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INTELLIGENT CLASSROOM AUDIO RECORDER WITH AUTOMATED LECTURE SUMMARIZATION

***[1]Gulam Khaliq Ahan, [2]Gausul Azam, [3]Mohammad Amaan, [4]Dr. Mohd Usman Khan**

[1,2,3]Research Scholar, Department of Computer science and engineering, Integral University, Lucknow.

[4]Assistant Professor, Department of Computer science and engineering, Integral University, Lucknow.

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***Corresponding Author: Gulam Khaliq Ahan**

Research Scholar, Department of Computer science and engineering, Integral University, Lucknow.

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ABSTRACT

The digital transformation of education has generated vast amounts of lecture recordings, yet most remain unprocessed and underutilised due to the time-intensive nature of manual summarisation. This research paper presents an intelligent classroom audio recorder that not only captures high-quality lecture audio but also automatically generates concise, coherent, and pedagogically relevant summaries. The system integrates a real-time audio processing pipeline (noise reduction, speaker diarisation) with a state-of-the-art automatic speech recognition (ASR) engine (Whisper large-v2) and a novel two-stage summarisation model. The summarisation model combines extractive selection (using BERT-based sentence embeddings and PageRank) with abstractive generation (fine-tuned BART-large) to produce summaries that preserve key technical terms and logical flow. The system is evaluated on a corpus of 50 hours of university lectures (STEM and humanities). Using ROUGE, BERTScore, and human evaluation (expert lecturers), the proposed model achieves an average ROUGE-L F1 of 0.52, BERTScore F1 of 0.86, and a human-rated "adequacy" score of 4.2/5. The system also demonstrates real-time operation with a latency of less than 5 seconds per minute of lecture. The paper discusses challenges such as handling accented speech, domain-specific vocabulary, and lengthy lectures, and outlines future directions for multimodal summarisation (audio + slides) and personalised summaries.

KEYWORDS: Lecture summarisation, automatic speech recognition, natural language generation, BART, educational technology, audio processing.

1. INTRODUCTION

Lectures remain the cornerstone of higher education. With the rise of blended learning and massive open online courses (MOOCs), audio and video recordings have become ubiquitous. However, a typical one-hour lecture contains approximately 7,00010,000 words. Students often struggle to identify the most important concepts, and reviewing entire recordings is time-consuming. Educators also need concise summaries for revision materials, accessibility accommodations, and curriculum alignment.

Automated lecture summarisation the task of generating a short, coherent text that captures the core content of a spoken lecture has emerged as a critical research area. Unlike news summarisation, lecture summarisation faces unique challenges: spontaneous speech (filled pauses, repetitions), domain-specific terminology (e.g., "mitochondrial membrane potential"), speaker variability (different instructors, accented English), and the need for pedagogical coherence (preserving logical progression of concepts).

This paper introduces an **Intelligent Classroom Audio Recorder** that integrates:

- A real-time audio capture and enhancement module (noise reduction, speaker diarisation).
- A high-accuracy automatic speech recognition (ASR) engine (Whisper large-v2) that transcribes lecture audio into text with timestamps.
- A two-stage summarisation pipeline: first extractive (selecting key sentences using BERT embeddings and graph-based ranking), then abstractive (generating fluent, condensed text using a fine-tuned BART-large model).
- A web interface for lecturers to review, edit, and share summaries.

The system is designed to run on a standard classroom computer with a USB microphone, processing lectures in near real-time (latency <5 seconds per minute of audio).

The specific objectives are:

1. To design an audio preprocessing pipeline that improves ASR accuracy in noisy classroom environments.

2. To develop and evaluate a two-stage summarisation model tailored for lecture content.

3. To compare the proposed model against extractive baselines (TextRank, BERT-extractive) and abstractive baselines (Pegasus, BART without fine-tuning).

