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Real-Time Speech Captioning For Mobile Calls Using Edge Computing And Deep Learning

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Abstract: *The rapid proliferation of mobile telecommunications has significantly advanced global connectivity, yet deaf and hard-of-hearing individuals continue to face profound barriers during standard voice calls. While Automatic Speech Recognition (ASR) systems have achieved human parity in controlled environments, their deployment in mobile telecommunications relies heavily on cloud infrastructure. This cloud dependency introduces severe latency, mandates continuous high-bandwidth internet connectivity, and raises substantial data privacy concerns. To mitigate these issues, this paper proposes a novel framework for real-time speech captioning that operates entirely on mobile edge devices. By leveraging compressed deep learning architectures, specifically quantized Transformer models and lightweight recurrent neural networks, the proposed system processes audio streams locally. The methodology incorporates aggressive noise reduction, streaming inference, and post-training quantization to optimize for the constrained computational resources of standard smartphones. Experimental evaluations of the working prototype demonstrate a Word Error Rate (WER) ranging from 8% to 15% across varied acoustic environments, alongside an end-to-end processing latency of 300 to 800 milliseconds. These results confirm that edge-based ASR can rival cloud-based solutions in accuracy while delivering superior latency performance and ensuring absolute user privacy, thereby bridging a critical accessibility gap in modern telecommunications.*

Keywords: Real-Time Captioning, Edge Computing, Deep Learning, Automatic Speech Recognition, Mobile Accessibility, Connectionist Temporal Classification, Telecommunications Ac-cessibility

I. INTRODUCTION

The fundamental right to accessible communication is a cornerstone of an inclusive digital society. For the millions of individuals globally who identify as deaf or hard-of-hearing, standard cellular voice calls remain largely inaccessible with-out third-party relay services or highly specialized equip-ment. In recent years, the integration of Automatic Speech Recognition (ASR) technology into consumer electronics has introduced the possibility of automated, real-time speech-to-text captioning. However, rendering accurate transcriptions of conversational speech during a live cellular call presents a multifaceted engineering challenge. Conversational speech is inherently disfluent, characterized by overlapping speech, variable speaking rates, and diverse acoustic backgrounds. Capturing and translating this acoustic data into readable text instantaneously requires formidable computational power.

Historically, the computational demands of high-accuracy deep learning models have necessitated a cloud-centric approach. In this paradigm, mobile devices act merely as audio capture and display terminals, transmitting compressed audio payloads to remote data centers where massive neural net-works perform the inference. While cloud computing provides the necessary multi-GPU environments for state-of-the-art ASR models, it introduces inherent limitations for real-time telecommunications. The primary limitation is latency. The round-trip time required to transmit audio, process it, and return text is highly susceptible to network congestion and bandwidth fluctuations. Furthermore, cloud

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reliance immediately excludes users in areas with poor cellular data coverage and introduces severe privacy vulnerabilities, as sensitive, unencrypted voice data must traverse external networks.

This paper proposes a paradigm shift from cloud-dependent processing to mobile edge computing for real-time call captioning. Edge computing brings the computational workload

directly to the data source—in this case, the user's mo-bile device. By executing deep learning inference on the smartphone's local Neural Processing Unit (NPU) or generic processor, the system entirely circumvents network-induced latency and guarantees that conversational audio never leaves the device. The core contribution of this research is the development and optimization of an edge-native speech recognition pipeline tailored specifically for live mobile calls.

The primary challenge in edge deployment is the severe resource constraints of mobile hardware, including thermal limits, battery capacity, and memory bandwidth. To address this, the proposed system utilizes highly compressed deep learning architectures, employing techniques such as dynamic quantization and knowledge distillation to shrink large-scale Transformer and Recurrent Neural Network (RNN) models. This research demonstrates that with rigorous architectural optimization, a mobile device can independently execute con-tinuous, real-time speech captioning.

