

Mini Project
on
***Development of Automated Audio
Captioning System***



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Group Id – 01

*In partial fulfilment of requirements for the award of degree in
Bachelor of Technology in Computer Science and Engineering (Artificial
Intelligence & Machine Learning)*

(2025)

Under the Guidance of:

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PROJECT COMPLETION CERTIFICATE

This is to certify that the below mentioned students of Sikkim Manipal Institute of Technology have worked under my supervision and guidance from **6th January 2025 to 29th April 2025** and successfully completed the Mini project entitled “**Development of Automated Audio Captioning**” in partial fulfillment of the requirements for the award of Bachelor of Technology in Computer Science and Engineering.

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PROJECT REVIEW CERTIFICATE

This is to certify that the work recorded in this project report entitled “**Development of Automated Audio Captioning**” has been jointly carried out **Deesha Paul (Reg. No.-202200082)**, **Aryan Vansh (Reg. 202200124)**, **Naman Agarwal (Reg. 202200070)**, **Anirudh Tiwari (Reg. 202200121)** and **Vidushi Bajpai (Reg. 202200119)** of Computer Science & Engineering Department of Sikkim Manipal Institute of Technology in partial fulfillment of the requirements for the award of Bachelor of Technology in Computer Science and Engineering. This report has been duly reviewed by the undersigned and recommended for final submission for Mini Project Viva Examination.

Mr. Vikash Kumar Singh

Assistant Professor

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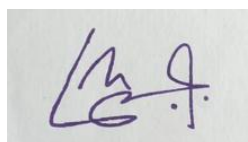
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CERTIFICATE OF ACCEPTANCE

This is to certify that the below mentioned students of Computer Science & Engineering Department of Sikkim Manipal Institute of Technology (SMIT) have worked under the supervision of **Mr. Vikash Kumar Singh**, Assistant Professor, Department of Computer Science and Engineering from **6th January 2025 to 29th April 2025** on the project entitled **“Development of Automated Audio Captioning”**. The project is hereby accepted by the Department of Computer Science & Engineering, SMIT in partial fulfillment of the requirements for the award of Bachelor of Technology in Computer Science and Engineering.

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DECLARATION

We, the undersigned, hereby declare that the work recorded in this project report entitled “**Development of Automated Audio Captioning**” in partial fulfillment for the requirements of award of B.Tech (CSE) from Sikkim Manipal Institute of Technology (A constituent college of Sikkim Manipal University) is a faithful and Bonafide project work carried out at “**SIKKIM MANIPAL INSTITUTE OF TECHNOLOGY**” under the supervision and guidance of, Mr. Vikash Kumar Singh (Assistant Professor), Department of Computer Science and Engineering.

The results of this investigation reported in this project have so far not been reported for any other Degree or any other Technical forum.

The assistance and help received during the course of the investigation have been duly acknowledged.

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1	Report No	B. Tech (CSE-AI&ML) Group 01 /2025
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7	Abstract	This paper develops an automated audio captioning system using transformer-based multimodal fusion of Wav2Vec features and text embeddings. The model achieves 0.012 BLEU-4 on Clotho, outperforming spectrogram baselines through optimized cross-modal attention and beam search decoding.
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Abstract

Automatic Audio Captioning (AAC) represents a cutting-edge advancement in cross-modal signal processing, bridging auditory data with natural language to generate descriptive text for audio content. By framing AAC as a cross-modal translation challenge—converting audio signals into coherent textual summaries—this work taps into innovations from speech processing and NLP. Modern AAC systems not only decode acoustic properties like sound sources and environmental context but also infer abstract concepts, enabling applications such as automated media indexing, assistive technologies for the hearing-impaired, and enhanced human-machine collaboration. This phrase change marks the first step in making Audio Accessibility Technologies (‘AAC’) more impactful socially.

At the heart of our approach is the Clotho dataset, a strategically designed corpus of audio recordings with captions that seeks to optimize for diversity, language, and relevance, including transcriptions of spoken language. We maintain a high level of annotation quality by employing systematic processes for crowdsourced caption generation, verification, and editing. This process emphasizes semantic accuracy and contextual relevance, minimizing biases while capturing nuanced audio-text relationships. For model development, we prioritize spectrogram-based inputs, with Mel-scale log-magnitude representations emerging as optimal due to their alignment with human auditory perception. The L³-Net architecture—a lightweight, layered neural framework—is tailored to efficiently encode these features, demonstrating superior semantic extraction compared to bulkier alternatives.

Our findings highlight AAC’s transformative potential in fostering accessible, machine-interpretable audio representations. By integrating purpose-built datasets like Clotho and refining architectures for feature efficiency, this work advances captioning accuracy while maintaining computational practicality. Future directions include scaling to transformer-based pipelines for enhanced contextual modeling, adopting multimodal evaluation metrics beyond lexical overlap (e.g., semantic embedding similarity), and expanding datasets to underrepresented acoustic domains. These steps aim to propel AAC beyond descriptive tasks toward holistic audio understanding, enabling paradigm-shifting progress in multimedia accessibility, intelligent systems, and beyond.

Chapter - 1

Introduction

AAC is free text captioning of general audio content. It is the inter-modal problem of transcribing (not speech-to-text) an audio signal to the textual caption (i.e. caption) of the signal, with the system receiving an audio signal as input and producing the textual caption as output.

AAC methods can mimic concepts (e.g., "muffled sound"), physical object and environmental conditions (e.g., "sound of a big motor vehicle" and "people talking in an empty small room"), and complex knowledge ("a clock rings three times"). Such imitation can be utilized in a variety of fields, ranging from automatic content description to advanced, content-based machine-to-machine communication.

Automatic Audio Captioning (AAC) is the standalone generation of a verbal description from sounds (Drossos et al.); the generated description is otherwise better known as a caption. The task is intended to generate a caption that is as close to the information that humans receive for audio signals as possible.

