

PROJECT REPORT

Title: Lip-Reading using Deep Learning

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Source Code GitHub & Project Demo Link

1. Introduction

In the realm of communication technology, lip reading stands as a remarkable facet, enabling individuals to comprehend spoken language through visual cues. Its significance extends beyond aiding those with hearing impairments, encompassing scenarios where traditional audio-based communication systems face challenges, such as noisy environments or cross-lingual interactions. The amalgamation of deep learning techniques with lip reading holds promise in revolutionizing how we perceive and interpret spoken language, offering an alternative modality that enhances accessibility and inclusivity.

1.1 Project Overview

This project embarks on a multifaceted journey, leveraging the potential of deep learning methodologies to craft a sophisticated lip reading system. At its core, the project involves the acquisition and curation of extensive datasets capturing diverse lip movements and speech patterns. These datasets serve as the foundation for training intricate neural network architectures, harnessing Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and advanced attention mechanisms. The synthesis of these components aims to empower the system with the ability to accurately predict spoken words solely from visual information in real time.

The development process spans various stages, encompassing data preprocessing, model training, validation, and the design of

an intuitive user interface. The system's interface, carefully crafted for simplicity and ease of use, aims to present predictions seamlessly, catering to a diverse user base ranging from individuals with varying technical expertise to corporate entities seeking efficient communication tools.

1.2 Purpose

At the heart of this endeavor lies a profound aspiration: to create a technological marvel that transcends limitations in communication. The primary purpose of this project is to design a system that empowers individuals with hearing impairments by providing a reliable, real-time interpretation of spoken language through lip movements. Beyond this core objective, the project seeks to explore the broader landscape of lip reading technology, delving into its potential applications in noisy environments where audio-based systems falter and in cross-lingual scenarios where language barriers pose challenges.

This project's purpose extends beyond innovation; it resonates with the vision of fostering inclusivity, accessibility, and efficiency in communication. By merging cutting-edge technology with a humanitarian cause, this initiative aspires to redefine how we perceive and engage with spoken language, transcending barriers and revolutionizing communication paradigms.

2. Literature Survey

Lip Reading Using Deep Learning

I. Introduction

Lip reading, an intricate process involving the interpretation of spoken language through observing lip movements, has garnered substantial interest in recent years. This comprehensive literature survey aims to delve into the extensive body of research and advancements in developing deep learning-based lip-reading systems. By exploring methodologies, current state-of-the-art techniques, challenges, and potential applications, this survey aims to provide a thorough understanding of the field.

II. Evolution of Lip-Reading Systems

Early Systems: Rule-Based Approaches

Early attempts relied on manual feature extraction and predefined rules to interpret lip movements. However, these systems struggled with accuracy due to their inability to encompass the complexity of natural speech movements.

Transition to Machine Learning

Moving away from rule-based systems, machine learning techniques like Hidden Markov Models and Support Vector Machines were explored. While an improvement, they still faced limitations in capturing the intricate temporal and spatial features of lip movements.

Emergence of Deep Learning

The advent of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) revolutionized lip reading. CNNs excel in spatial feature extraction, while RNNs model temporal dynamics, significantly enhancing accuracy.

Advances in Model Architectures

Refinement and adaptation of neural network architectures, including 3D CNNs and LSTM networks, enabled better capture of both spatial and temporal information, leading to improved accuracy.

Integration of Attention Mechanisms

The introduction of attention mechanisms allowed models to dynamically focus on crucial lip regions, significantly boosting accuracy, especially in challenging scenarios.

This progression signifies a shift from rule-based methods to the integration of sophisticated deep learning techniques, driving lip reading systems towards enhanced accuracy, adaptability, and inclusivity in communication technologies.

III. Current Landscape of Deep Learning in Lip Reading

Deep Learning Architectures

i. Convolutional Neural Networks (CNNs)

CNNs have been pivotal in extracting spatial features from visual inputs. In lip reading, these networks excel at capturing lip movement patterns, leveraging their ability to detect and analyze spatial features over time. Their hierarchical structure enables the extraction of increasingly complex representations, aiding in accurate feature extraction from lip sequences.

ii. Recurrent Neural Networks (RNNs)

RNNs specialize in handling sequential data, making them invaluable for modeling the temporal dynamics inherent in lip movements. By considering the sequential nature of lip motion, RNNs capture dependencies over time, enabling context-aware predictions and improving accuracy in interpreting spoken language from lip movements.

iii. 3D Convolutional Neural Networks

These architectures extend CNNs to capture spatial and temporal information simultaneously. By incorporating the temporal dimension, these models provide a more comprehensive understanding of lip movements over time, resulting in improved feature extraction and predictive capabilities.