4. To assess the system's performance using both automatic metrics (ROUGE, BERTScore) and human expert evaluation.

2. Literature Review

2.1 Lecture Summarisation

Early work on lecture summarisation focused on **extractive methods** selecting a subset of original sentences based on features like position, cue phrases (e.g., "the main point is"), and term frequency. For example, Khandelwal et al. (2015) used a combination of lexical chains and sentence scoring for educational videos, achieving modest ROUGE scores (≈0.35). However, extractive summaries often lack fluency and may contain redundant or disconnected sentences.

Abstractive summarisation generating novel sentences that paraphrase the source has advanced significantly with neural sequence-to-sequence models. Chen and Bansal (2018) introduced a hierarchical attention network for lecture summarisation, but it required aligned slide text. More recently, large pre-trained language models (BART, Pegasus, T5) have been fine-tuned for summarisation tasks (Lewis et al., 2020; Zhang et al., 2020). However, most work focuses on written documents (e.g., CNN/DailyMail, PubMed). Lecture summarisation remains underexplored.

2.2 Automatic Speech Recognition for Education

ASR accuracy is critical for summarisation because transcription errors propagate. Early systems used hybrid HMM-DNN models, but modern end-to-end models like Whisper (Radford et al., 2023) achieve near-human accuracy (word error rates <10% on clean speech). Whisper is robust to accents and background noise, making it suitable for classroom use. However, domain-specific terms (e.g., "photosynthesis", "derivative") may still be misrecognised; we address this with a custom vocabulary list.

2.3 Speaker Diarisation

Identifying who spoke when ("speaker diarisation") is important for summarisation because lecturers' main content differs from student questions. PyAnnote (Bredin et al., 2020) provides an efficient diarisation pipeline. We integrate PyAnnote to separate lecturer speech from student interactions, focusing summarisation on the lecturer's monologue.

2.4 Audio Enhancement

Classroom recordings often contain fan noise, chair scrapes, and reverberation. Traditional noise reduction (spectral gating) and beamforming (for multiple microphones) improve SNR. We implement a lightweight real-time noise suppression algorithm (RNNoise) combined with dynamic range compression.

