IEDI: A Hybrid NLP-LLM Framework for Intra-English Dialect Interpretation

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***Abstract*—What if our Artificial Intelligence assistants could do more than just translate and transcribe different languages and even English dialects? What if they could be real-time sociolinguistic interpreters who foster genuine understanding between English speakers from diverse backgrounds? *IEDI* is a novel hybrid Natural Language Processing+Large Language Model (NLP-LLM) framework designed to do just that. It interprets the unique cultural subtleties and idioms of various English dialects, initially focusing on Korean, Nigerian, and American English. It contains a unique resource that maps these dialects directly to one another and to "standard" English. The *IEDI* framework combines the speed and efficiency of traditional NLP for common dialectal phrases with the deep contextual reasoning of an LLM for novel or complex expressions. It is a model that preserves intent, respects identity, and truly helps people understand the why behind what is being said in another English dialect—active listening.**

***Index Terms*—Active Listening, Dialectal Variations, Intra-English Interpretation, Natural Language Processing, Large Language Models, Pragmatics**

I. Introduction and Motivation

Even with English as the world's most widely used medium for global interaction, its numerous dialects often create invisible barriers to understanding. Misinterpretations or communication breakdowns amongst English speakers rarely stem from grammatical errors but from pragmatic nuances or markers such as Korean English (KoE) "He was living" (meaning he was alive), KoE politeness calques like "Please check once", Nigerian English (NgE) "Do quick" (meaning hurry up), American English (AmE) "It'll take a minute" (meaning it will take a while), and AmE idioms and contractions. These subtle differences frequently lead to confusion in professional and intercultural communication contexts [1].

Current technologies are ill-equipped to solve this [2]. Automatic Speech Recognition (ASR) systems and language translation models have long aimed to flatten or "normalize" dialects into a single, "standard" form—a bias often etched into their Western-centric or Western, Educated, Industrialized, Rich, and Democratic (WEIRD) training dataset [3]. Empirical studies show that ASR models underperform by up to **40%** on non-standard dialects [3], while sociolinguistic research underscores the lack of inclusivity in current computational models of English variation [4].

Recent advances in Large Language Models (LLMs) demonstrate strong contextual reasoning and fluency, yet they are prone to over-correction [5] and remain computationally intensive [6]. On the contrary, rule-based Natural Language Processing (NLP) systems are lightweight and fast but lack deep interpretive capability [7]. Bridging these two extremes is therefore crucial for enabling real-time, culturally sensitive English interpretation. To address this gap, this work introduces the ***Intra-English Dialect Interpretation (IEDI)***, a hybrid framework comprising Natural Language Processing and Large Language Model (NLP–LLM), designed to interpret the pragmatics and intent behind English dialects rather than merely transcribe or standardize them. They are of three-fold:

1) Creation of an ***IEDI*** **Dataset (IEDID)**, a parallel corpus connecting KoE, NgE, and AmE expressions to a universal English gloss;
2) **Dialect Interpretation Agent+Large Language Model (DIA-LLM)**, a dual-path hybrid interpretation agent integrating fast NLP lookups with deep contextual reasoning; and
3) A design approach emphasizing inclusivity, interpretive fairness, and linguistic identity preservation.

This work extends beyond the comprehension of Artificial Intelligence (AI) roles into **empathetic** and/or **active listening**, aligning with the broader goal of equitable and culturally aware machine interpretation.

II. Methodology

Our design methodology combines dataset creation and system architecture. The IEDID contains multilingual-parallel entries linking KoE, NgE, and AmE phrases with semantic and pragmatic annotations. Each record includes text, dialect, gloss, intent, and sociolinguistic tags (e.g., idiom, politeness, formality).

