traditional GMM-HMM and modern DNN-HMM	End-to-End model with RNN, based on Baidu's DeepSpeech	End-to-End model, highly scalable cloud-based
Language Model	N-gram models, RNNLM for rescoring	N-gram models for decoding	N-gram models, with support for custom context-specific models (custom phrase hints)
Feature Extraction	MFCC, PLP	MFCC	MFCC, Mel-spectrograms
Training Algorithm	GMM-HMM trained with Expectation-Maximization (EM); DNN/TDNN trained with backpropagation, LF-MMI (chain models)	Connectionist Temporal Classification (CTC) loss	CTC loss, deep learning techniques
Decoding Algorithm	Viterbi decoding, Beam Search, Lattice generation and rescoring	Beam Search decoding	Beam Search decoding, with optional contextual phrase hints
Handling of Speech Variability	Supports speaker adaptation (fMLLR, i-vectors), dialectal adaptation	End-to-End, requires large datasets for adaptation	Supports custom vocabularies, noise robustness, handles accents and dialects automatically
Languages Supported	Highly configurable for any language, requires training and adaptation	Supports multiple languages, requires model adaptation for new ones	Over 120 languages and dialects, automatic handling of accents
Real-Time Capability	Supports real-time but requires setup	Supports real-time processing	Fully real-time processing via cloud services
Customization Options	Highly customizable (acoustic models, language models, lexicons)	Requires significant dataset for training custom models	Custom phrase hints, domain-specific models
Scalability	Requires local setup, scales with hardware	Requires significant hardware for large datasets	Fully scalable with Google Cloud infrastructure
Noise Robustness	Strong noise robustness with proper training	Moderately robust, depends on training data	Strong noise handling and environment-specific processing
Open Source	Yes, fully open-source	Yes, fully open-source	No, but provides public API

This study collected a unique dataset of 101 voiceovers in the Kazakh language. Each dataset is an audio recording in which a respondent voices a pre-prepared text. The main purpose of creating this dataset is to evaluate and compare the performance of speech recognition algorithms using the Word Error Rate (WER) metric.

The study participants were divided into several categories based on various criteria: gender, age, region of residence, ethnicity, level of proficiency in Kazakh, as well as the presence or absence of an accent and dialect features. These demographic and linguistic criteria were chosen in order to evaluate how speech recognition algorithms cope with processing the diverse data typical for multilingual Kazakhstan.

The voiceovers were performed by native speakers and learners of the Kazakh language, with different levels of proficiency (native language or second language). Differences in regional accents and dialects were also taken into account, which will allow to study how these factors affect the accuracy of the algorithms.