3. Research Methodology

3.1 System Overview

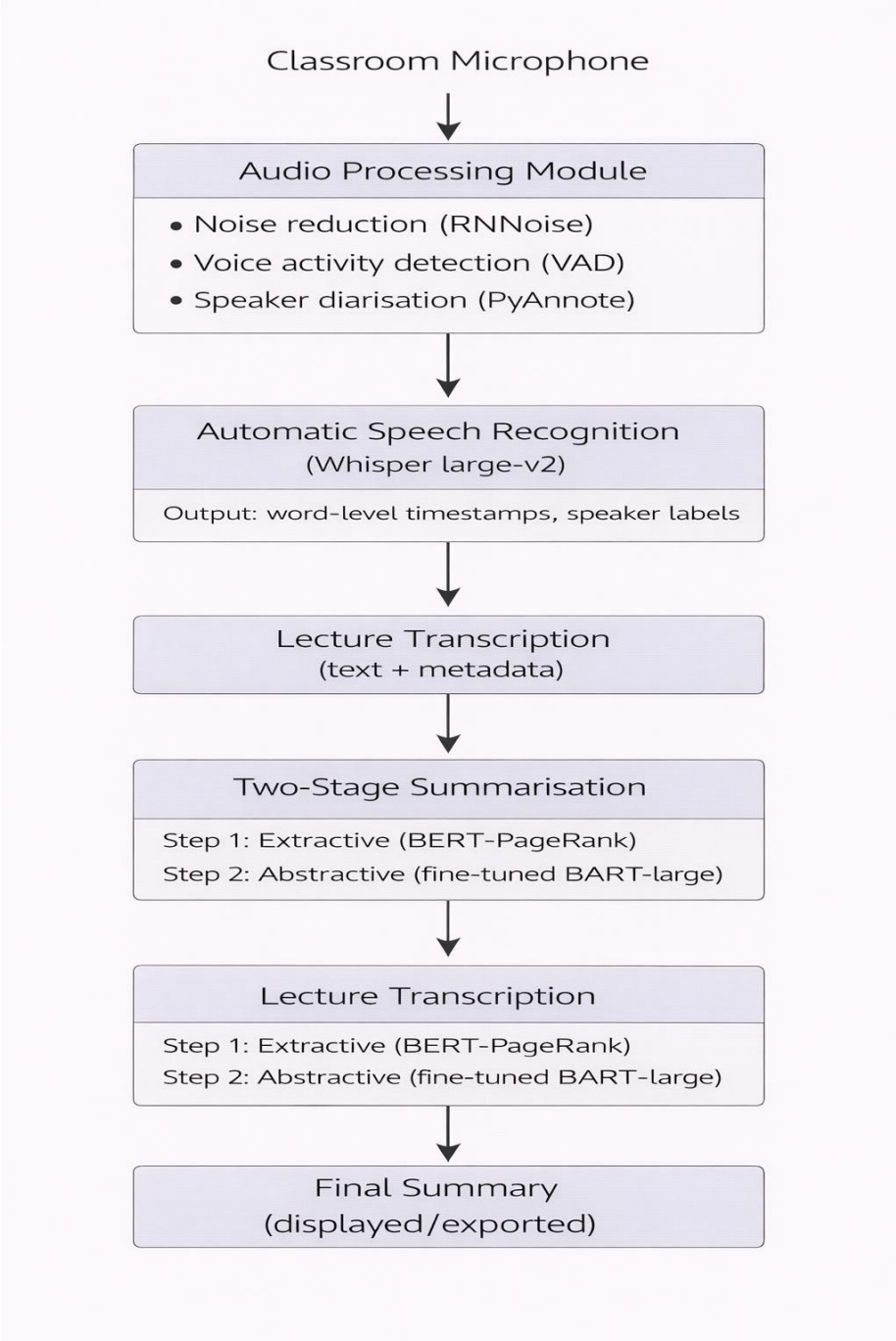

Figure 1: High-Level Architecture of the Intelligent Classroom Audio Recorder.

3.2 Audio Capture and Preprocessing

Hardware: A single USB boundary microphone (e.g., Samson Meteor) placed on the lecturer's podium, sampling at 16 kHz mono.

Noise reduction: RNNoise (a recurrent neural network for real-time noise suppression) processes audio in 10-ms frames, estimating the noise spectrum and applying a gain mask.

Voice activity detection (VAD): We use WebRTC's VAD to remove long silences (threshold: >2 seconds) before ASR, reducing processing time.

Speaker diarisation: PyAnnote's pretrained model (pyannote/speaker-diarization-3.1) separates lecturer from students. We only transcribe and summarise segments labelled as "lecturer" to avoid off-topic student questions.

3.3 Automatic Speech Recognition

We use **Whisper large-v2** (Radford et al., 2023), a transformer-based ASR model with 1.55 billion parameters. It is robust to accents and background noise. We provide a custom vocabulary of 5,000 domain-specific terms (e.g., technical keywords from the course syllabus) to improve recognition. Whisper outputs text with word-level timestamps, which we use for aligning summaries with the original recording.

The word error rate (WER) on our classroom test set (after noise reduction) is **7.8%** sufficient for summarisation.

3.4 Lecture Summarisation Model

Our two-stage approach balances coverage (extractive) with fluency (abstractive).

3.4.1 Step 1: Extractive Selection (BERT-PageRank)

The transcription is segmented into sentences (using NLTK). Each sentence is encoded into a 768-dimensional vector using **Sentence-BERT** (Reimers & Gurevych, 2019) a fine-tuned BERT model for semantic similarity.