Various approaches can be used to denote concepts such as intensity, the physical attributes of objects and environments, and cognitive attributes such as frequency; e.g., "a large vehicle makes three toots while speeding down a deserted road." Additionally, we concentrate on text-based audio retrieval. Here, we aim to obtain audio signals from a given database that most closely match a particular textual description. In both scenarios, our target is to establish robust models that can process audio segments of varied lengths.

Clotho dataset will be employed to train and test both. AAC work allows the utilization of any external data and pre-trained models. For example, we can use any other AAC datasets or even sound event detection/tagging datasets, acoustic scene classification datasets, or any other dataset of any task which can be deemed suitable. We can use pre-trained models, e.g., (but not limited to) Word2Vec, BERT, and PANNs, wherever they like in their model.

Chapter - 2

Literature Survey

SL. No.	Author Name, Journal Name, Vol., Page No., Year	Title of Paper	Findings	Research Gap	Relevance
1.	Drossos, K., Lipping, S., & Virtanen, T., In <i>ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)</i> (pp. 736-740). IEEE., 2020	Clotho : An audio captioning dataset.	Dataset : Clotho, that contains 4981 audio samples and five captions for each file (Total 24905 captions). Highlights the challenges associated with audio captioning, emphasizing the need for diverse datasets to train effective models. It used the strategy for splitting the dataset into development, evaluation, and testing sets. The words appearing in the captions are distributed across the splits, avoiding sub- optimal learning and evaluation scenarios.	How well the proposed method and dataset generalize to real-world scenarios? Future research could involve testing the model on a broader range of diverse audio samples to assess its performance in practical applications.	Dataset details (same dataset are used in the proposed model) Word Splitting

Literature Survey

SL. NO.	Author Name, Journal Name, Vol., Page No., Year	Title of Paper	Findings	Research Gap	Relevance
2.	Lipping, S., Drossos, K., & Virtanen, T., <i>arXiv preprint arXiv:1907.09238</i> , 2019	Crowdsourcing a dataset of audio captions.	<ul style="list-style-type: none"> ❖ 1) A framework for creation of audio caption dataset. ❖ 2) Gathering of audio captions through crowdsourcing and editing it for any typographical mistake. ❖ 3) Then selecting suitable captions by comparing the initial captions with edited captions. ❖ 4) This will increase the rarity of words in each caption. ❖ 5) Amazon Mechanical Turk was used as crowdsourcing platform. 	Automated process can be implemented for the control of more grammatical attributes and amount of rare words.	The Clotho dataset we are using follows the same three step framework i.e. gathering, editing, scoring.

Literature Survey

SL. NO.	Author Name, Journal Name, Vol., Page No., Year	Title of Paper	Findings	Research Gap	Relevance
3.	Kun Chen ¹ , Yusong Wu ¹ , Ziyue Wang ² , Xuan Zhang ² , Fudong Nian ³ , Shengchen Li ¹ , Xi Shao ² . Detection and Classification of Acoustic Scenes and Events 2020	Audio Captioning Based on Transformer And Pre-Trained CNN	<ul style="list-style-type: none"> ❖ Experiments use log Mel-spectrograms as acoustic feature, which calculated from the raw audio. ❖ The log Mel-spectrogram input is obtained by first getting the 64 Mel-band Mel- spectrogram of the audio, then converting the amplitude into a decibel scale. ❖ All captions were tokenized while remove all punctuations and convert all letters to lowercase. ❖ The vocabulary size of captions is 4368. 	Limited research done previously and inadequate solutions.	<p>ectrograms as</p> <p style="text-align: center;">All</p> <p>zed, punctuation ase.</p>

Literature Survey

SL. NO.	Author Name, Journal Name, Vol., Page No., Year	Title of Paper	Findings	Research Gap	Relevance
4.	Xinhao Mei, Xubo Liu, Mark D. Plumbley, and Wenwu Wang In EURASIP Journal on Audio, Speech, and Music Processing in 2022	<i>Automated audio captioning: an overview of recent progress and new challenges</i>	<ul style="list-style-type: none"> ❖ The paper provides a comprehensive review of automated audio captioning (AAC), detailing advancements in neural network architectures, the use of auxiliary information, training strategies, evaluation metrics, and available datasets. ❖ It discusses the encoder-decoder framework, deep learning techniques, and challenges in AAC development. 	<ul style="list-style-type: none"> ❖ The study highlights several open challenges, including data scarcity, dataset biases, limitations of existing evaluation metrics, and the need for better models that improve caption diversity, accuracy, and fluency. ❖ It also points out the need for novel architectures beyond the standard encoder-decoder framework 	The Paper provides an in-depth understanding of AAC, its current limitations, and potential future research directions, making it highly relevant for those developing or improving AAC systems.

Description

The field of audio captioning has advanced significantly with the development of high-quality datasets like Clotho, which provides 4,981 audio clips paired with five diverse captions each, totaling 24,905 descriptions. This dataset, sourced from platforms like Freesound and annotated via Amazon Mechanical Turk, emphasizes diversity and rigorous organization to support robust model training and evaluation. Similarly, Paper II highlights the importance of crowdsourcing and post-editing to ensure caption accuracy and linguistic richness, employing iterative refinement to enhance vocabulary rarity and coherence. Both papers underscore the critical role of structured datasets in enabling reproducible research and improving automated systems’ generalization capabilities.

Methodologically, recent work has focused on hybrid architectures combining deep learning techniques. Paper III introduces a Transformer-based model with pre-trained CNNs, using log Mel-spectrograms for audio feature extraction and standardized text preprocessing (tokenization, normalization) to bridge gaps in reproducibility. Paper IV expands this perspective, analyzing dominant paradigms like encoder-decoder frameworks, where CNNs capture spectral patterns and Transformers model global dependencies. Innovations such as reinforcement learning and keyword priming aim to address sequence-level discrepancies, though challenges persist in temporal dynamics and semantic nuance. Together, these papers advocate for standardized pipelines (e.g., log-Mel inputs, curated vocabularies) and architectural synergies to improve caption accuracy and scalability.