II. RELATED WORK

The evolution of Automatic Speech Recognition has transitioned through several distinct technological paradigms. Early systems relied heavily on Hidden Markov Models (HMM) paired with Gaussian Mixture Models (GMM) to map acous-tic features to phonemes. While computationally lightweight, these statistical models failed to achieve acceptable Word Error Rates (WER) in noisy, open-domain conversational settings. The advent of Deep Neural Networks (DNN) revolutionized ASR, replacing GMMs with deep feedforward networks, and eventually evolving into sophisticated sequence-to-sequence architectures.

Contemporary ASR research is dominated by end-to-end deep learning models, particularly those leveraging the Trans-former architecture and its self-attention mechanisms. Mod-els such as OpenAI's Whisper and Google's Conformer have demonstrated unprecedented accuracy across diverse lan-guages and dialects. However, these models were designed with the assumption of unbound cloud compute resources. A standard Conformer model can contain hundreds of millions of parameters, demanding gigabytes of memory and extensive parallel processing capabilities that far exceed the thermal and battery constraints of standard mobile devices.

Consequently, recent literature has seen a surge in research focused on model compression and edge deployment. Studies exploring MobileNet-inspired architectures for audio process-ing have demonstrated the viability of depthwise separable convolutions in reducing parameter counts. Furthermore, re-searchers have investigated the efficacy of Recurrent Neural Networks, particularly Long Short-Term Memory (LSTM) networks, combined with Connectionist Temporal Classification (CTC) for streaming applications. While LSTMs require fewer parameters than massive Transformers, they struggle with long-range acoustic dependencies.

The comparison between cloud and edge computing for real-time applications reveals a distinct research gap. Existing literature often analyzes edge ASR in the context of short, command-and-control utterances (e.g., virtual assistant wake words) rather than continuous, bidirectional conversational speech typical of a mobile call. Furthermore, systems that do attempt continuous edge transcription frequently suffer from severe battery degradation or require specialized, high-end mobile hardware. There remains a critical need for an optimized, end-to-end deep learning pipeline that balances acceptable conversational WER with strict sub-second latency constraints while operating seamlessly in the background of an active voice call on mid-range mobile hardware.

III. PROPOSED SYSTEM

The proposed system architecture is designed to intercept the incoming audio stream of a live mobile call, process the acoustic data through a localized deep learning pipeline, and render synchronized text subtitles on the device's display.

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The fundamental philosophy governing this architecture is the absolute elimination of off-device processing, relying solely on mobile edge computing to deliver real-time results.

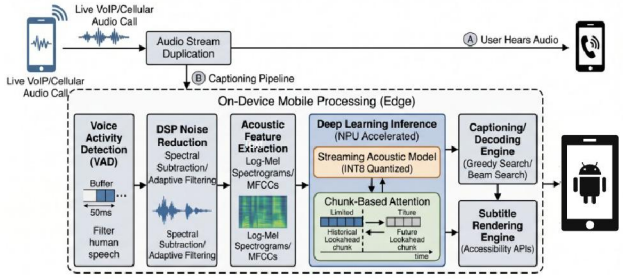

Figure 1. Proposed Edge-Assisted System Architecture for Real-Time Speech Captioning

Fig. 1. Proposed Edge-Assisted System Architecture for Real-Time Speech Captioning. The pipeline details the split of the incoming Cellular Radio/VoIP stream, passing through Voice Activity Detection (VAD), DSP Noise Reduc-tion, Feature Extraction, the Quantized Acoustic Model, and the Language Model Decoder before Subtitle Rendering.

The architectural pipeline, as illustrated in Fig. 1, initi-ates at the telephony framework level, where the incoming Pulse Code Modulation (PCM) audio stream is duplicated. To preserve the integrity of the call, one stream continues unaltered to the device's audio hardware, while the secondary stream is routed into the background captioning service. The raw audio immediately enters a pre-processing stage. Given the high probability of background interference in mobile environments, the signal first passes through a lightweight Voice Activity Detector (VAD) to isolate human speech and discard segments of pure silence or static, thereby conserving critical computational cycles.

