Identifying and Removing Advertisements from Nepali Video

(M.Sc. Project Mid Defense)

Presenter
Sarthak Pokharel
THA078MSISE18

Supervisor
Er. Bibek Ropakheti
Assistant Professor

M.Sc. in Informatics and Intelligent Systems Engineering
Department of Electronics and Computer Engineering
Institute of Engineering, Thapathali Campus

Presentation Outline

Motivation

Background

Problem Statement

Objectives of Project

Scope of Project

• Originality of Project

• Potential Applications

• Literature Review

Proposed Methodology

Results

Discussion and Analysis

References

Motivation



Background

- Video advertisement : a major marketing strategy
- Companies in FMCG, financial institutions, body products and many other industries all invest heavily

- Advertisements does not always reach target audience
- Identifying advertisements makes it easier to reach target group

Problem Statement

- Nepalese media have a different broadcasting pattern
- Previous researches fail in classifying Nepali advertisement
- Media-houses/Broadcasters are not able to insert advertisement of choice

Nepali media dataset is inadequate for proper research

Objectives of Project

- To identify advertisement sections in Nepali videos
- To crop the advertisement and prepare a clean feed video

Scope of Project

- Project Capabilities:
 - Is able to classify advertisements that are in Nepali videos
 - Is able to provide the medium for inserting new contents
- Project Limitations
 - Is not able to detect advertisements that are part of the movies
 - Is not able to classify advertisements into different categories
 - Is not able to identify musical advertisement in between movies

Originality of Project

- The major contributions of this project work are as follows:
 - Automatic advertisement detection in Nepali videos is explored
 - MFCC and LSTM are used in detecting advertisements
 - ANepali video dataset having uniform format is prepared

Potential Applications

- Broadcasters:
 - Previously contained ads can be eliminated to insert new ones
- Creators:
 - Own contents can be implemented by creators
- Audience:
 - Irritating ads can be removed by audiences
 - Contents could be made more engaging
- Government Bodies:
 - Manual work can be eliminated while applying clean feed
 - Potential researches can be performed on the domain

Literature Review - [1]

Paper	Year	Author	Methodology	Results	Weaknesses	Strengths
Robust	2005	Xian-	Context based	The technique	Exclusive to	Accuracy
Learning Based TV commerci		Sheng Hua, Lie Lua,	feature derived from set of 6 features	worked well on identifying black frames of ads	US adverts.	with post processin g was
al		et. al.	were used			95.84%
detection						and without was 94.42%
Identification	2005	J.M.	Features	Worked well on	Dataset	KNN had an
of new commercial s using repeated video		Gauc h, A. Shivadas	extracted from commercials were matched and embedded codes	unseen ads and detected the previous occurrence of ads by video	confined to US and used traditional ML algorithms	F measure of 95% for ad- detection
sequenc			were	transition marking		10
6 /19/2024			detected			

Literature Review - [2]

Paper	Year	Author(s)	Methodology	Results	Weaknesses	Strengths
Detecting Ads in Video Stream using Acoustic and Visual Cues	2006	Michele Covell, Shumeet Baluja, et. al.	Identifying/ Interpreting the visual cues with dataset from 4 days	The use of visual cues were able to increase efficiency than other traditional techniques by 40%	Only worked on rebroadcast e d programs	Precision was above 99% and recall rate was 95%
Audio and Video Processing for Automatic TV Advertisement Detection 5/19/2024	2008	Sean Marlow, David A. Sadlier, et. al.	Ad-breaks were detected by finding patterns of silent black frames	Were tested in 3 different videos and provided satisfactory result	Only worked in mpeg video stream and used 3 videos as testing datas	Precision figure s over 99.7 % were achieved