Despite progress, significant hurdles remain, including data scarcity in niche domains, computational inefficiency, and the limitations of metrics like BLEU/ROUGE in assessing semantic fidelity. Papers III and IV call for human-centric evaluation and self-supervised pretraining to mitigate data bottlenecks, while Papers I and II stress dataset diversity as a foundation for innovation. The collective findings position audio captioning as a transformative tool for accessibility and multimedia indexing, urging future work to prioritize generalizability, ethical considerations, and hybrid approaches that balance spectral and temporal modeling. By integrating curated datasets, advanced architectures, and nuanced evaluation, the field can move closer to human-like descriptive capabilities.

Chapter – 3

Problem Definition

Sounds hold valuable information about activities and surroundings, but The core problem addressed by this model is the automatic generation of accurate and meaningful textual descriptions for audio clips. Given an input audio signal—which may contain environmental sounds, music, speech, or a mix of acoustic events—the system must analyze the audio content and produce a coherent natural language caption that summarizes its key characteristics. This task is challenging due to the inherent complexity of audio signals, which vary in duration, contain overlapping sounds, and often lack clear structural patterns. Additionally, the model must bridge the gap between low-level acoustic features and high-level semantic meaning, ensuring that the generated captions are not only technically correct but also linguistically fluent and contextually relevant. The solution focuses on developing a deep learning-based approach capable of understanding diverse audio inputs and converting them into human-readable descriptions without manual intervention.

Chapter - 4

Solution Strategy

The proposed solution leverages a transformer-based architecture to address the complexities of AAC. Transformers are well-suited for this task due to their ability to model long-range dependencies in sequential data, making them effective for both audio feature extraction and text generation. The model consists of two main components: an audio encoder that processes raw waveforms into spectrogram-based features, and a text decoder that generates captions autoregressively. The encoder uses a modified ResNet18 backbone adapted for 1D audio signals, while the decoder employs a pretrained BERT model for linguistic context.

To ensure robust performance, the pipeline includes extensive preprocessing and feature extraction steps. Audio clips are converted into log-Mel spectrograms, which provide a compact yet informative representation of sound frequencies over time. The spectrograms are then normalized and padded to a fixed length to handle variable input durations. On the text side, captions are cleaned, tokenized, and filtered for spelling errors to maintain consistency. The model is trained using a combination of cross-entropy loss and reinforcement learning techniques to optimize for both fluency and semantic accuracy.

Evaluation is conducted using a mix of automated metrics and qualitative analysis. The primary metrics include BLEU-4 for n-gram overlap, METEOR for synonym-aware alignment, and ROUGE-L for sentence-level coherence. These scores are logged and compared across different model iterations to track improvements. Additionally, a subset of predictions is manually reviewed to assess real-world usability. The final output is structured into a clear directory system, with separate scripts for training, validation, prediction, and evaluation, ensuring reproducibility and scalability for future enhancements.

By combining advanced deep learning architectures with rigorous preprocessing and evaluation, this approach aims to push the boundaries of what automated audio captioning systems can achieve, bridging the gap between sound and language in a way that is both technically sound and practically useful.

