Project Introduction

- The primary goal is to process raw audio inputs and generate sentiment predictions through sequential speech-to-text transcription and sentiment classification.
- It aims to establish a modular and scalable architecture capable of integrating multiple ASR and sentiment models.
- The objective is to benchmark these model combinations based on accuracy, latency, throughput, and overall efficiency.
- Ultimately, it seeks to evolve into an operational and deployable system suitable for real-time audio sentiment analysis.

Group Members

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Settings

Models Included

1. Audio to Text

- AventIQ-AI/whisper-audio-to-text
  - Base Architecture: OpenAI Whisper
  - Dataset / Fine-Tuning: Mozilla Common Voice 13.0 dataset
  - Task / Use-Case: Speech-to-Text (Automatic Speech Recognition, ASR)
  - Parameter Size: 72M

1. Text to Sentiment

- distilbert-base-uncased-finetuned-sst-2-english (Small)
  - Base Architecture: DistilBERT-base-uncased
  - Dataset / Fine-Tuning: Stanford Sentiment Treebank (SST-2)
  - Task / Use-Case: Sentiment Analysis
  - Parameter Size: 66M
- siebert/sentiment-roberta-large-english (Large)
  - Base Architecture: RoBERTa-Large
  - Dataset / Fine-Tuning: 15 mixed English sentiment datasets
  - Task / Use-Case: Sentiment Analysis
  - Parameter Size: 355M
- cardiffnlp/twitter-roberta-base-sentiment-latest (Medium)
  - Base Architecture: RoBERTa-Base
  - Dataset / Fine-Tuning: 124 M tweets (TweetEval benchmark)
  - Task / Use-Case: Sentiment Analysis
  - Parameter Size: 125M

Model Variant

1. Quantitatively Evaluated
- fp32 - audio to text models and text to sentiment models
- fp16 - text to sentiment models
1. Provided in Web Service (will be quantitatively evaluated in Milestone 3)
- fp32 - audio to text models and text to sentiment models
- int8 - text to sentiment models

Model Storage

- MinIO
  - An open-source, high-performance object storage server compatible with Amazon S3 APIs.
  - Usage in this pipeline: Store our models in ONNX

Temporal File Storage

- Redis
  - A high-speed, in-memory key-value store that can act as a cache, database, or message broker.
  - Usage in this pipeline: Cache frequent inference results to reduce model load.

Web Server

- FastAPI
  - A lightweight, asynchronous web framework built on Starlette (for async I/O) and Pydantic (for data validation).
  - Usage in this pipeline: deploy docker containers as web service.

Flexible Container-Based Web Service:

- We kept both audio-to-text and text-to-sentiment models as flexible options when we create a container
- We assigned different ports to different model combinations
- Example:
  - input: .wav file
  - output:
    - transcripted text
    - sentiment classification
    - inference time