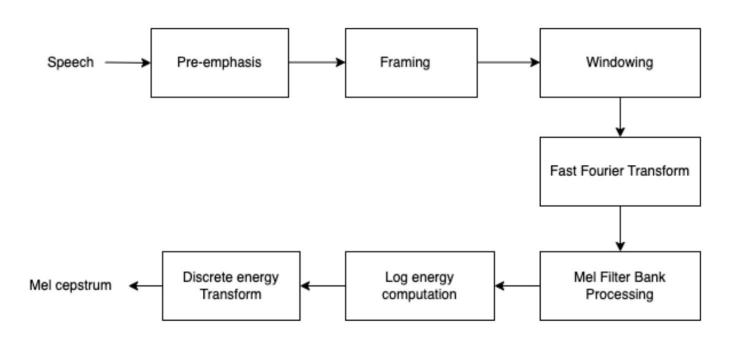
Literature Review - [3]

Paper	Year	Author(s)	Methodology	Results	Weaknesses	Strengths
AdNet: A Deep Network for Detecting Adverts	2018	Murhaf Hossari, Soumyab r ata Dev, et. al.	Adding 4 more layers in the VGG19 architecture	The model compared far well than the then state of the art Inception-V3 model which had accuracy of 56%	Didn't work in outdoor scenario ads and other than billboard ads	The model had an accuracy of 94% on detecting billboar d ads
An Automated Framework for Advertisement Detection and Removal from Sports Videos	2021	Abeer Toheed, Ali Javed, et. Al	Audio-visual cues of sports videos	Performance were evaluated among different SOTA techniques and performed well.	Only worked on sports videos	Provided an average accurac y of 98.75% over 5

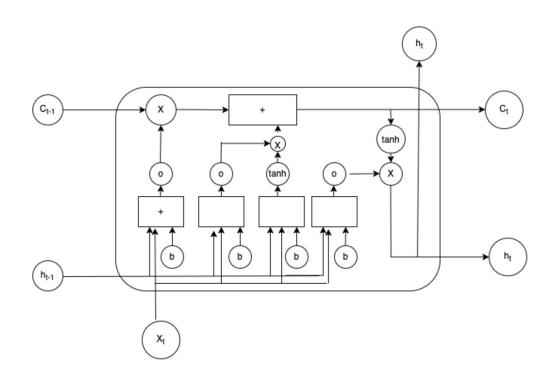
(Theoretical Formulations)

- MFCC with LSTM will be used as a deep learning model
- MFCC will extract different features from audio file
- LSTM then learns the features and classifies input into 3 different categories
- The classified advertisements are removed and clean feed is generated

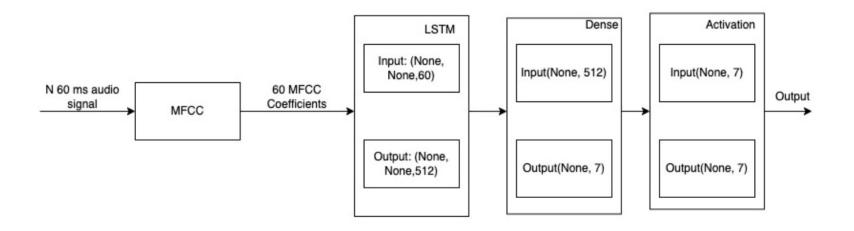
Methodology (Mathematical Modeling - [1])



Methodology (Mathematical Modeling - [2])



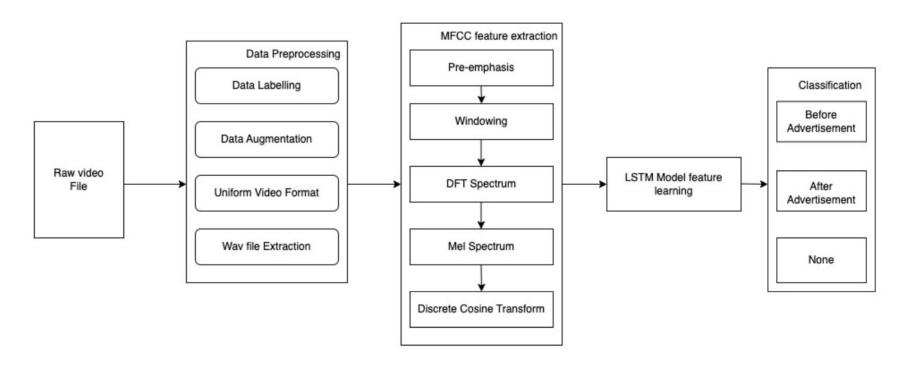
(Mathematical Modeling - [3])