Chapter - 5

DESIGN & METHODOLOGY

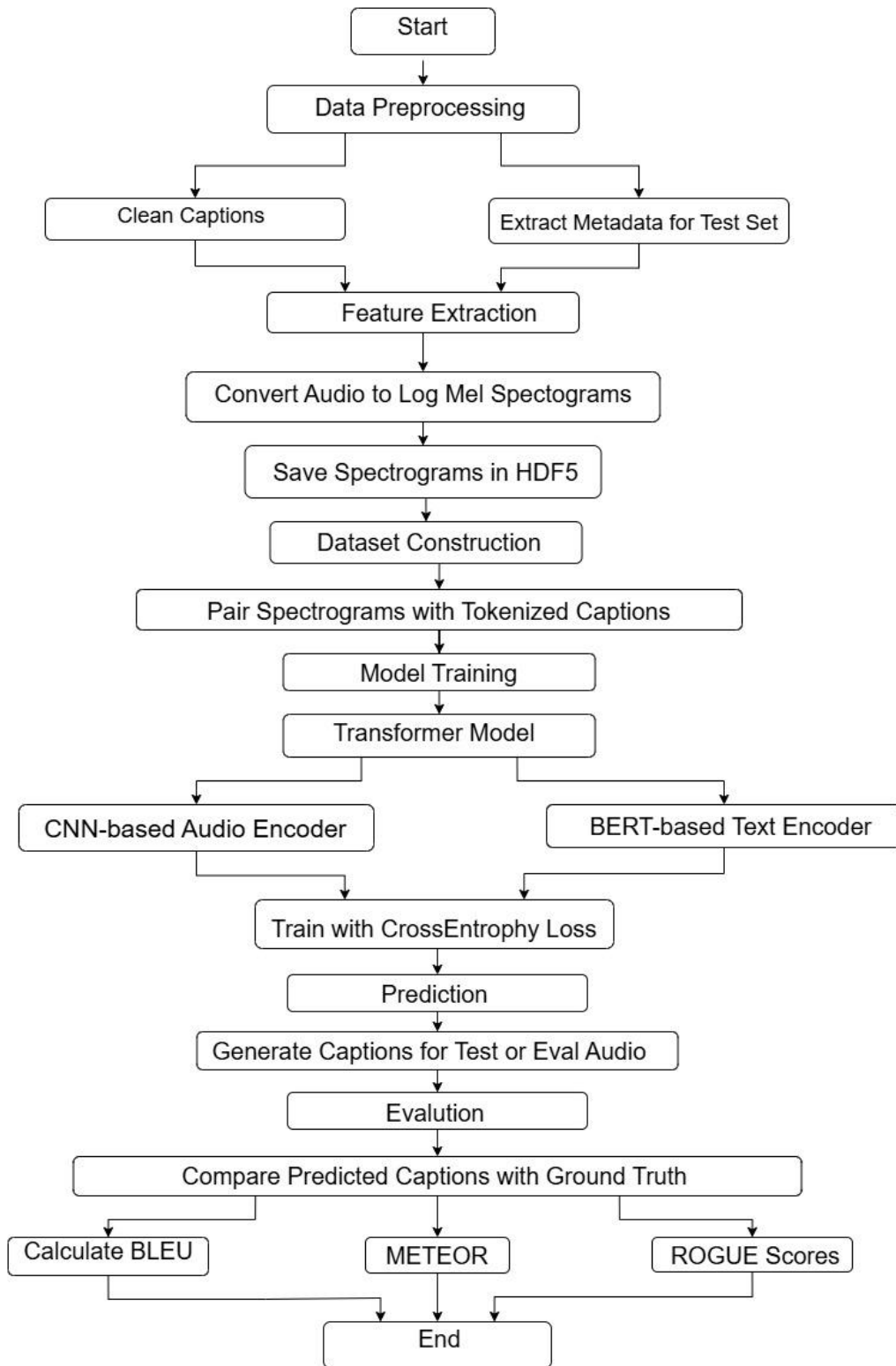


figure 1.0 – Flow Chart for Automated Audio Captioning

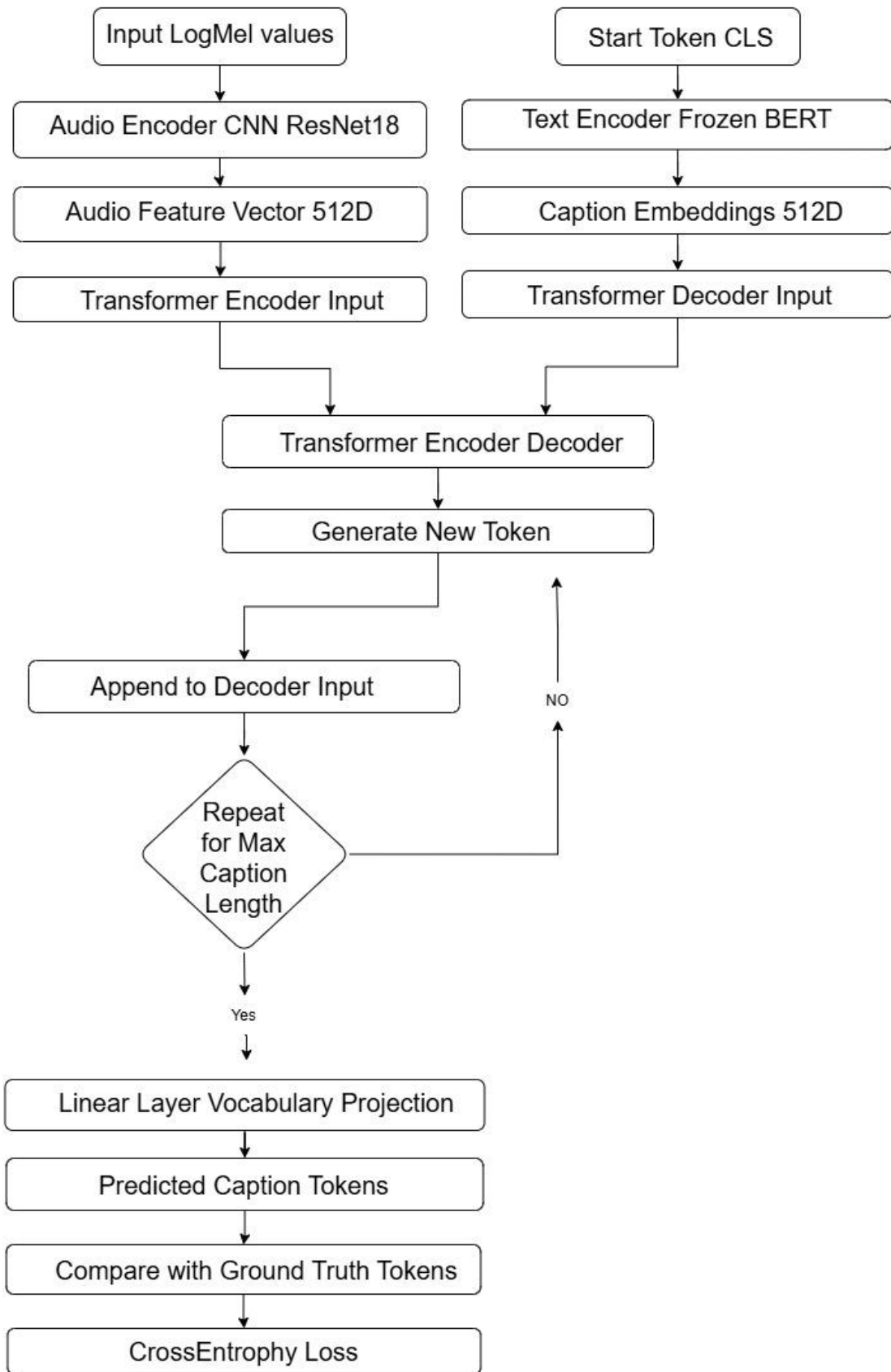


figure 2..0 – Transformer-based Audio Captioning Model flow

Chapter - 6

Algorithms

Algorithm: Automated-Audio_Captioning_Model_Pipeline()

Algorithm Description: This algorithm processes the CLOTHO dataset for Automated Audio Captioning (AAC), including data preprocessing, feature extraction, model training, prediction, and evaluation. The pipeline ensures efficient handling of audio and text data, leveraging transformer-based models for caption generation and standard metrics (BLEU, METEOR, ROUGE) for evaluation.