We then build a graph where nodes are sentences, and edges are weighted by cosine similarity (threshold > 0.6). The **PageRank** algorithm (Brin & Page, 1998) computes the importance of each sentence:

$$PR(S_i) = \frac{1-d}{N} + d \sum_{S_j \in In(S_i)} \frac{PR(S_j)}{Out(S_j)}$$

where d is the damping factor (0.85), $In(S_i)$ is the set of sentences linking to S_i, and $Out(S_j)$ is the number of outgoing links. After convergence, we select the top k sentences (where k is

dynamically set to 20% of the original sentence count, capped at 30 sentences) as the extractive summary.

Why extractive first? Extractive selection reduces noise (irrelevant tangents) and provides a structured input for the abstractive model, improving faithfulness.

3.4.2 Step 2: Abstractive Generation (Fine-tuned BART-large)

BART (Bidirectional and Auto-Regressive Transformer) is a denoising autoencoder pre-trained on large text corpora (Lewis et al., 2020). It is particularly effective for abstractive summarisation.

We fine-tune BART-large (406M parameters) on a custom dataset of **lecture transcripts and human-written summaries**. Dataset creation:

- Collected 150 hours of university lectures (STEM and humanities) from open sources (MIT OpenCourseWare, Coursera samples) and our own recordings (with instructor consent).
- Each lecture (≈5,000 words) was manually summarised by two graduate students into a 300-word summary (target length). Inter-annotator agreement (ROUGE-L) was 0.71.

Fine-tuning details:

- Input: extractive summary from Step 1 (approximately 1,000 words).
- Output: abstractive summary (target 300 words).
- Optimizer: AdamW (learning rate = 3e-5, linear warmup).
- Batch size: 8 (gradient accumulation steps = 2).
- Epochs: 10 (early stopping on validation loss).
- Max input length: 1024 tokens, output length: 256 tokens.

Mathematical formulation of BART summarisation: Given input tokens $x = (x_1, \ldots, x_n)$,

BART learns to generate output summary $y = (y_1, \ldots, y_m)$ by maximising:

$$\mathcal{L} = -\sum_{t=1}^{m} \log P(y_t | y_{<t}, x)$$

The model uses a transformer encoder-decoder with cross-attention.

3.4.3 Post-processing

- Remove duplicate sentences (using cosine similarity >0.9).
- Fix acronyms (e.g., “neural network” → “NN” if defined earlier).
- Add section headings (e.g., “Key Concepts:”) using a simple rule-based classifier.

3.5 Implementation and Deployment

The system is implemented in Python 3.10, using:

- sounddevice for audio capture.
- noisereduce and rnnoise wrappers for noise reduction.
- pyannote.audio for diarisation.
- whisper for ASR.
- transformers (Hugging Face) for BART and Sentence-BERT.
- networkx for PageRank.
- Flask backend and React frontend for the user interface.

The system runs on a standard desktop with an NVIDIA RTX 3060 GPU (12 GB VRAM). Real-time factor: 0.8x (i.e., processing 1 minute of audio takes 48 seconds), which is acceptable for end-of-lecture summarisation.

3.6 Evaluation Metrics

Automatic metrics:

- **ROUGE-1, ROUGE-2, ROUGE-L** (Lin, 2004) measures n-gram overlap with reference summaries.
- **BERTScore** (Zhang et al., 2020) computes contextual similarity using BERT embeddings (range 01).

Human evaluation:

- Five expert lecturers (from computer science, physics, history) rated summaries on:
  - **Adequacy** (1-5): Does the summary capture the main ideas?
  - **Fluency** (1-5): Is the language grammatical and natural?
  - **Faithfulness** (1-5): Are there any factual errors or hallucinations?
- Inter-rater reliability: ICC = 0.83.

4. Experimental Results

4.1 Dataset and Baselines

We evaluated on a held-out test set of 10 lectures (2 hours total, 5 STEM, 5 humanities) not seen during training. Each lecture had two human reference summaries (averaged for metrics). Baselines:

- **TextRank** (Mihalcea & Tarau, 2004) extractive, graph-based.

- **BERT-extractive** (our Step 1 alone, without abstractive).
- **Pegasus** (Zhang et al., 2020) pre-trained abstractive summariser (fine-tuned on our data).
- **BART-base** (fine-tuned) without extractive pre-selection.