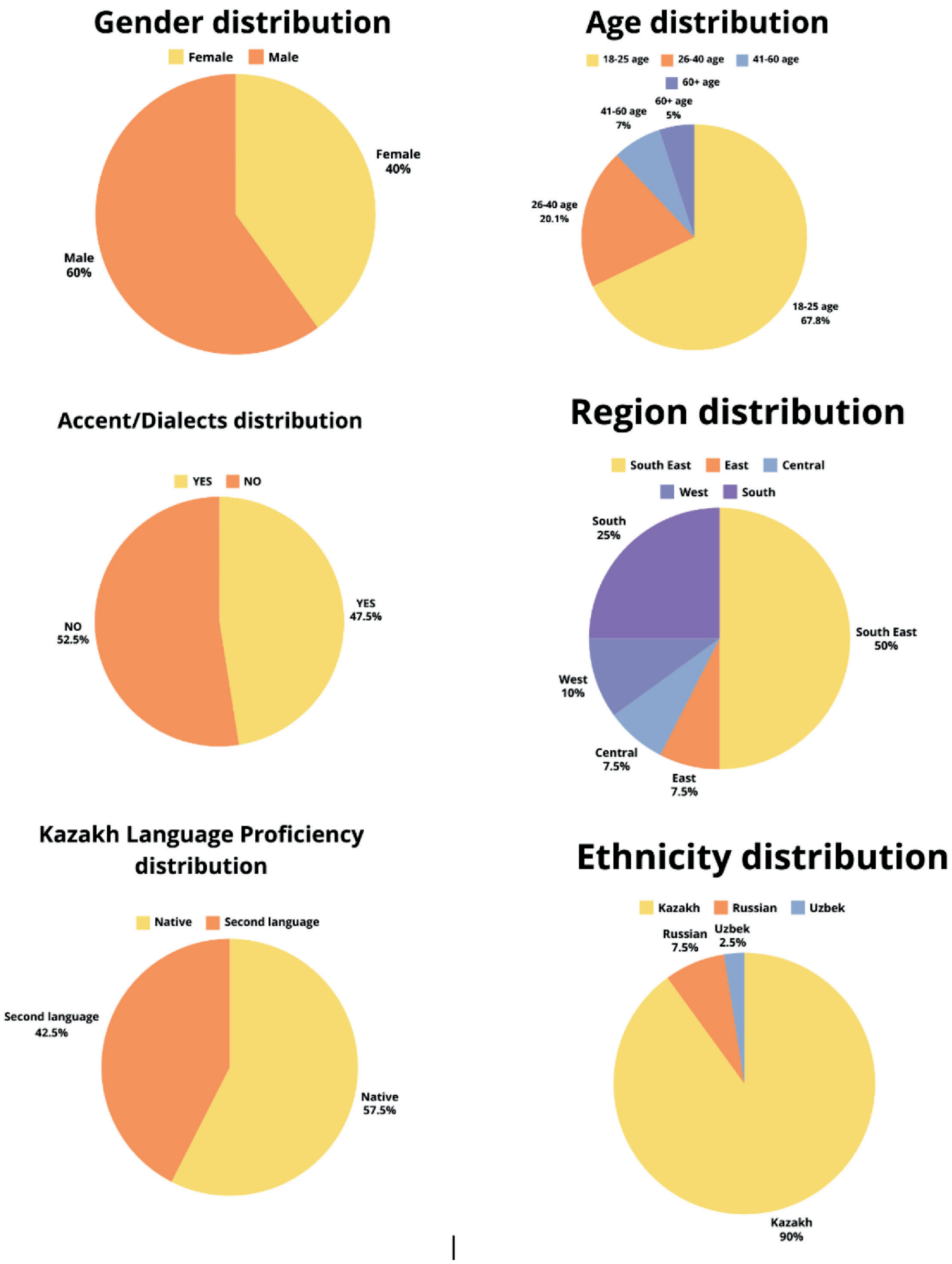

Figure 1. Demographic Distribution of Participants by Gender, Age, Region, Ethnicity, Language Proficiency, and Accent Characteristic

For this speech recognition experiment, the chosen criteria – Gender, Age, Region, Ethnicity, Kazakh Language Proficiency, and Accent/Dialects – were crucial because:

1. Gender: Different vocal ranges (male vs. female) affect how speech is recognized, impacting the accuracy of models.
2. Age: Speech patterns change with age, and including a range of ages ensures the model learns varied pronunciations and intonations.
3. Region: Regional differences can lead to dialectal variations, affecting phoneme articulation.
4. Ethnicity: Ethnic background may influence pronunciation, especially for bilingual individuals.
5. Kazakh Language Proficiency: Proficiency levels impact clarity and fluency in speech.
6. Accent/Dialects: Diverse accents introduce additional variability, which tests the robustness of recognition systems[15], [16]. The data are shown in Figure 1.

Speech Recognition Methods and Mathematical Models

Since the paper compares Kaldi, Mozilla DeepSpeech, and Google Speech-to-Text, mathematical descriptions of each method's core approach can be incorporated. Below there are proposed additions for each ASR method to align with the feedback.