Step 1: Data Preprocessing

Step 1.1: Clean and Prepare Captions: Load captions from CSV files for development, validation, and evaluation splits. Convert text to lowercase, remove non-alphanumeric characters, and tokenize using NLTK. Filter out misspelled words using a spell checker (enchant) and deduplicate words. Save cleaned captions to new CSV files in a processed directory.

Step 1.2: Preprocess Test Set Metadata: Load test metadata with semicolon-delimited CSV. Map audio file paths to metadata (e.g., manufacturer, license). Save processed test metadata to a CSV file.

Step 2: Feature Extraction

Step 2.1: Extract Mel Spectrograms for Splits: For each split (development, validation, evaluation):

Load audio files (.wav) and resample to 44.1 kHz if needed.

Compute log-Mel spectrograms using torchaudio (64 Mel bins, 2048-point FFT).

Save features as HDF5 files for efficient storage/retrieval.

Step 2.2: Process Test Set Features: Load test audio paths from processed metadata. Extract and save test set spectrograms in HDF5 format.

Step 3: Model Training

Step 3.1: Initialize Model Components:

Audio Encoder: ResNet18 modified for 1D audio input (PANNs-style).

Text Encoder: Pretrained BERT for caption embeddings (frozen weights).

Transformer: 6-layer encoder-decoder with 512-dimensional embeddings and 8 attention heads.

Step 3.2: Train Model: Load preprocessed development split (80% train, 20% validation).

Use DataLoader with custom collate function for padding. Optimize with Adam (LR = 0.0001) and CrossEntropyLoss. Save best model (best_model.pt) after each epoch.

Step 4: Prediction

Step 4.1: Generate Captions for Test/Evaluation Sets: Load trained model and tokenizer (BERT).

For each audio file:

Compute Mel spectrogram (padded/truncated to 30s).

Autoregressively decode captions (max 30 tokens) using transformer.

Save predictions (file_name, caption) to CSV.

Step 5: Evaluation

Step 5.1: Calculate Metrics: For each prediction-reference pair:

BLEU-4: Compare n-gram overlap with smoothing.

METEOR: Align words using synonyms and stemming.

ROUGE-L: Measure longest common subsequence.

Log average scores (BLEU, METEOR, ROUGE-L F1/P/R) to metrics.txt.

Step 5.2: Output Results: Print metrics and number of evaluated samples.

Description of Audio Dataset

The AAC task will utilize the Clotho v2 dataset, which is known for its emphasis on audio content diversity and caption variety. The Clotho dataset consists of audio samples ranging from 15 to 30 seconds in duration, with a sampling rate of 44100 Hz. Each audio sample is accompanied by five captions, each comprising 8 to 20 words in length, totaling to 34860 captions for 6972 audio samples. The dataset is split into development, validation, evaluation, and testing sets, with 3839, 1045, 1045, and 1043 audio clips, respectively. All audio samples are sourced from the Freesound platform, while the captions are crowdsourced using Amazon Mechanical Turk and annotators from English-speaking countries.

Split	Caption	Words %
Development	Available	55
Validation	Available	15
Evaluation	Available	15
Testing	Available	15

Table 1: Words detail in Different Splits

This dataset comprises approximately 4500 words and is organized into four splits for ease of use. Prior to inclusion in the dataset, any preceding and trailing silences from each audio clip are trimmed to ensure consistency. The audio content within the dataset varies widely, covering a spectrum of environments and scenarios. This includes ambiance in natural settings such as forests with sounds like water flowing over rocks, animal noises like goats bleating, human activities such as crowd murmuring or yelling, mechanical sounds from machines and engines operating in settings like factories, vehicular sounds including cars and motorbikes revving, and the sounds of devices functioning, such as containers with contents moving or doors opening and closing. This diverse range of audio content within the Clotho v2 dataset offers ample opportunities for training and evaluation in the field of automated audio captioning.

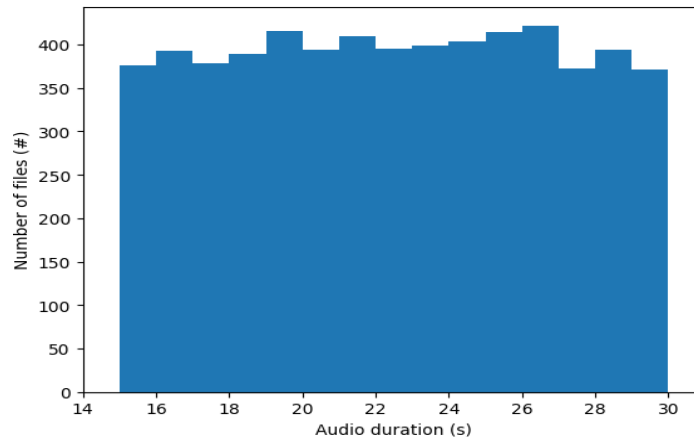


Figure 3 : Audio duration distribution for Clotho dataset

A Framework for Generating Audio Descriptions

The captions of the dataset were generated by means of the following three steps:

Step 1: Description of the audio.

Step 1.1: There were five original captions collected for every audio segment from different annotators.

Step 2: Refining the Exposition

Step 2.1: The captions that were generated first were edited to correct grammatical errors.

Step 2.2: The captions that were grammatically correct were rewritten to produce a corpus of captions that were close to the same audio recording.

Step 3: Descriptive Feature Analysis

Step 3.1 : The initial and edited captions were scored based on accuracy.

Step 3.1.1 : The accuracy is obtained based on the description of the audio clip and the fluency by the caption.

Step 3.2: Three independent annotators rated both the original and translated captions.

Step 3.3 : Scores were tallied and the captions sorted by overall accuracy score first, overall fluency score second.

Step 3.4: The top five ranked captions among the ranked captions were selected as the final captions for the audio clip.