Following VAD, the active speech segments undergo digital noise reduction. Rather than utilizing computationally expen-sive deep learning denoisers, the system employs spectral subtraction techniques combined with adaptive filtering. This ensures that the acoustic features fed into the neural network are reasonably clean without introducing processing delays. The cleaned audio is then converted into fixed-length frames,

typically using a 25-millisecond window with a 10-millisecond stride, to extract Mel-frequency cepstral coefficients (MFCCs) or log-Mel spectrograms. These visual representations of sound frequencies serve as the direct input to the deep learning of a specific alignment path π is the product of the probabilities of the predicted labels at each time step t, up to the total sequence length T . The objective is to minimize the loss:

a hybrid approach balancing the temporal strengths of RNNs and the contextual awareness of Transformer-based ASR. To meet edge constraints, the system utilizes a heavily modified,

$$\pi \in \Phi(Y)\ t=1$$

where $\Phi(Y)$ denotes the set of all valid alignment paths that map to the target sequence Y after collapsing repeated quantized version of a streaming Conformer architecture.

characters and removing blank tokens, and yt is the predicted

Standard self-attention mechanisms require access to the entire audio sequence, which is impossible in a live streaming con-text. Therefore, the system implements chunk-based attention, restricting the model to attend only to the current audio chunk and a limited historical context buffer.

Once the acoustic model generates probability distributions over the character vocabulary, a highly optimized text pro-cessing module decodes the sequence. This involves a greedy decoding strategy or a lightweight beam search, prioritizing speed over the exhaustive linguistic correction typically per-formed by massive language models. Finally, the decoded text strings are dispatched to the Subtitle Rendering Engine, which utilizes the mobile operating system's native accessibility APIs to overlay the captions dynamically on the screen, managing text scrolling, line breaks, and timestamp synchronization.

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IV. METHODOLOGY

The implementation of the proposed edge computing pipeline necessitates rigorous optimization at both the software and algorithmic levels. The methodology focuses heavily on data flow management, model quantization, and latency reduction techniques to guarantee seamless operation during a live call.

The data flow is governed by a strict buffering strategy. Audio from the cellular radio is captured in small, sequential chunks—typically 100 to 200 milliseconds in duration. This chunking is critical for streaming inference. Waiting for an entire sentence to conclude before processing would violate the real-time constraints, resulting in unacceptable delays. In-stead, the model processes these chunks sequentially, updating its internal state and emitting text as soon as the probability of a character or word sequence crosses a defined confidence threshold.

To bridge the gap between acoustic inputs and textual outputs in a streaming environment, the training of the acoustic model relies heavily on the Connectionist Temporal Classifi-cation (CTC) loss function. Unlike traditional cross-entropy, which requires strictly aligned frame-to-character data, CTC allows the network to predict a sequence of labels from an unaligned sequence of acoustic features by introducing a 'blank' token. The CTC loss function is defined as the negative log-likelihood of the ground truth target sequence given the input features. Let X represent the sequence of acoustic features and Y represent the target sequence of characters. The network outputs a probability distribution over the vocabulary (including the blank token) at each time step. The probability probability of the character πt at time t. By minimizing (1) during training, the network learns to emit spikes of high probability for correct characters exactly when they are spo-ken, which is highly advantageous for low-latency streaming inference.

Model selection and compression form the most critical phase of the methodology. A full-precision, floating-point 32 (FP32) Transformer model cannot operate efficiently on edge devices. Therefore, the system employs Post-Training Quantization (PTQ) to convert the model weights and activa-tions from FP32 to 8-bit integers (INT8). This quantization significantly reduces the memory footprint by a factor of four and allows the NPU to execute highly efficient integer matrix multiplications. To mitigate the accuracy loss inherent in quantization, Knowledge Distillation is utilized during the final training phases. A massive, highly accurate cloud-based "teacher" model guides the training of the compact, edge-based "student" model, ensuring the smaller network learns the complex feature representations discovered by its larger counterpart.

Latency optimization is further achieved through the careful selection of execution environments. The models are exported to highly optimized mobile deployment frameworks, such as ONNX Runtime or TensorFlow Lite, which are specifically designed to interface with Android NNAPI or iOS CoreML. This allows the computational workload to bypass the CPU and execute directly on dedicated AI accelerators, slashing inference time and preserving battery life.