Feature Representation

i. Optical Flow Estimation

Optical flow techniques estimate the motion of pixels between consecutive frames in video sequences. In lip reading, this method aids in understanding the dynamics of lip movements, providing valuable information about the speed and direction of motion, contributing to more precise feature extraction.

ii. Appearance-Based Features

These features capture the visual appearance of lips, focusing on color, texture, and shape variations. Extracting appearance-based features helps in understanding lip shapes and patterns, enhancing the discriminative power of lip reading models.

iii. Attention Mechanisms

Attention mechanisms dynamically focus on relevant regions of lip sequences. By adaptively highlighting significant parts during the prediction process, these mechanisms significantly enhance accuracy, particularly in scenarios with varying lip movements, facial expressions, or occlusions.

IV. Methodologies and Techniques

Model Training and Optimization

i. Large-Scale Training Datasets

Efforts have been directed towards collecting and curating extensive annotated datasets. Large-scale datasets aid in training robust models, enabling them to generalize well to various lip movement patterns and conditions.

ii. Transfer Learning

Transfer learning techniques leverage pre-trained models on large datasets for initializing lip reading models. This approach allows the utilization of learned representations from related tasks, enhancing the model's performance in lip reading tasks, particularly in scenarios with limited labeled data.

Fusion of Modalities

Integration of audio and visual information through multimodal learning has been explored to improve lip reading accuracy. Combining lip movements with corresponding audio signals enhances the contextual understanding, contributing to more accurate speech recognition from visual cues.

By integrating and innovating on these methodologies and techniques, researchers aim to create more accurate, adaptable, and context-aware lip reading systems, fostering advancements in communication technologies and assistive applications.

V. Evaluation and Benchmarking

Datasets:

Analysis of benchmark datasets such as GRID, LRW, LRW-1000, LRW-5000, and the challenges they pose in terms of variability,

size, and annotation quality. Emphasis on the need for diverse and comprehensive datasets for robust model development.

Performance Metrics:

Utilization of various evaluation metrics including word accuracy, sentence-level accuracy, and frame-level accuracy to benchmark and compare the performance of lip reading systems.

VI. Challenges and Limitations

Variability in Lip Movements:

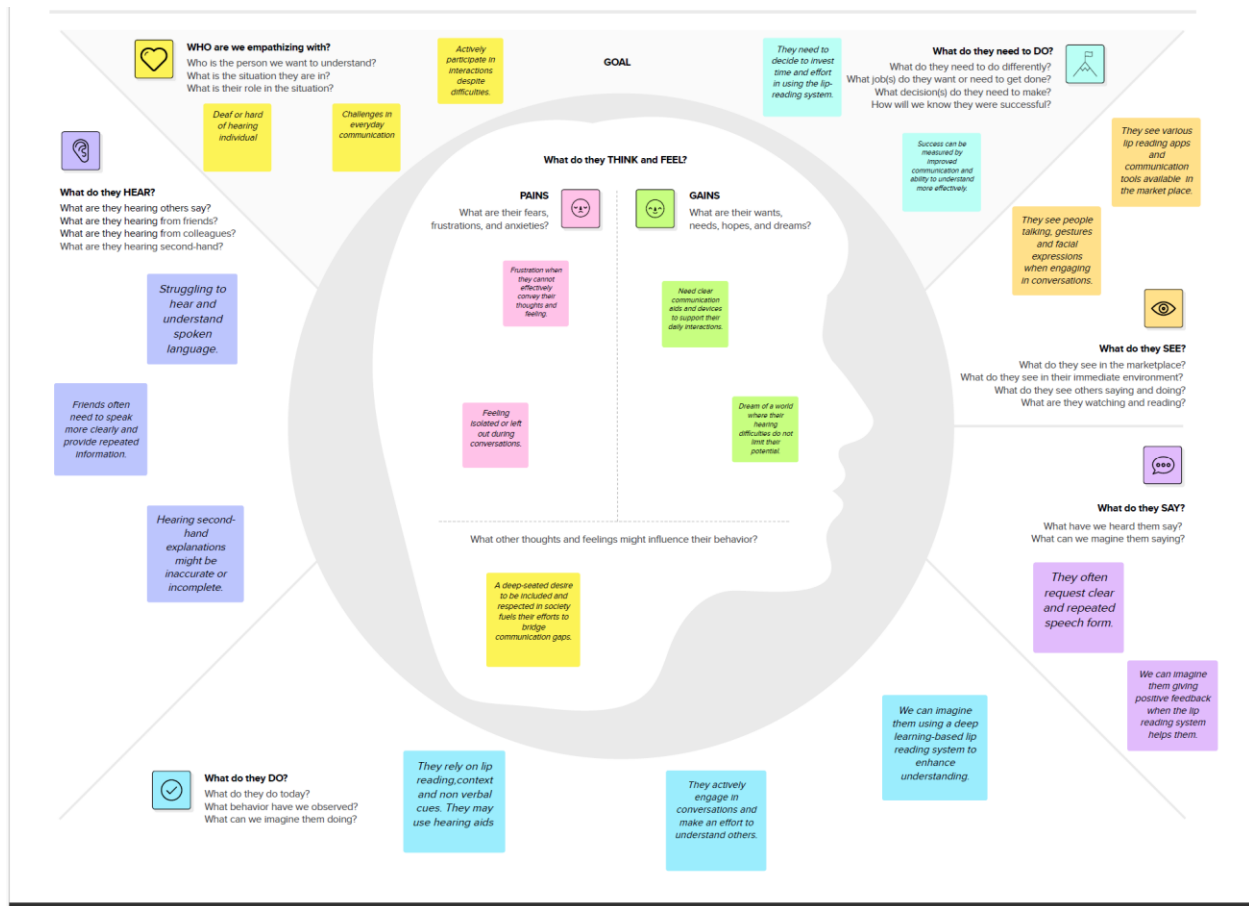
Speech variability, accents, facial expressions, lighting conditions, and occlusions pose challenges in accurately interpreting lip movements, impacting system accuracy.