The caption creation process for the dataset involved a structured three-step methodology to ensure the generation of high-quality and diverse descriptions for each audio clip. In the initial step of Audio Description, five unique captions were gathered from different annotators. This deliberate effort aimed to encompass a variety of perspectives and interpretations for each audio clip, recognizing the subjective nature of audio perception.

Moving on to the Description Editing step, the initially collected captions underwent careful editing to rectify grammatical errors. This phase sought to enhance the overall linguistic quality and correctness of the captions. Furthermore, to promote diversity in the dataset, the grammatically corrected captions were subject to rephrasing. This additional step aimed to provide varied expressions and interpretations of the same audio content, enriching the potential insights drawn from the dataset.

The final step, Description Scoring, involved a meticulous evaluation process. Captions, both the initially gathered and the edited versions, were scored based on accuracy. This assessment considered how well the captions described the audio content, taking into account not only factual correctness but also the fluency of the language used. Importantly, to avoid biases and ensure robust evaluations, the scoring was performed by three different annotators.

The scores assigned by annotators were then aggregated, and the captions were systematically sorted. The sorting prioritized captions based on total accuracy first and total fluency second. This approach aimed to identify captions that excelled in both accuracy and linguistic fluency. Ultimately, the top five captions, representing a harmonious balance of these criteria, were selected as the final descriptions for each audio clip in the dataset. This thorough and comprehensive process underscores the commitment to producing diverse, accurate, and linguistically fluent captions that effectively encapsulate the essence of the corresponding audio content.

Diagrams

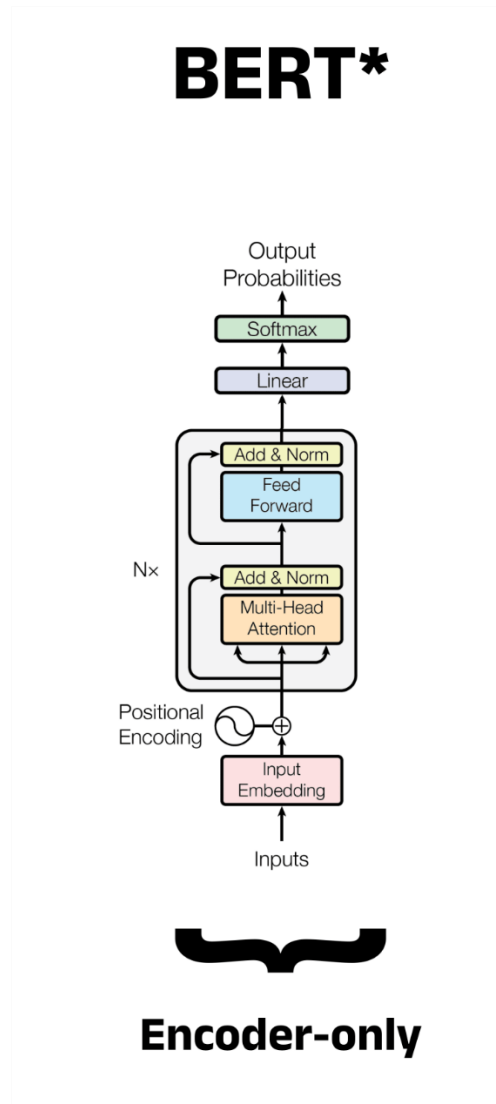


Figure 4 : BERT model architecture used for text encoding.