(Combining MFCC with LSTM)

- MFCC enables the ability to analyze the audio signal
- LSTM learn features generated from MFCCs to learn long-term dependencies
- LSTM has four neural network layer which interacts in a very special way

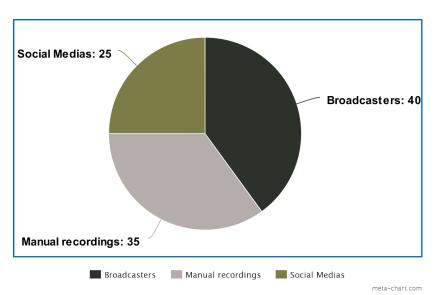
(System Block Diagram)

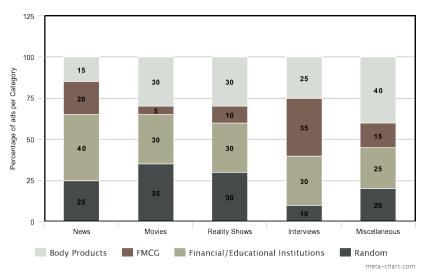


Methodology (Instrumentation)

Hardware Requirements	Software Requirements
 TPU: Needed to execute computation intensive tasks Obtained from TPU Research Cloud 	 Python: Code for the project will be written in Python programming language Python version 3.x will be used
 GPU: Needed to facilitate processing Obtained from local computer(M1 MacBook Pro) 	 IDE: Jupyter Notebook will be used for local development Google collar will be used for web development
 High Core CPU: High performance RAM will be used to make execution faster Obtained from local computer(M1 Macbook Pro) 	Tensorflow: • Tensorflow 2.0 will be used as a Machine Learning framework

(Sources and Analytics of Dataset)



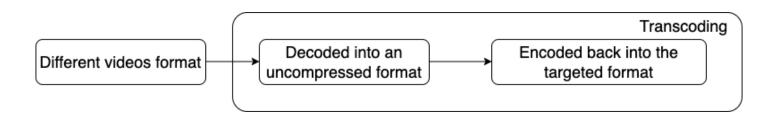


Sources of Dataset

Category of Ads

(PreprocessingAlgorithms - [1])

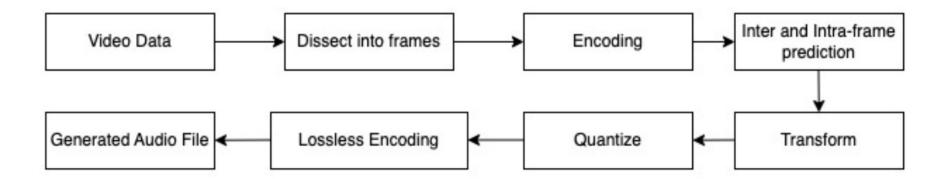
- Movavi video converter will be used
- Videos are first decoded into uncompressed to produce higher quality frames



Videos are encoded back into targeted format

(PreprocessingAlgorithms - [2])

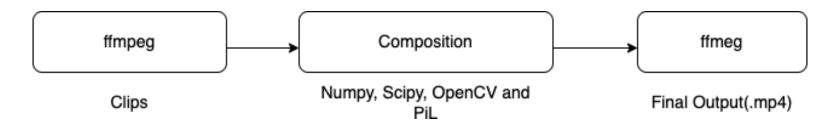
FFMPEG will be used to extract audio from raw video



(Post-processingAlgorithm)