Data Scarcity and Diversity:

The scarcity of diverse, large-scale annotated datasets hinders the training of robust and adaptable models, limiting real-world applicability.

3. Ideation and Proposed Solution

3.1 Empathy Map



3.2 Brainstorming and Prioritising

1

Define your problem statement

What problem are you trying to solve? Frame your problem as a How Might We statement. This will be the focus of your brainstorm.

PROBLEM

How might we create a lip reading system that offers speech recognition, enabling individuals with hearing difficulties to participate fully in spoken conversations and overcome communication barriers?

2

Brainstorm

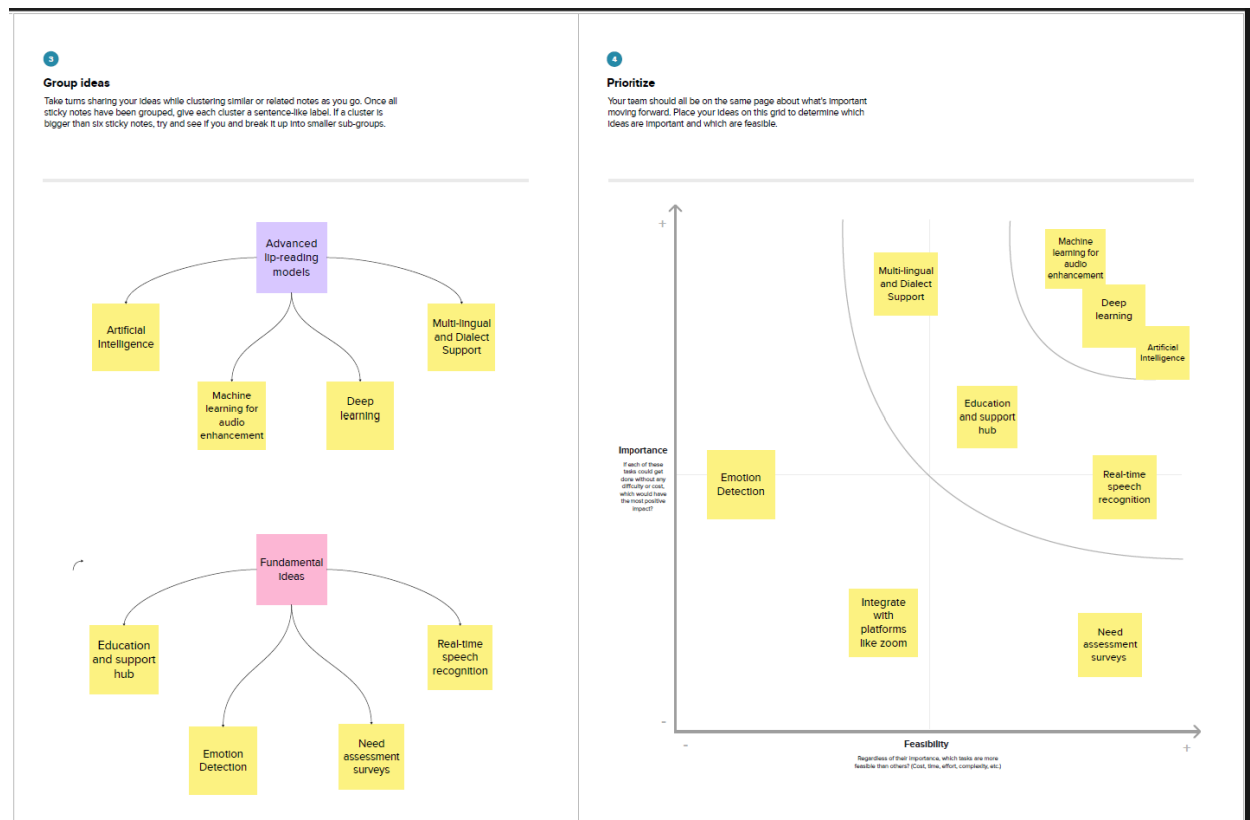
Write down any ideas that come to mind that address your problem statement.