Windows PowerShell

```
(whisper_export) PS D:\Mizzou\25fall\eeml\project\e2eml-audio\ms_2> docker run -d -p 8002:8000 `
>>   -e A2T_MODEL_PATH="/models/a2t_AventIQ-AI_whisper-audio-to-text_fp32" `
>>   -e T2S_MODEL_PATH="/models/t2s_distilbert-base-uncased-finetuned-sst-2-english_fp32.onnx" `
>>   -v "${PWD}\app:/app" `
>>   -v "${PWD}\models:/models" `
>>   audio-sentiment
d9042b02240a979ed0b68e127cbf2a1ee6edb9b5bead1458387571cf1b962122
(whisper_export) PS D:\Mizzou\25fall\eeml\project\e2eml-audio\ms_2> docker ps
CONTAINER ID   IMAGE             COMMAND                  CREATED         STATUS         PORTS
  NAMES
d9042b02240a   audio-sentiment   "uvicorn main:app --…"   4 seconds ago   Up 4 seconds   0.0.0.0:8002->8000/tcp, [::]:8002->8000/tcp
  intelligent_zhukovsky
(whisper_export) PS D:\Mizzou\25fall\eeml\project\e2eml-audio\ms_2> $FilePath = "D:\Mizzou\25fall\eeml\project\e2eml-audio\data\audio
s\audio_00000.wav"
(whisper_export) PS D:\Mizzou\25fall\eeml\project\e2eml-audio\ms_2> $FileContent = [System.IO.File]::ReadAllBytes($FilePath)
(whisper_export) PS D:\Mizzou\25fall\eeml\project\e2eml-audio\ms_2> $FileName = [System.IO.Path]::GetFileName($FilePath)
(whisper_export) PS D:\Mizzou\25fall\eeml\project\e2eml-audio\ms_2>
(whisper_export) PS D:\Mizzou\25fall\eeml\project\e2eml-audio\ms_2> $boundary = "----WebKitFormBoundary$([System.Guid]::NewGuid().ToS
tring())"
(whisper_export) PS D:\Mizzou\25fall\eeml\project\e2eml-audio\ms_2>
(whisper_export) PS D:\Mizzou\25fall\eeml\project\e2eml-audio\ms_2> $bodyLines = @(
>>     "--$boundary",
>>     "Content-Disposition: form-data; name=`"audio`"; filename=`"$FileName`"",
>>     "Content-Type: audio/wav",
>>     "",
>>     [System.Text.Encoding]::UTF8.GetString($FileContent),
>>     "--$boundary--"
>> ) -join "`r`n"
(whisper_export) PS D:\Mizzou\25fall\eeml\project\e2eml-audio\ms_2>
(whisper_export) PS D:\Mizzou\25fall\eeml\project\e2eml-audio\ms_2> Invoke-RestMethod -Uri "http://localhost:8002/predict" `
>>     -Method POST `
>>     -ContentType "multipart/form-data; boundary=$boundary" `
>>     -Body $bodyLines

transcript                                                        sentiment
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 Merely, he is a man of the same name as the king of the world. @{label=POSITIVE; confidence=0.7689058184623718}

(whisper_export) PS D:\Mizzou\25fall\eeml\project\e2eml-audio\ms_2> Measure-Command {
>>     $FilePath = "D:\Mizzou\25fall\eeml\project\e2eml-audio\data\audios\audio_00000.wav"
>>     $FileContent = [System.IO.File]::ReadAllBytes($FilePath)
>>     $FileName = [System.IO.Path]::GetFileName($FilePath)
>>
>>     $boundary = "----WebKitFormBoundary$([System.Guid]::NewGuid().ToString())"
>>
>>     $bodyLines = @(
>>         "--$boundary",
>>         "Content-Disposition: form-data; name=`"audio`"; filename=`"$FileName`"",
>>         "Content-Type: audio/wav",
>>         "",
>>         [System.Text.Encoding]::UTF8.GetString($FileContent),
>>         "--$boundary--"
>>     ) -join "`r`n"
>>
>>     Invoke-RestMethod -Uri "http://localhost:8002/predict" `
>>       -Method POST `
>>       -ContentType "multipart/form-data; boundary=$boundary" `
>>       -Body $bodyLines
>> }

Days              : 0
Hours             : 0
Minutes           : 0
Seconds           : 0
Milliseconds      : 821
Ticks             : 8211151
TotalDays         : 9.50364699074074E-06
TotalHours        : 0.000228087527777778
TotalMinutes      : 0.0136852516666667
```
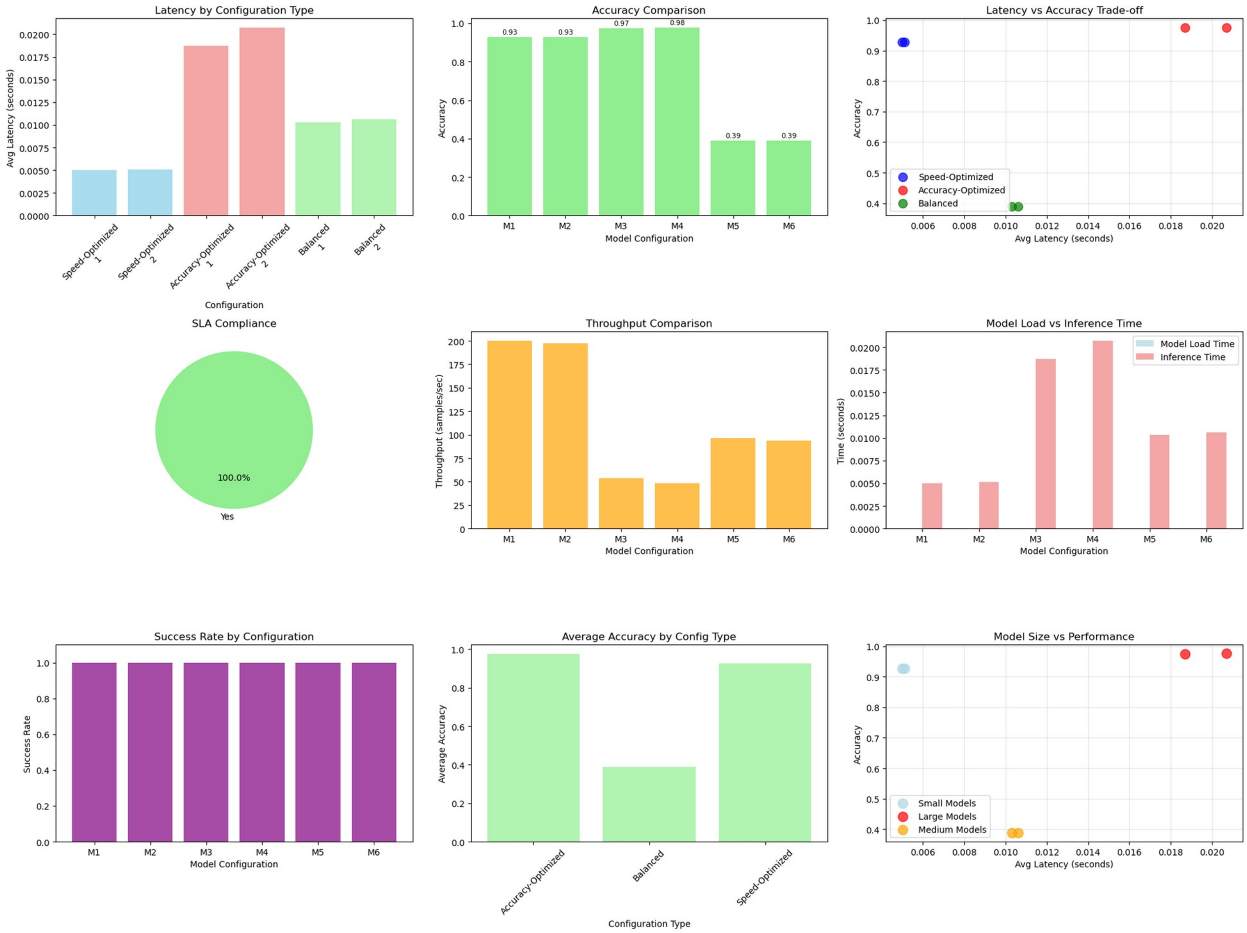