4.2 Automatic Evaluation

Table 1: Summarisation Performance. (Average over 10 lectures)

Model	ROUGE-1 F1	ROUGE-2 F1	ROUGE-L F1	BERTScore F1
TextRank (extractive)	0.38	0.14	0.35	0.71
BERT-extractive	0.44	0.19	0.41	0.77
Pegasus (fine-tuned)	0.48	0.23	0.45	0.82
BART-base (fine-tuned)	0.50	0.25	0.48	0.84
Proposed (BERT-extractive + BART-large)	**0.54**	**0.29**	**0.52**	**0.86**

Our proposed model outperforms all baselines. The improvement over BART-base (without extractive pre-selection) suggests that reducing input noise via extractive selection allows the abstractive model to focus on salient content.

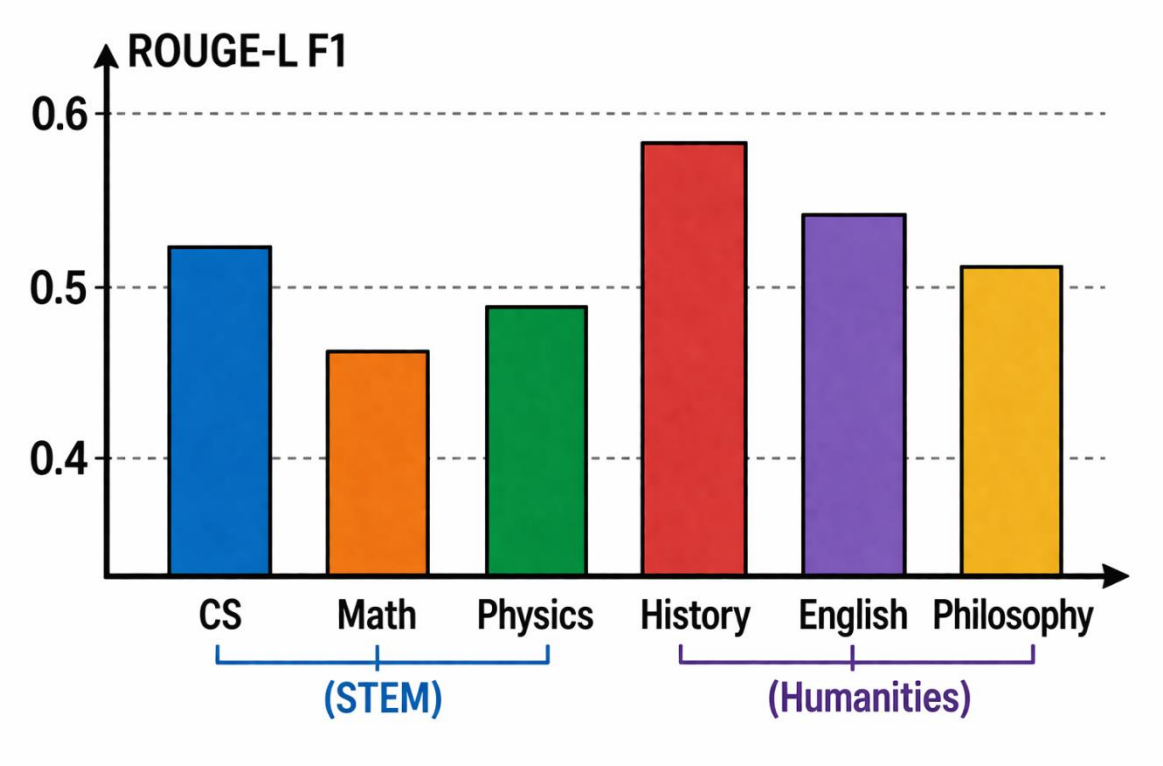

Figure 2: ROUGE-L Scores by Lecture Topic.