Rashmi MT

Artificial Intelligence	Deep learning	Mobile app
Audio and facial recognition + lip reading	Real-time speech recognition	Education and support hub

Siddharth Bhardwaj

Lip reading smart glasses	Machine learning for audio enhancement	Integrate with platforms like zoom
Multi-lingual and Dialect Support	Emotion Detection	Need assessment surveys



3.3 Proposed Solution

S.No.	Parameter	Description
1.	Problem Statement (Problem to be solved)	How might we create a lip reading system that offers speech recognition, enabling individuals with hearing difficulties to participate fully in spoken conversations and overcome communication barriers?
2.	Idea / Solution description	To create a lip-reading system aiding those with hearing difficulties, employ deep learning techniques. Begin by amassing a diverse dataset featuring video clips of speakers, then transcribe the spoken content for ground truth. Build a two-part model: a lip-reading component (CNN or CNN-RNN) to process video frames, and a speech recognition module (RNN or transformer) to convert audio into text. Fuse their outputs for optimal results. Train the model with the dataset, optimize for both tasks, and offer real-time processing. Design a user-friendly interface for real-time text transcription, considering privacy and ethics. This empowers individuals with hearing difficulties to participate fully in spoken conversations.

- | | | |
|----|---------------------------------------|---|
| 3. | Novelty / Uniqueness | <p>The distinctiveness of this solution is its integration of deep learning for both lip reading and speech recognition. It uses diverse data for robustness, includes real-time processing, offers user customization, and prioritizes privacy. These aspects make it uniquely comprehensive and user-focused, effectively addressing communication barriers for individuals with hearing difficulties while respecting ethical data practices. This innovative approach fosters inclusivity and empowers users to actively participate in spoken conversations.</p> |
| 4. | Social Impact / Customer Satisfaction | <p>The social impact and customer satisfaction of this solution are substantial. It greatly enhances the lives of individuals with hearing difficulties by enabling them to actively engage in spoken conversations, breaking down communication barriers. Users experience increased independence and inclusion, which positively impacts their quality of life. The customizable features and real-time transcription ensure high customer satisfaction, as the system is tailored to individual needs. Overall, this innovative solution not only improves communication but also fosters a more inclusive and empathetic society.</p> |
| 5. | Business Model (Revenue Model) | <p>The business model for the lip-reading system for individuals with hearing difficulties can include various revenue streams:</p> <ul style="list-style-type: none"> - Subscription model for users and institutions. - Licensing to hearing aid and device manufacturers. - Enterprise solutions with training and support services. - Data monetization through anonymized, aggregated data. - Donations and grants for accessibility initiatives. - Collaborations with relevant organizations. - Specialized hardware device sales. - Custom development services. - Consulting and training for effective integration. - Advertising and sponsorship opportunities. - Data analytics services for user insights. - Accessibility certification services. |
| 6. | Scalability of the Solution | <p>The solution is highly scalable:</p> <ul style="list-style-type: none"> - Cloud-based infrastructure for flexible resource allocation. - Parallel processing for efficient model training. - Expanding data and language support. - Integration into various platforms. - Global accessibility. - Continuous improvement through user feedback. |

- Potential for business model diversification and partnerships to facilitate scalability.

4. Requirement Analysis

4.1 Functional Requirements

i. Lip Movement Recognition:

The system should accurately recognize and interpret various lip movements to derive spoken words.

It should differentiate between different phonemes and syllables to construct accurate word predictions.

ii. Real-Time Processing:

The system must process lip movements swiftly, providing near real-time predictions for seamless communication.