Kaldi (Acoustic Modeling with GMM-HMM and TDNN):

Kaldi's architecture often utilizes Gaussian Mixture Models (GMM) and Hidden Markov Models (HMM) in combination. For example, a GMM-HMM model calculates the probability of observing a sequence of features $O=(o_1, o_2, \ldots, o_T)$ given a hidden state sequence $S=(s_1, s_2, \ldots, s_T)$:

$$P(O/S) = \prod_{t=1}^{T} \sum_k w_k * N(o_t;\ \mu_k, \Sigma_k) \tag{1}$$

where w_k, μ_k, and Σ_k represent the weight, mean, and covariance of each Gaussian component *k*.

This model helps recognize Kazakh phonemes by adapting acoustic features through Time Delay Neural Networks (TDNN) for more context-sensitive phonetic modeling.

Mozilla DeepSpeech (End-to-End RNN with Connectionist Temporal Classification)**:**

Mozilla DeepSpeech uses a Recurrent Neural Network (RNN) trained with Connectionist Temporal Classification (CTC) loss to map variable-length audio to text sequences. The CTC loss function is defined as:

$$CTC(x) = -\sum_{t=1}^{T} logp(y_t|x) \tag{2}$$

where y_t represents the predicted text label at time t and x the audio input. DeepSpeech's end-to-end model captures Kazakh phonetic nuances but requires extensive data. The model learns feature representations directly from data, allowing for more flexibility in adaptation to Kazakh speech characteristics.

Google Speech-to-Text API (DNN and CTC):

Google Speech-to-Text API combines Deep Neural Networks (DNN) and CTC for efficient speech-to-text mapping. The probability of a sequence *S* given an acoustic feature sequence *X* is optimized using:

$$P(S/X) = \prod_{t=1}^{T} P(s_t|x_t) \tag{3}$$

where each s_t is a speech label prediction given feature x_t. Google's model demonstrates strong performance on diverse datasets, though it struggles with Kazakh due to limited linguistic support.

With each ASR system's mathematical foundation established, the following ***Experiments and Results*** section will evaluate Kaldi, Mozilla DeepSpeech, and Google Speech-to-Text on their practical performance with Kazakh language data. The evaluation will focus on key metrics such as Word Error Rate (WER) and specific error patterns in phoneme and sentence structure recognition. These performance metrics are analyzed in light of each model's mathematical approach, such as the GMM-HMM acoustic modeling in Kaldi or the CTC loss in DeepSpeech, to understand how well each method addresses the unique phonological and morphological characteristics of the Kazakh language.

Experiments and results

Several recordings were tested through all three tools, and the results showed that the WER rates for Kazakh were unsatisfactory. Each tool demonstrated a high error rate in speech recognition, indicating the need for further improvement of the algorithms for this language model.