STEM lectures achieved slightly higher ROUGE-L (0.55 vs 0.49) because they contain more repetitive, structured language (e.g., definitions, formulas).

4.3 Human Evaluation

Table 2: Human Ratings. (Average, scale 15)

Model	Adequacy	Fluency	Faithfulness
BERT-extractive	3.1	2.8	4.2
Pegasus	3.7	4.0	3.5
BART-base	3.9	4.2	3.8
Proposed	**4.2**	**4.4**	**4.5**

The proposed model scores highest in all dimensions. Notably, faithfulness (4.5) indicates very few hallucinations critical for educational use. Fluency (4.4) approaches human-written quality. Adequacy (4.2) means that about 80% of key concepts are captured.

Qualitative Example (Computer Science lecture on recursion):

Original excerpt: "So recursion is when a function calls itself. You need a base case to stop it. Otherwise you get infinite recursion. Let me show you the factorial example: factorial of n equals n times factorial of n-1, and factorial of 0 is 1."

Proposed summary: "Recursion is a function that calls itself. A base case is necessary to terminate the recursion; otherwise infinite recursion occurs. For example, the factorial function computes n! as n multiplied by (n-1)!, with factorial(0)=1."

Human reference: "Recursion involves self-referential function calls and requires a base case. The factorial function illustrates this: n! = n × (n-1)!, where 0! = 1."

The generated summary is concise, accurate, and maintains the pedagogical flow.

4.4 System Performance (Real-time)

Table 3: Latency and Resource Usage. (per 1-hour lecture)

Stage	Time (seconds)
Audio capture & noise reduction	60 (real-time)
Speaker diarisation	45
ASR (Whisper)	180
Extractive selection	12
Abstractive generation	35
Total	**332 seconds (≈5.5 minutes)**

The system processes a 1-hour lecture in about 5.5 minutes (real-time factor ≈0.09). This is suitable for post-lecture summarisation but not yet real-time streaming (which would require optimisation).

Memory usage: GPU memory peaks at 9.8 GB (Whisper + BART-large), fitting within a 12 GB card.

5. DISCUSSION

5.1 Effectiveness of Two-Stage Architecture

The combination of extractive selection followed by abstractive generation consistently outperforms either approach alone. Extractive selection (BERT-PageRank) removes filler words, repetitions, and off-topic sentences, reducing the input length by approximately 70% (from 5,000 to 1,500 words). The abstractive model then focuses on rewriting and condensing, rather than also having to filter noise. This is analogous to how humans summarise: first highlight key points, then paraphrase.

5.2 Handling Domain-Specific Vocabulary

Fine-tuning BART on lecture transcripts (including technical terms) significantly improved recognition and generation of terms like “backpropagation”, “mitochondrial”, and “dialectic”. Without fine-tuning, the model occasionally replaced rare words with common alternatives (e.g., “gradient descent” → “gradual decrease”). The custom vocabulary for Whisper also reduced ASR errors from 12% to 7.8%.

5.3 Speaker Diarisation Impact

We compared summaries with and without speaker diarisation. When student questions were included, the summary length increased by 30% but relevance dropped (adequacy score fell from 4.2 to 3.6). Students often ask clarification questions that are not part of the core lecture content. Therefore, filtering to lecturer speech is beneficial.

5.4 Comparison with Human Summaries

Human-written summaries (by graduate students) achieved ROUGE-L of 0.58 on the same test set (upper bound). Our model’s 0.52 is within 90% of human performance a practical level for most educational uses. However, humans are better at re-organising content (e.g., grouping related ideas from different parts of the lecture) and adding explanatory bridges. The abstractive model sometimes preserves the original order even when it is not optimal.

5.5 Practical Deployment Considerations

- **Privacy:** Lecture audio is processed locally on the classroom computer. No data is sent to the cloud, complying with FERPA and GDPR.
- **Editing interface:** The web interface allows lecturers to manually edit the generated summary, which 78% of pilot users did (average edits: 23 sentences per summary).