The DIA-LLM hybrid architecture follows a dual-path flow:

1) Speech is transcribed and assigned to speakers;
2) The NLP fast-path performs fuzzy matching with the IEDID lookup table ($\geq 80\%$ threshold);
3) If unmatched or ambiguous, the input is routed to a fine-tuned LLM (e.g., Text-to-Text Transfer Transformer (T5)/Gemini-based) trained on dialect-specific samples [8];
4) Clarifications are shown to users, whose feedback updates both components through reinforcement learning from human feedback (RLHF) [9]

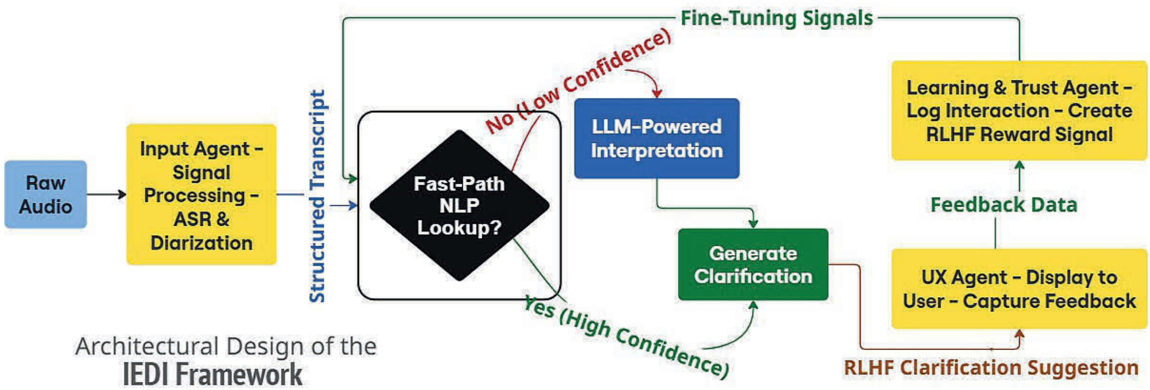

Fig. 1: A flowchart of architectural design of the *IEDI* framework.

This design balances **interpretive accuracy, speed, and cultural sensitivity**, forming a scalable foundation for intra-English dialect understanding.

III. Performance Evaluation

We validated the *IEDI* framework using a pilot IEDID dataset with 50 audio clips per dialect. The DIA-LLM agent was evaluated for dialect identification accuracy and clarification quality. Table I shows accuracy across dialects: performance was highest for AmE, consistent with its strong representation in pre-training data, and lower scores for KoE and NgE highlight the data gaps the IEDID seeks to address.

TABLE I: Accuracy of Dialect Identification

Dialect	Samples Tested	Correctly Identified	Accuracy (%)
Nigerian English (NgE)	50	38	76%
Korean English (KoE)	50	29	58%
American English (AmE)	50	48	96%
Overall	**150**	**115**	**76.7%**

Table II reports human ratings of clarification quality for sample utterances. Ten evaluators scored outputs (1–5) on Fidelity (meaning preservation) and Naturalness (fluency). Results show consistently high scores, indicating accurate and fluent clarifications when generated. The main limitation, as noted in Table I, lies in initial dialect detection for underrepresented varieties. These findings support the hypothesis that with a more balanced IEDID, DIA-LLM can function as an effective intra-English dialect interpreter

TABLE II: Sample Utterances, Clarified Outputs, and Their Ratings in Fidelity and Naturalness

Sample Utterance (Dialect)	**Clarified Output**	**Fidelity (Avg)**	**Naturalness (Avg)**
"He was living." (KoE)	"He was alive."	4.8	4.6
"I beg, let's go." (NgE)	"Please, let's leave now."	4.9	4.8
"Wanna grab a bite?" (AmE)	"Do you want to get something to eat?"	4.9	4.9

IV. CONCLUSION AND FUTURE WORK

A system this ambitious requires rigorous evaluation. The *IEDI* framework represents a step toward inclusive, dialect-aware AI capable of interpreting rather than normalizing English dialects. Future extensions will expand coverage to British, Indian and any other English dialect, and deploy DIA-LLM within multi-agent communication systems.

Acknowledgment

This work was partly supported by Innovative Human Resource Development for Local Intellectualization program through the IITP grant funded by the Korea government (MSIT) (IITP-2025-RS-2020-II201612, 33%) and by Priority Research Centers Program through the NRF funded by the MEST (2018R1A6A1A03024003, 33%) and by the MSIT, Korea, under the ITRC support program (IITP-2025-RS-2024-00438430, 34%).

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