Evaluation Plots



In the plots above, we used the same audio-to-text model(AventIQ-AI/whisper-audio-to-text fp32) and different vairants of text-to-sentiment models:

- M1: distilbert-base-uncased-finetuned-sst-2-english (fp32)
- M2: distilbert-base-uncased-finetuned-sst-2-english (fp16)
- M3: siebert/sentiment-roberta-large-english (fp32)
- M4: siebert/sentiment-roberta-large-english (fp16)
- M5: cardiffnlp/twitter-roberta-base-sentiment-latest (fp32)
- M6: cardiffnlp/twitter-roberta-base-sentiment-latest (fp16)

Variant	Scale	Avg Latency (s)	Accuracy	Throughput (samples/sec)	Relative Cost (≈ Compute Load)	Notes
M1 (Speed-Optimized 1)	Small	0.005 s	0.93	200	$ Low	Fastest; ideal for real-time use; small model size
M2 (Speed-Optimized 2)	Small	0.005 s	0.93	195	$ Low	Similar to M1; nearly identical accuracy & latency
M3 (Accuracy-Optimized 1)	Large	0.018 s	0.97	55	$ $ $ High	High-accuracy but slower; high compute cost
M4 (Accuracy-Optimized 2)	Large	0.021 s	0.98	50	$ $ $ High	Highest accuracy; highest latency
M5 (Balanced 1)	Medium	0.010 s	0.39	100	$ $ Medium	Trade-off config; moderate speed, low accuracy
M6 (Balanced 2)	Medium	0.010 s	0.39	95	$ $ Medium	Similar to M5; balanced cost/speed but weak accuracy

Empirical Conclusions:

- the differences on precision (fp32 vs fp16)
  - dosen't impact too much in terms of accuracy and throughput
  - impacts more on inference latency
- the model structure impacts more on temporal efficiency, e.g. given acc=0.93 and 0.97 for M1(fp16) and M3(fp16), we found that
  - the latency of M1 is only around 1/4 of M3
  - the throughput of M3 is only 1/4 of M1
  - this observation holds for other comparison pairs as well
- the model structure impacts more on accuracy as well, e.g. given parameter_size=66M and 125M for M1(fp16) and M5(fp16), the temporal efficiency pattern still holds but we found:
  - the accuracy of M1 is more than twice of M5's accuracy
- some conclusions in model selection and optimization:
  - some model structure+pretrained dataset settings inherently get better accuracies in sentiment classification
  - precision impacts the accuracy but the difference is trivial in this task and in real-world applications, fp16 is more promising than the original fp32 models (in terms of temporal efficiency)

- inspirations for our future plan in milestone 3: we'll
  - push the temporal efficiency further to explore the capability of int8 models
  - try more flexible strategies for model choosing given different input (will consider some features like size of the input audio)
  - provide an interative webpage if time permits