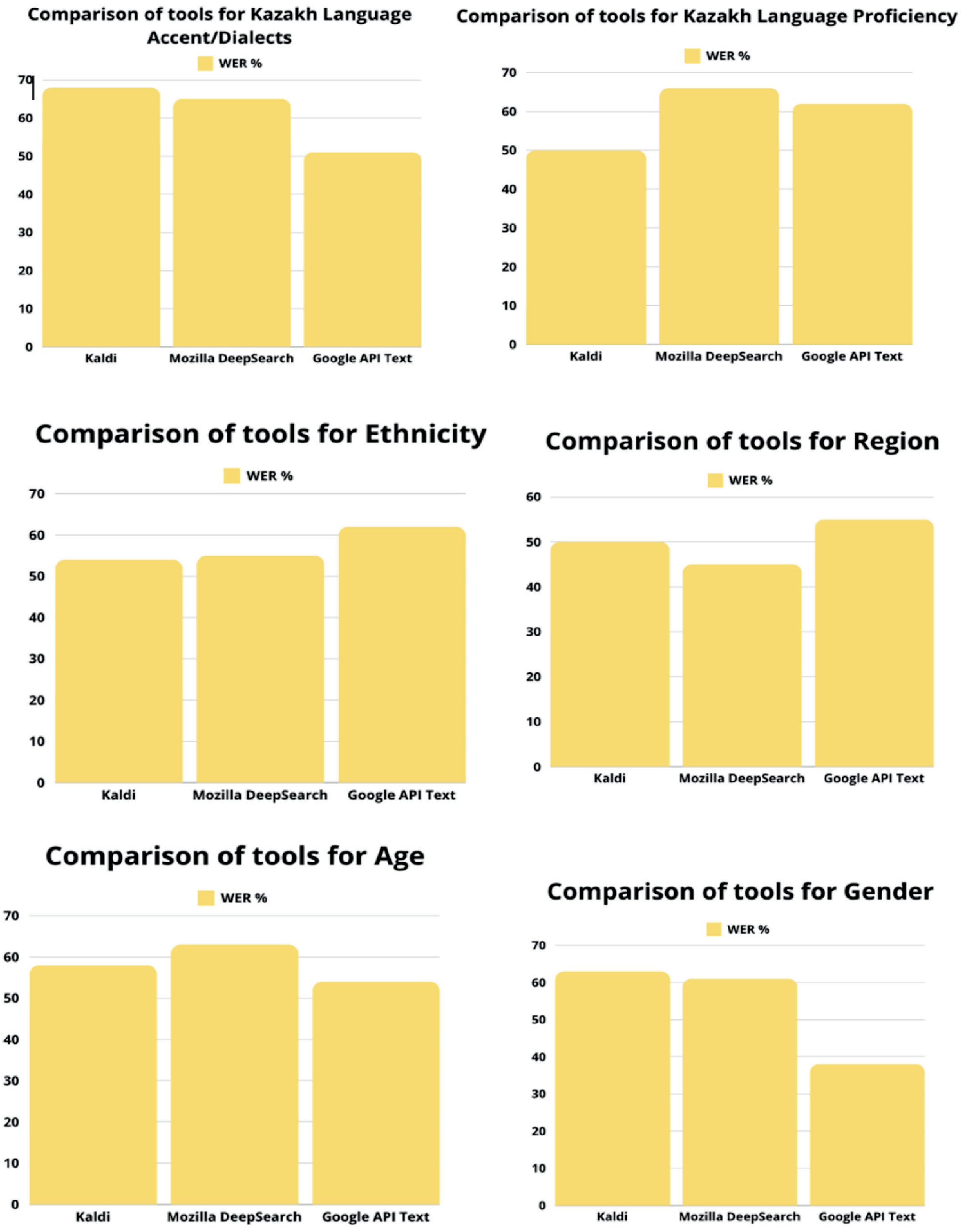

Figure 2. Comparative Analysis of WER Performance Across Speech Recognition Tools by Various Criteria

Kaldi demonstrated moderate results in WER, but showed certain difficulties when working with Kazakh due to the lack of adapted models and insufficient data.

Mozilla DeepSpeech showed less efficiency in conditions of limited data, which is due to its need for a large amount of diverse data for training.

Google Speech-to-Text API showed the lowest WER among all tools, but the results also did not reach a satisfactory level for high-quality application in everyday practice of Kazakh speech recognition (Figure 2) [17], [18].

Table 3. Performance Evaluation of Kazakh Speech Recognition Tools: WER and Common Errors

The tool	Average WER for Kazakh speech	Typical recognition errors	Causes of errors
Kaldi	56.87%	Errors with unique Kazakh sounds (for example, ″a″, ″k″, ″a″), complex consonants, errors in long phrases	Insufficient data for teaching the acoustic model of the Kazakh language, limited adaptation to regional dialects
Mozilla DeepSpeech	55.36%	Problems with accuracy in long sentences, mistakes with Kazakh vowels and consonants, confusion in morphology	It requires a large amount of data for learning, poor adaptation to the phonetic features of the Kazakh language, problems with contextual understanding of complex sentences
Google Speech-to-Text API	52.97%	Mistakes with Kazakh consonants (for example, ″k″ and ″y″), confusion with endings and cases, especially in long phrases	Teaching on common language models with insufficient localization for the Kazakh language, lack of support for the specific morphology and syntax of the Kazakh language