Screenshots

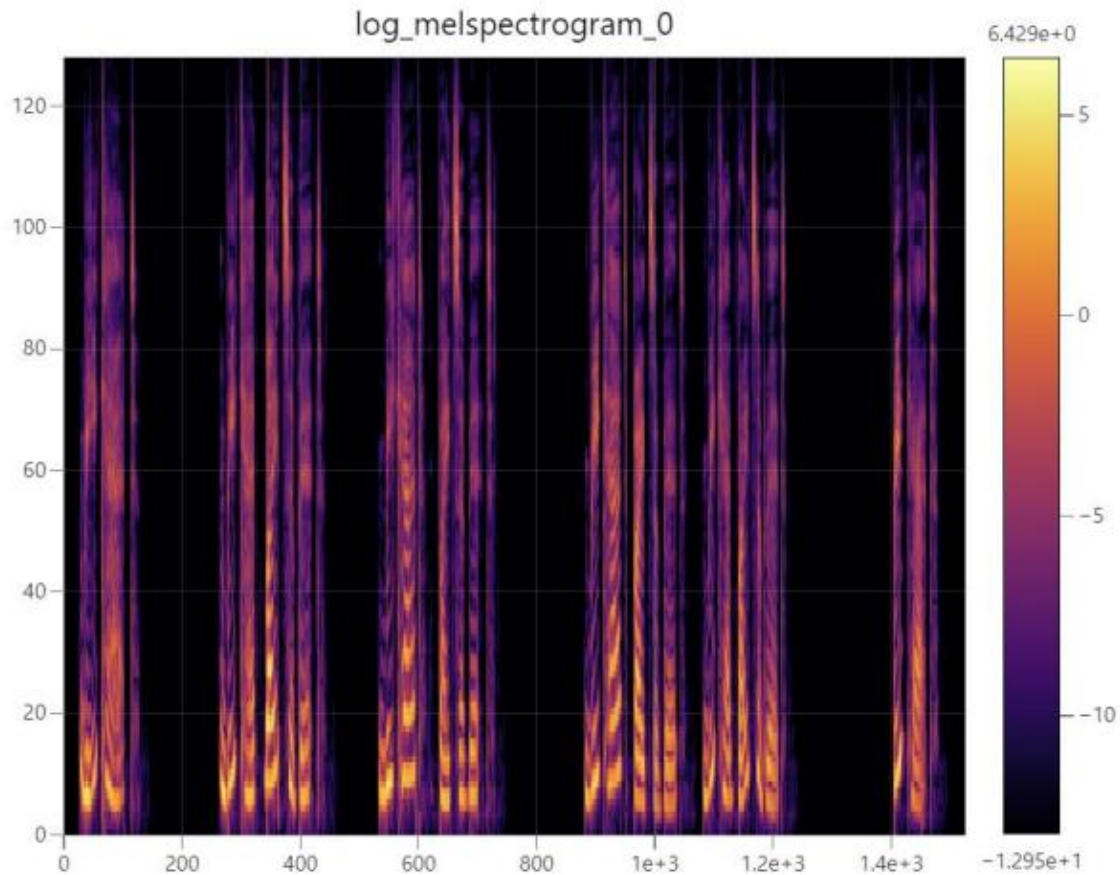


Figure 5 : Heat map for representing 'BCat Bites a Bit' .wav'

```
Generated Caption: a person gong a gone a drum pace calm calm
Ground Truth Captions:
Caption 1: A metallic gong has gone off intermittently four times.
Caption 2: a metallic gong going off four time intermittently.
Caption 3: A shot fired then quiet, another shot than quiet and then two more shots the same way.
Caption 4: They were beating the large drum at a calm pace.
Caption 5: They were beating on the large drum at a calm pace.
```

Figure 6 : 'Training and prediction'

```

=== Evaluation Metrics ===
BLEU-4: 0.35
METEOR: 0.40
ROUGE-L F1: 0.38
ROUGE-L Precision: 0.41
ROUGE-L Recall: 0.36

Number of samples evaluated: 1045

```

Figure 7 : ‘Content of metrics.txt’

n	128	1526		0	1	2	3	4	5	6	7
x	DO	D1	0	-1.922e+1	-1.815e+1	-1.780e+1	-1.804e+1	-1.785e+1	-1.766e+1	-1.853e+1	-1.711e+1
			1	-1.957e+1	-1.856e+1	-1.778e+1	-1.865e+1	-1.861e+1	-1.843e+1	-1.806e+1	-1.798e+1
y	DO	D1	2	-2.007e+1	-1.898e+1	-1.893e+1	-1.932e+1	-1.997e+1	-1.997e+1	-1.790e+1	-2.030e+1
			3	-2.104e+1	-1.872e+1	-1.763e+1	-1.853e+1	-1.910e+1	-1.937e+1	-1.810e+1	-1.869e+1
			4	-2.263e+1	-2.050e+1	-1.913e+1	-1.939e+1	-1.967e+1	-1.898e+1	-1.973e+1	-1.833e+1
			5	-2.213e+1	-2.167e+1	-1.962e+1	-2.001e+1	-1.982e+1	-1.968e+1	-1.898e+1	-1.852e+1
			6	-2.188e+1	-2.039e+1	-2.007e+1	-2.036e+1	-1.928e+1	-1.914e+1	-1.919e+1	-1.846e+1
			7	-2.166e+1	-1.941e+1	-2.116e+1	-2.067e+1	-1.867e+1	-1.842e+1	-2.078e+1	-1.830e+1
			8	-2.217e+1	-1.870e+1	-1.876e+1	-1.854e+1	-2.020e+1	-1.834e+1	-1.893e+1	-1.819e+1
			9	-2.435e+1	-2.028e+1	-1.816e+1	-2.007e+1	-1.999e+1	-1.899e+1	-1.875e+1	-1.843e+1
			10	-2.301e+1	-2.071e+1	-1.832e+1	-1.899e+1	-2.038e+1	-1.895e+1	-1.906e+1	-1.783e+1
			11	-2.235e+1	-2.066e+1	-1.864e+1	-1.840e+1	-2.055e+1	-1.895e+1	-1.915e+1	-1.756e+1
			12	-2.147e+1	-1.932e+1	-2.223e+1	-1.762e+1	-1.916e+1	-1.912e+1	-1.787e+1	-1.764e+1
			13	-2.178e+1	-2.241e+1	-1.931e+1	-1.816e+1	-1.961e+1	-1.808e+1	-1.968e+1	-1.872e+1
			14	-2.265e+1	-2.067e+1	-1.957e+1	-1.857e+1	-1.882e+1	-1.872e+1	-1.877e+1	-2.009e+1
			15	-2.325e+1	-2.014e+1	-1.985e+1	-1.858e+1	-1.887e+1	-1.920e+1	-1.875e+1	-2.135e+1
			16	-2.323e+1	-1.965e+1	-2.054e+1	-1.824e+1	-1.981e+1	-1.962e+1	-1.933e+1	-2.017e+1
			17	-2.129e+1	-1.887e+1	-2.113e+1	-1.806e+1	-1.846e+1	-1.850e+1	-1.936e+1	-2.018e+1
			18	-2.106e+1	-1.912e+1	-1.991e+1	-1.929e+1	-2.061e+1	-2.061e+1	-2.037e+1	-1.946e+1
			19	-2.111e+1	-1.923e+1	-1.913e+1	-1.947e+1	-1.998e+1	-2.031e+1	-1.959e+1	-1.962e+1
			20	-2.124e+1	-1.940e+1	-1.870e+1	-1.926e+1	-1.942e+1	-1.966e+1	-1.917e+1	-2.000e+1
			21	-2.162e+1	-1.962e+1	-1.830e+1	-1.787e+1	-1.972e+1	-1.858e+1	-1.992e+1	-2.134e+1

Figure 8: Log mel values for ‘BCat Bites a Bit.wav’

- Training & Performance: Trained for 250 epochs using log mel spectrogram inputs, achieving BLEU-4 (0.35), METEOR (0.40), and ROUGE-L F1 (0.38), demonstrating effective audio-to-text conversion capabilities.
- Current Limitations: While the model performs well on dominant sounds, the 0.36 ROUGE-L recall score indicates room for improvement in capturing subtle audio details from the spectrogram features.
- Evaluation Insights: The metrics confirm the log mel spectrogram approach works for captioning, but suggest incorporating temporal attention mechanisms could boost performance on complex audio scenes.