 After classifying advertisements, MoviePy will be used to merge the frames

 The ffmpeg clips are composited using Python libraries and final output(.mp4) is generated



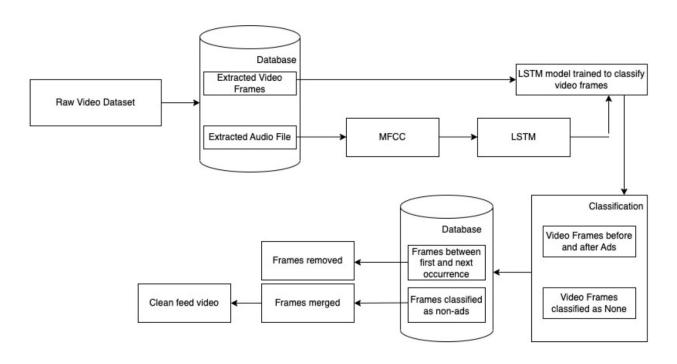
(Elaboration of Working Principle - [1])

- The raw video is passed and stored in temporary database
- The video is converted into a audio(.wav) file
- MFCC features are extracted and is followed by LSTM model
- The LSTM model learns the feature and classifies it into before ad, after ad and none category

(Elaboration of Working Principle - [2])

- The frames classified as none gets tired in database with nonad category column
- The frames after first occurrence of break emphasis are stored as advertisement category
- The frames get stored until the next occurrence of word
- The frames with none category are combined to produce a clean feed video

(Elaboration of Working Principle - [3])



(Model Evaluation - [1])

 Categorical cross entropy loss function is used in the classification block

The model terminates when the epochs is equal to 100

Precision/Recall and F1 score is used to evaluate model performance

(Model Evaluation - [2])

Some manually developed metrics will also be used

$$CCR = \frac{CorrectlyClassifiedFrames}{TotalFrames} * 100$$

$$NCR = \frac{FalselyClassifiedFrames}{TotalFrames} * 100$$

Correctly Classified Rate

Negatively Classified Rate

$$PPCR = \frac{FramesIdentifiedasAdvertisement}{TotalAdvertisementFrames} * 100$$

$$PPCR = \frac{FramesIdentifiedasAdvertisement}{TotalAdvertisementFrames}*100 \quad PNCR = \frac{FramesIdentifiedasAdvertisement}{TotalNon-Advertisement}*100$$

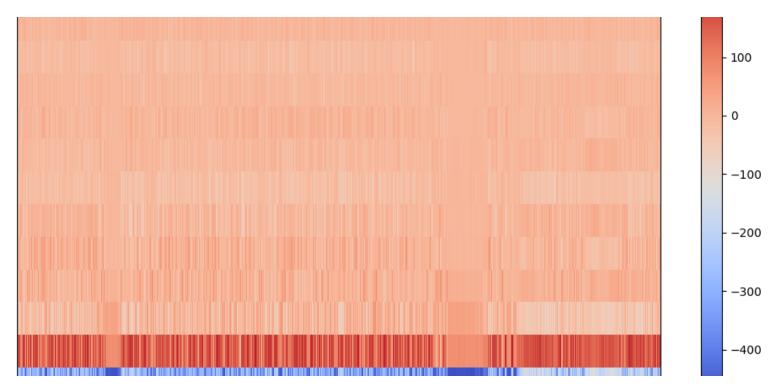
Partially Positive Classified Rate Partially Negative Classified Rate

Results - [1]

 MFCC of advertisements and non-advertisements are generated

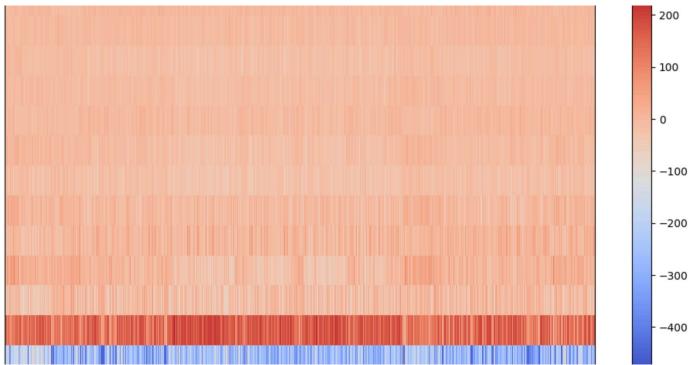
The MFCC plots of these sections are visibly different.