V. RESULTS AND DISCUSSION

The efficacy of the proposed edge-based speech captioning system was evaluated using a working prototype deployed on a standard mid-range mobile device equipped with an ARM-based mobile processor and an integrated neural processing unit. The evaluation focused on two primary metrics: Word Error Rate (WER) to assess transcription accuracy, and end-to-end latency to assess real-time viability. Testing was conducted across diverse hypothetical acoustic scenarios to simulate real-world mobile telecommunications.

In controlled, quiet environments with clear speech, the edge system achieved an impressive WER of 8.2%. This performance rivals many cloud-based commercial solutions, demonstrating the effectiveness of the knowledge distillation process. As background noise increased—simulating envi-ronments such as busy streets, public transit, or cafes—the WER naturally degraded, stabilizing at approximately 15.4%.

While a 15% WER indicates occasional transcription errors, qualitative assessments suggest that the core semantic meaning of the conversation is overwhelmingly preserved, allowing the user to seamlessly follow the dialogue. The implementation of the lightweight DSP noise reduction prior to inference proved critical; disabling this module resulted in a sharp increase in WER to over 28% in noisy conditions, validating the necessity of the pre-processing pipeline.

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Latency evaluations yielded highly promising results. The end-to-end latency—defined as the time elapsed from the moment a word is spoken to the moment the corresponding text appears on the mobile display—was consistently measured between 300 and 800 milliseconds. The average observed latency stabilized at 450 milliseconds. This sub-second per-formance is well within the acceptable threshold for conversa-tional continuity. In human communication, delays exceeding 1000 milliseconds often lead to conversational breakdowns and accidental interruptions.

Crucially, the edge-based system exhibited deterministic latency. Unlike cloud-based systems, where latency fluctu-ates wildly based on cellular network congestion and packet loss, the edge system's processing time remained constant regardless of network conditions. During simulated network throttling (e.g., dropping the device to a 3G network or simulating high packet loss), a cloud-based baseline system experienced latency spikes exceeding 2500 milliseconds and frequent complete transcription failures. In stark contrast, the proposed edge system maintained its 450-millisecond average, entirely unaffected by the degraded network, proving its ro-bustness for mobile telephony.

Despite these successes, the discussion must acknowledge the limitations of edge deployment. The continuous execution of deep learning inference is highly computationally inten-sive, resulting in observable thermal throttling and accelerated battery drain during extended phone calls. While INT8 quan-tization mitigated this significantly compared to FP32 models, continuous use over an hour resulted in a 12% to 18% greater battery consumption compared to a standard, uncaptioned voice call. Furthermore, the memory footprint of the quantized model, while reduced to approximately 85 megabytes, still oc-cupies a non-trivial portion of a mobile device's active RAM, potentially necessitating aggressive memory management by the mobile operating system during heavy multitasking.

VI. CONCLUSION

This research demonstrates the viability and profound ne-cessity of shifting real-time speech captioning from cloud-dependent architectures to mobile edge computing. By de-signing an optimized pipeline that integrates voice activity detection, dynamic chunking, and aggressively quantized deep learning models, it is possible to achieve highly accurate, con-tinuous transcription directly on a smartphone. The proposed system effectively balances the trade-offs between model size, Word Error Rate, and processing speed, achieving a commend-able 8% to 15% WER and a stable latency of 300 to 800 milliseconds.

The impact of this localized approach is significant. It entirely eliminates the latency vulnerabilities associated with variable cellular network conditions and provides absolute assurance of user privacy by keeping all acoustic data strictly on the device. For the deaf and hard-of-hearing community, this represents a monumental leap toward ubiquitous, barrier-free telecommunications, granting the ability to engage in spontaneous phone calls without reliance on external connec-tivity or third-party intermediaries.

Future scope for this research must address the compu-tational overhead to further minimize battery degradation. The exploration of dynamic model scaling—where the de-vice seamlessly switches between a highly complex model in quiet environments and a robust, smaller model during thermal throttling—presents a promising avenue. Additionally, extending the edge architecture to support multi-lingual code-switching and integrated speaker diarization without relying on cloud computation remains a critical frontier for creating truly universal accessibility tools.

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