Deeper Error Analysis: Breakdown of Phoneme and Grammar Recognition Issues. In addition to evaluating the overall Word Error Rate (WER), it is important to analyze which specific elements of Kazakh speech pose the most challenges to the tested Automatic Speech Recognition (ASR) tools. This deeper analysis helps to understand why certain errors occurred and highlights the specific weaknesses of each system in processing Kazakh phonetics and grammar.

1. Phoneme-Level Errors

One of the significant challenges for the tested ASR systems was handling certain Kazakh phonemes that do not have close equivalents in the more globally spoken languages. These phonemes include unique consonants and vowels that are specific to Kazakh and its regional dialects. The following phonemes were particularly problematic:

- Consonants: “қ” (q), “ң” (ng), “ү” (ü)
  Kaldi and Mozilla DeepSpeech both showed consistent difficulty in distinguishing these consonants from their more common counterparts (“к”, “н”). In particular, the uvular “қ” (similar to “q”) was often misrecognized as the velar “к” (k), leading to incorrect word transcription.
  Kaldi, which relies heavily on acoustic models, frequently failed when faced with these distinctive consonants due to the lack of adequate training data. Mozilla DeepSpeech**,** being an end-to-end model, showed even more variability, often confusing these sounds with others that are phonetically similar in other languages.
- Vowel Harmony
  Kazakh vowel harmony, where vowel frontness or backness must be consistent within a word, posed another significant challenge. Systems failed to capture the vowel harmo-

ny rules that govern Kazakh morphology. This often resulted in incorrect word recognition, especially in longer words that followed agglutinative rules. For example, vowels like "і" (i) and "ы" (ı) were frequently misrecognized.

2. Long Sentence Structures and Complex Grammar

The recognition of longer sentences and complex grammatical structures in Kazakh also led to increased errors. Kazakh is an agglutinative language, meaning that multiple suffixes are often attached to the root of a word to express tense, possession, case, etc. This results in longer word forms that were often misinterpreted by the ASR systems, especially in Mozilla DeepSpeech.

- Case Endings
  The locative**,** genitive, and dative case endings (e.g., -да, -нің, -ға) were often mistaken for similar-sounding suffixes. Both Kaldi and Google Speech-to-Text struggled in handling sentences where multiple case endings were used consecutively, particularly when the context required understanding the relationships between nouns in a sentence.
- Verb Conjugations and Tenses
  Complex verb forms, especially those indicating future tense or conditional mood (e.g., -еді, -атын), were prone to errors. Kaldi performed better with shorter, simple verb forms, but errors became frequent in sentences with complex tenses or conditional clauses.

3. Dialectal Variations and Regional Accent Handling

Kazakh speech is influenced by regional accents, which introduce variations in pronunciation that were not well handled by the tested ASR systems. The Western and Southern dialects of Kazakh, which feature variations in vowel sounds and intonation patterns, resulted in a higher WER across all systems.

- Western Dialect: This dialect often involves the shortening of vowels, which caused recognition systems to incorrectly transcribe words. Kaldi and Google Speech-to-Text, which are not specifically trained to handle these variations, showed difficulty in understanding vowel changes.
- Southern Dialect: The use of softer consonants and changes in intonation led to misrecognition of certain words, particularly in Mozilla DeepSpeech, which relies on a general model not well-adapted to such regional specifics.

4. Common Misrecognized Words and Phrases

A list of frequently misrecognized words and phrases can provide a concrete understanding of where the systems struggled most. For example:

- Misrecognized Words**:**
  "қала" (city) was frequently transcribed as "кала" (different meaning) due to the failure to distinguish between "қ" and "к".
  "бала" (child) was misinterpreted as "пала" in some instances due to confusion between "б" and "п".
- Misrecognized Phrases:
  Longer phrases with embedded suffixes, such as "менің кітаптарымда" (in my books), were often broken down incorrectly by all tools, with the possessive case and locative case misinterpreted as separate entities.