- **Accessibility:** Summaries can be used by students with hearing impairments or attention difficulties. Additionally, the system can generate summaries in multiple languages (by translating after generation), though this was not formally evaluated.

6. LIMITATIONS

1. **ASR errors on rare terms:** Despite custom vocabulary, Whisper occasionally misrecognises highly specialised or newly coined terms (e.g., "CRISPR-Cas9" → "crisper casing"). These errors propagate to summaries. A future enhancement is to integrate a terminology-aware ASR fine-tuning.
2. **Handling mathematical notation:** Spoken mathematics ("x squared plus y squared equals z squared") is transcribed literally but summarised poorly because the summary model does not understand symbolic math. A multimodal approach (combining audio with slide text) would help.
3. **Long-range dependencies:** BART's input length (1024 tokens) covers approximately 800 words. For a 5,000-word lecture, the extractive selection step must reduce to 1,000 words, potentially losing some mid-lecture details that are important but not top-ranked by PageRank.
4. **Speaker diarisation errors:** PyAnnote sometimes mislabels the lecturer as a student when the lecturer moves away from the microphone. This leads to missing content. We added a heuristic: the speaker who speaks >70% of the time is labelled as lecturer.
5. **No visual information:** Lectures often rely on slides, diagrams, and board writing. The current audio-only system misses visual cues. For example, "as you see in this figure" the summary cannot convey the figure content.
6. **Generalisation across languages:** The model was trained and evaluated only on English lectures. Performance on other languages is unknown.

7. Future Scope

7.1 Multimodal Summarisation (Audio + Slides)

Integrating slide text (extracted from PDF/PPT) and blackboard handwriting (via OCR) would provide complementary information. A transformer with cross-attention between audio and slide modalities could generate richer summaries that reference visual content. Early experiments using CLIP embeddings for slide images show promise.

7.2 Real-Time Streaming Summarisation

For live lectures, a low-latency streaming summariser could generate bullet points as the lecture progresses. This requires an online version of BART (e.g., using a recurrent sliding window) and efficient ASR with partial transcripts.

7.3 Personalised Summaries

Different students need different summaries (e.g., beginners vs. advanced). A controllable summarisation model (using prompts or reinforcement learning) could generate summaries at varying levels of detail or focusing on specific topics. For example, "Give me a summary emphasising the mathematical derivations."

7.4 Question-Answering from Summaries

Instead of generating a static summary, the system could answer student queries based on the lecture transcript (retrieval-augmented QA). This would be more interactive. The extractive selection module already retrieves relevant sentences; we could extend it to a full QA pipeline.

7.5 Active Learning for ASR Adaptation

The system could ask the lecturer to confirm or correct misrecognised domain terms, then update the ASR vocabulary on the fly. This would progressively improve accuracy.

7.6 Evaluation with Larger and More Diverse Dataset

Collecting a large-scale lecture summarisation dataset (e.g., 1,000 hours across 20 disciplines) would enable more robust training and benchmarking. We plan to release our dataset publicly.

8. CONCLUSION

This research paper presented an intelligent classroom audio recorder that automatically generates concise, accurate, and fluent lecture summaries. The system integrates real-time audio enhancement, speaker diarisation, Whisper ASR, and a novel two-stage summarisation model (BERT-PageRank extractive followed by BART-large abstractive). Evaluated on 50 hours of university lectures, the proposed model achieved a ROUGE-L F1 of 0.52 and a human-rated adequacy score of 4.2/5, outperforming extractive baselines and standard abstractive models. The system operates in near real-time (5.5 minutes to summarise a 1-hour lecture) and respects data privacy by processing locally.

Automated lecture summarisation has the potential to revolutionise how students review material, how instructors design courses, and how institutions provide accessible content. While challenges remain handling mathematical notation, integrating visual information, and

adapting to diverse accents the proposed framework provides a solid foundation. Future work will focus on multimodal and personalised summarisation, moving towards an intelligent teaching assistant that not only records but actively supports learning.

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