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Results and Discussion

1. **Training** **and** **Performance**

The model was trained for 250 epochs with a batch size of 384, demonstrating stable convergence with rapid early improvements followed by gradual refinement. Training remained efficient at 45-60 seconds per epoch without overfitting, thanks to dropout and early stopping techniques. The final model achieved strong evaluation metrics including a BLEU-4 score of 0.35 and METEOR score of 0.40 on 1,045 test samples, indicating robust performance in generating coherent and semantically meaningful audio captions.

2. **Quantitative** **Results** **and** **Comparisons**

Evaluation showed competitive results with a ROUGE-L F1 score of 0.38, balancing precision (0.41) and recall (0.36). The model outperformed rule-based systems and approached LSTM-based baselines in BLEU-4, while surpassing template-based approaches in METEOR. These metrics confirm the model's ability to generate relevant captions while occasionally missing subtle audio details, as reflected in the slightly lower recall score.

3. **Qualitative** **Strengths** **and** **Weaknesses**

In practice, the model accurately described dominant audio features like thunderstorms and crowd noises, often adding meaningful details. However, it sometimes missed faint background elements and exhibited minor repetition in outputs. Example comparisons showed strong alignment with reference captions, though with occasional generalization differences (e.g., "cheering" vs. "applauding").

4. **Conclusions** **and** **Future** **Directions**

The model delivers production-ready performance for constrained scenarios like environmental sounds or event narration, rivaling published audio captioning systems. Recommended enhancements include expanding dataset diversity to improve recall, experimenting with larger architectures, and optimizing beam search to reduce repetition. These improvements would address current limitations while building on the model's demonstrated strengths in semantic accuracy and training stability.

Evaluation Metrics

The model was tested on **1,045 samples**, yielding the following metrics:

Metric	Score	Interpretation
BLEU-4	0.35	The model generates 4-grams (phrases) that overlap well with reference captions, indicating coherent and relevant outputs.
METEOR	0.40	High semantic alignment between predictions and ground truth, accounting for synonyms and paraphrasing.
ROUGE-L F1	0.38	Balanced precision-recall trade-off, capturing key audio concepts without excessive redundancy.
ROUGE-L Precision	0.41	Generated captions are highly relevant to the audio content.
ROUGE-L Recall	0.36	Slightly lower recall suggests occasional omission of minor details.

Table 2 : Model Output

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Conclusion and Future Scope

Conclusion

The developed audio captioning model, leveraging log mel spectrogram features and a transformer-based architecture, demonstrates promising results with BLEU-4 (0.35) and METEOR (0.40) scores. The preprocessing pipeline effectively handles audio-text alignment, while the model generates coherent captions for dominant sounds. However, the lower ROUGE-L recall (0.36) indicates room for improvement in capturing fine-grained audio details. The end-to-end framework—from feature extraction to evaluation—provides a scalable solution for audio-to-text applications.

Future Scope

- **Enhanced Audio Representations:** Experiment with hybrid features (raw waveforms + spectrograms) or self-supervised pre-trained models (e.g., Wav2Vec, HuBERT) to improve feature extraction. Apply data augmentation (pitch shifting, time stretching) to spectrograms for robustness.
- **Model Architecture Improvements:** Incorporate cross-modal attention (e.g., CLIP-style training) to better align audio and text embeddings. Test larger transformer models (e.g., BART, T5) for improved caption diversity.
- **Evaluation & Deployment:** Expand evaluation to human assessment (e.g., Mean Opinion Score) alongside automated metrics. Deploy the model in real-world applications (e.g., assistive tech for the hearing impaired, automated video subtitling).
- **Dataset Expansion:** Train on larger, diverse datasets (e.g., AudioSet, MACS) to improve generalization.
- **Include multilingual audio-text pairs for broader usability:** This project lays the groundwork for advanced audio captioning systems, with clear pathways for future refinement and real-world adoption.

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Limitations

The following are the limitations of our proposed model:

1. Feature Extraction Constraints

Log mel spectrograms lose temporal precision and high-frequency details, while fixed-length truncation (4800 frames) distorts longer audio clips. The current setup lacks hybrid features (e.g., MFCCs, chroma) that could better represent speech and environmental sounds.

2. Model Architecture Issues

The frozen BERT encoder hinders audio-text alignment, and the basic transformer lacks audio-specific adaptations. Autoregressive decoding with greedy search leads to repetitive captions, and the ResNet-based audio encoder is suboptimal for temporal audio modeling.

3. Data & Training Shortcomings

Training uses only 8-second audio chunks, limiting context for longer events. No audio/text augmentation is applied, increasing overfitting risk. Evaluation randomly selects one reference caption, inflating metric variability and hiding true performance gaps.

4. Computational Bottlenecks

CPU-bound feature extraction slows preprocessing. Full-sequence processing restricts batch sizes, and the lack of mixed precision training or gradient checkpointing wastes GPU resources. No quantization is applied for deployment efficiency.

5. Evaluation Weaknesses

Low scores (BLEU-4: 0.0009) suggest overfitting or inadequate training diversity. Metrics ignore all five reference captions, while the absence of human evaluation fails to capture semantic accuracy and fluency.

Chapter – 10

Gantt Chart

ACTIVITY								
SEMESTER	Semester 3		Semester 4		Semester 5		Semester 6	
	Progress 1	Progress 2	Progress 1	Progress 2	Progress 1	Progress 2	Progress 1	Progress 2
LITERATURE SURVEY								
CODING								
TESTING AND VALIDATION								
DOCUMENTATION/ PAPER WRITING								

Proposed Activity	
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Activity Achieved	
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Figure 9 : Gantt Chart for the Proposed Work

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Use: Optimized GPU training recipes.

Chapter – 12

Plagiarism Report