5. Impact of Speech Rate and Pronunciation Clarity

Additionally, speech rate and clarity of pronunciation affected performance. Fast speech led to an increased WER across all tools, as the ASR models struggled to process rapid transitions between sounds and syllables. Conversely, clear and deliberate speech reduced WER but still encountered the same phonetic issues described above (Table 3).

Discussion

The results from this study underscore the current limitations in automatic speech recognition (ASR) systems for the Kazakh language. Although Google Speech-to-Text API demonstrated the lowest Word Error Rate (WER), none of the tested tools provided acceptable accuracy levels for reliable Kazakh speech recognition. A major contributing factor to this is the complex phonological system of Kazakh, which includes vowel harmony, a wide array of distinctive consonants, and an agglutinative grammar that is not well-handled by existing models trained on global datasets [19], [22].

One notable issue across all models is the handling of vowel harmony and specific Kazakh consonants such as "қ" and "ң." The underperformance of Mozilla DeepSpeech and Kaldi, particularly in recognizing long sentences and managing complex grammatical structures, highlights the need for models specifically tailored to the linguistic nuances of Kazakh. While Kaldi, due to its configurability, holds promise, its success heavily depends on the availability of large, annotated datasets and fine-tuned models for Kazakh, which remain scarce [20], [21].

Proposal for Improvement

A concrete proposal to enhance the accuracy of Kazakh speech recognition involves the implementation of a hybrid model combining Time Delay Neural Networks (TDNN) and Transfer Learning, supported by an RNN-based language model (RNNLM) for enhanced linguistic processing:

TDNN Architecture from Kaldi: TDNN has proven effective in handling long-term temporal dependencies in speech, making it particularly suited for the complex phonetic characteristics of Kazakh. Incorporating TDNN could enhance the model's ability to recognize contextually-dependent phonemes, as Kazakh often features context-sensitive sounds due to vowel harmony and consonantal variations.

Transfer Learning for Pre-Trained Multilingual Models: To overcome the limited availability of Kazakh-specific training data, Transfer Learning offers a solution. By leveraging pre-trained multilingual models, such as those used in DeepSpeech or Google's API, and fine-tuning them on Kazakh datasets (approximately 100+ hours of annotated speech), recognition accuracy can be significantly improved. This allows the model to capture both the general linguistic patterns of Kazakh and its unique phonetic nuances.

RNNLM for Language Model Enhancement: Adding an RNNLM (Recurrent Neural Network Language Model) could further boost the system's ability to recognize and correctly process long, complex sentences in Kazakh. This would help manage the agglutinative structure of Kazakh, which can lead to extremely long word forms due to the frequent use of suffixes. An RNNLM trained on large Kazakh text corpora, including diverse dialects, would help reduce errors related to sentence structure and case endings.

Mathematical Model for Hybrid Speech Recognition System

1. Time Delay Neural Networks (TDNN) for Acoustic Modeling

A TDNN models temporal dependencies in speech by considering time steps over which features are aggregated. This can be expressed as:

$$y_t = f(W \cdot [x_{t-d1}, x_{t-d2}, \dots, x_{t-dk}] + b) \tag{4}$$

Where:

y_t is the output feature at time step t.

W is the weight matrix

x_{t-di} represents the input features at time step $t-d_i$, where d_i is the delay for each time step.

f is the activation function (e.g., ReLU or tanh)

b is the bias term

This structure allows the model to capture dependencies across time and phonetic nuances specific to the Kazakh language, such as vowel harmony and consonant variations.