Results - [2]



MFCC plot of advertisement

Results - [3]



MFCC of news section

Results - [4]

```
youtube = build('youtube', 'v3', developerKey=api_key)
def download youtube video(video url, output path='downloaded video.mp4'):
    yt = YouTube(video_url)
    stream = yt.streams.filter(only_audio=True).first()
    stream.download(filename=output_path)
    return output_path
# Convert video file to .wav
def convert to wav(video path, audio path='output audio.wav'):
    # Extract audio from video
    audio_clip = AudioFileClip(video_path)
    audio_clip.write_audiofile(audio_path, codec='pcm_s16le')
    audio clip.close()
def search videos(query, max results=10):
    # Make an API call to search for videos
    request = youtube.search().list(
        q=query,
        part='id, snippet',
```

Python code to download YouTube video and convert it to audio

Results - [5]

```
Response', 'etag': 'QV1cp069YAk3ES1Tg9PEIle6iwM', 'nextPageToken': 'CAEQAA', 'regionCode': 'US', 'pageInfo': {'to
नियाँका दिनभरका मुख्य समाचार | असार १८, मंगलबार, बिहान ११ बजे | AP1HD
NIRAJAN BHANDARI HEADLINES: १.प्रधानमन्त्रीलाई भेटन एमाले ...
```

/watch?v=Ad930CNE780
utput audio.wav

MoviePy - Done.

Response of YouTube downloading code

Discussion And Analysis

Google project creation

- Youtube download and conversion to audio
- MFCC plot of advertisement and news section manually

MFCC is good for audio signals.

Remaining Tasks

Dataset finalization

LSTM Model creation

Model building, training and evaluation.

Result interpretation

References - [1]

1Xian-Sheng Hua, Lie Lu, and Hong-Jiang Zhang. Robust learning-based tv commercial detection. In 2005 *IEEE International Conference on Multimedia and Expo,* pages 4 pp.—, 2005.

2J.M. Gauch and A. Shivadas. Identification of new commercials using repeated video sequence detection. In *IEEE International Conference on Image Processing 2005*, volume 3, pages II–1252, 2005.

3Michele Covell, Shumeet Baluja, and Michael Fink. *Detecting ads in video streams using acoustic and visual cues.* Computer, 39:135 – 137, 01 2007.

4Shervin Minaee, Imed Bouazizi, Prakash Kolan, and Hossein Najafzadeh. *Ad-net: audio-visual convolutional neural network for advertisement detection in videos.* arXiv preprint arXiv:1806.08612, 2018.

References - [2]

5Abeer Toheed, Ali Javed, Aun Irtaza, Hassan Dawood, Hussain Dawood, and Ahmed S Alfakeeh. *An automated framework for advertisement detection and removal from sports videos using audio- visual cues.* Frontiers Comput. Sci., 15(2):152313, 2021.

6Zihang Dai, Hanxiao Liu, Quoc V Le, and Mingxing Tan. Coatnet: Marrying convolution and attention for all data sizes. Advances in Neural Information Processing Systems, 34:3965–3977, 2021.

7SeÅLan Marlow, David A Sadlier, Karen McGeough, Noel E O'Connor, and Noel Murphy. *Audio and video processing for automatic tv advertisement detection.* 2001.

8Ramin Zabih, Justin Miller, and Kevin Mai. A feature-based algorithm for detecting and classifying scene breaks. In *Proceedings of the third ACM international conference on Multimedia*, pages 189–200, 1995.

Thank You!