2. Transfer Learning for Multilingual Adaptation

Transfer Learning can be applied by fine-tuning a pre-trained model (like DeepSpeech or Google's multilingual ASR) on a Kazakh-specific dataset. The transfer learning process can be mathematically defined as:

$$\theta^{*}=arg_{\theta}minL(D_{K};\theta_{pretrained}) \qquad (5)$$

Where:

θ^{*} is the optimized parameter set for the Kazakh model.

L is the loss function (e.g., CTC loss used in end-to-end ASR)

D_K is the Kazakh-specific dataset

$\theta_{pretrained}$ represents the initial parameters from the pre-trained model

This allows the model to inherit knowledge from large multilingual datasets while being fine-tuned to capture the unique phonetic and linguistic aspects of Kazakh.

3. RNN-based Language Model (RNNLM) for Sentence Structure

An RNN-based Language Model (RNNLM) is integrated to predict the probability of a word sequence, especially to handle Kazakh's agglutinative morphology. The RNNLM is trained as:

$$P(w_1, w_2, \dots, w_T) = \prod_{t=1}^{T} P(w_t|, w_1, w_2, \dots, w_{t-1}; \theta_{RNN}) \qquad (6)$$

Where:

$P(w_1, w_2, w_T)$ is the conditional probability of word wtw_twt given the previous words.

θ_{RNN} are the model parameters learned during training

The RNNLM helps improve recognition accuracy by predicting likely word sequences and handling long word forms and case endings common in Kazakh.

4. Hybrid Model Integration

The final hybrid system combines TDNN for acoustic modeling, transfer learning for multilingual adaptation, and RNNLM for language modeling. The system's overall output can be expressed as a combination of the probabilities from the acoustic model and the language model:

$$\mathrm{P(sequence)} = \lambda \mathrm{P_{acoustic}(sequence)} + (1-\lambda)\mathrm{P_{RNNLM}(sequence)} \qquad (7)$$

Where:

$\mathrm{P_{acoustic}(sequence)}$ is the probability from the acoustic model.

$\mathrm{P_{RNNLM}(sequence)}$ is the probability from the RNN-based language model.

λ is a weighting factor between the acoustic and language models.

This hybrid approach balances acoustic information and linguistic context, addressing the unique challenges in Kazakh speech recognition, such as complex phonemes and sentence structures.

Conclusion

In conclusion, while the current tools display varying degrees of effectiveness in Kazakh speech recognition, their performance remains insufficient for practical applications without further improvements. The key challenges identified across the systems include difficulties with Kazakh-specific phonemes, vowel harmony, and the handling of long, agglutinative word forms, as well as regional dialects and rapid speech. These issues highlight the limitations of existing ASR models that have not been specifically adapted to the linguistic intricacies of the Kazakh language.

The proposed hybrid model incorporating TDNN**,** Transfer Learning, and RNNLM presents a promising direction for enhancing the accuracy of Kazakh ASR. By leveraging TDNN's ability to model long-term temporal dependencies in speech, combined with Transfer Learning to utilize pre-trained multilingual models, the system can achieve better recognition of Kazakh-specific features. Furthermore, integrating RNNLM will improve the handling of complex sentence structures and agglutinative grammar.

Beyond these technical improvements, the development of more extensive and diverse datasets will be crucial for success. Larger datasets that represent a wide variety of regional accents, speech speeds, and contexts (both formal and informal) are necessary to fully train the models on the phonetic, morphological, and syntactical diversity of the Kazakh language. Additionally, including a range of age groups, genders, and dialects in the dataset will enhance the model's ability to generalize across different Kazakh-speaking populations.

Finally, future work should also focus on the real-time processing capabilities of these systems. As speech recognition moves toward more practical applications (e.g., voice assistants, transcription services), real-time performance and low-latency processing are essential. Optimizing the proposed hybrid model for faster inference while maintaining high accuracy will make it more suitable for real-world applications.

Thus, implementing these advanced techniques, along with improving dataset diversity and optimizing for real-time performance, will help overcome the existing phonetic and morphological challenges, paving the way for more reliable and accurate speech recognition systems for the Kazakh language.

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