It should maintain low latency to ensure quick responses to lip movement inputs.

iii. *Adaptability to Diverse Speech Patterns:*

It should be capable of accommodating diverse speech patterns, accents, and speaking speeds for broad applicability.

iv. *Multimodal Integration:*

If applicable, the system can integrate additional modalities (such as audio) to enhance accuracy and contextual understanding.

v. *User Interface:*

A user-friendly interface that presents predictions in an intuitive and easily understandable manner.

Options for customization, allowing users to adjust settings based on preferences.

4.2 Non- Functional Requirements

i. *Accuracy:*

The system should achieve a high level of accuracy in predicting spoken words from lip movements.

Aim for a word-level accuracy rate of 90% or higher.

ii. *Reliability and Robustness:*

The system should perform consistently across various scenarios, including different lighting conditions and lip movement variations.

It should handle occlusions or partial visibility of lips without compromising accuracy significantly.

iii. Scalability:

Scalable architecture to handle increased loads or larger datasets without degradation in performance.

Ability to maintain accuracy even with increased usage and diverse user inputs.

iv. Accessibility and Inclusivity:

Ensure the system is accessible and user-friendly for individuals with varying technical expertise.

Compliance with accessibility standards to cater to users with disabilities.

v. Security and Privacy:

Implement measures to ensure data security and user privacy, especially if incorporating additional modalities.

Adherence to data protection regulations and encryption of sensitive user information.

vi. Performance Efficiency:

Optimize resource utilization (e.g., memory, processing power) to ensure efficient system performance, particularly in resource-constrained environments.

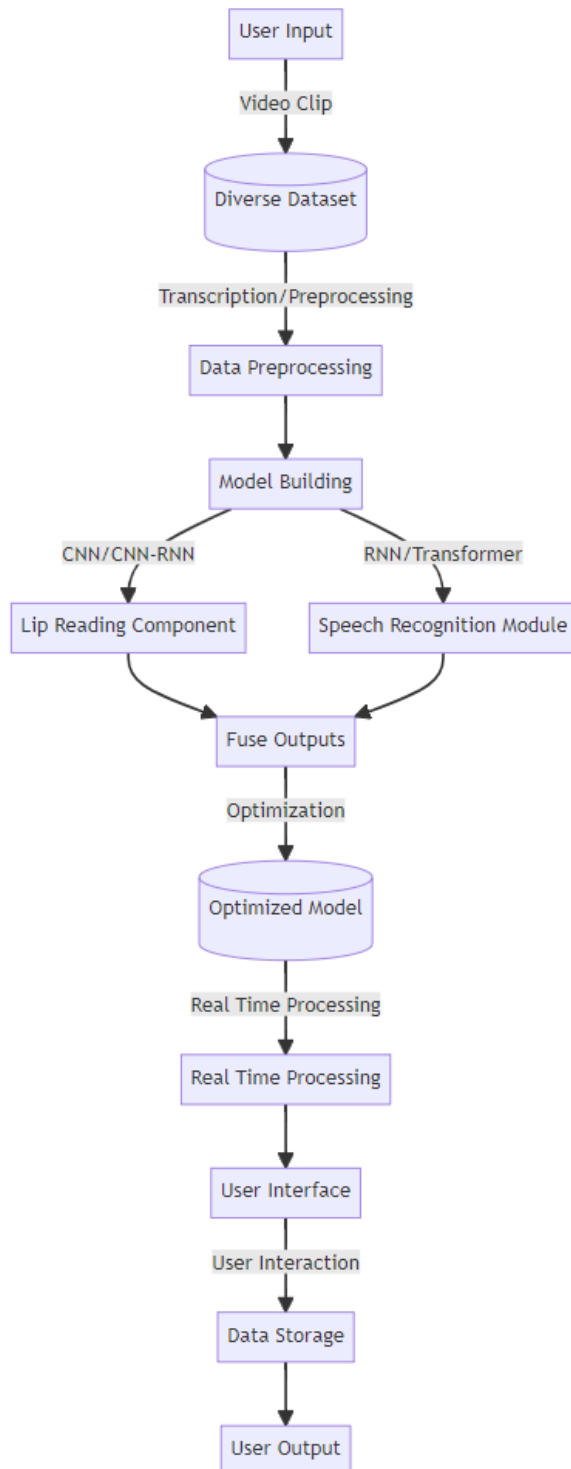
vii. Documentation and Support:

Comprehensive documentation and user support materials to assist users in understanding and utilizing the system effectively.

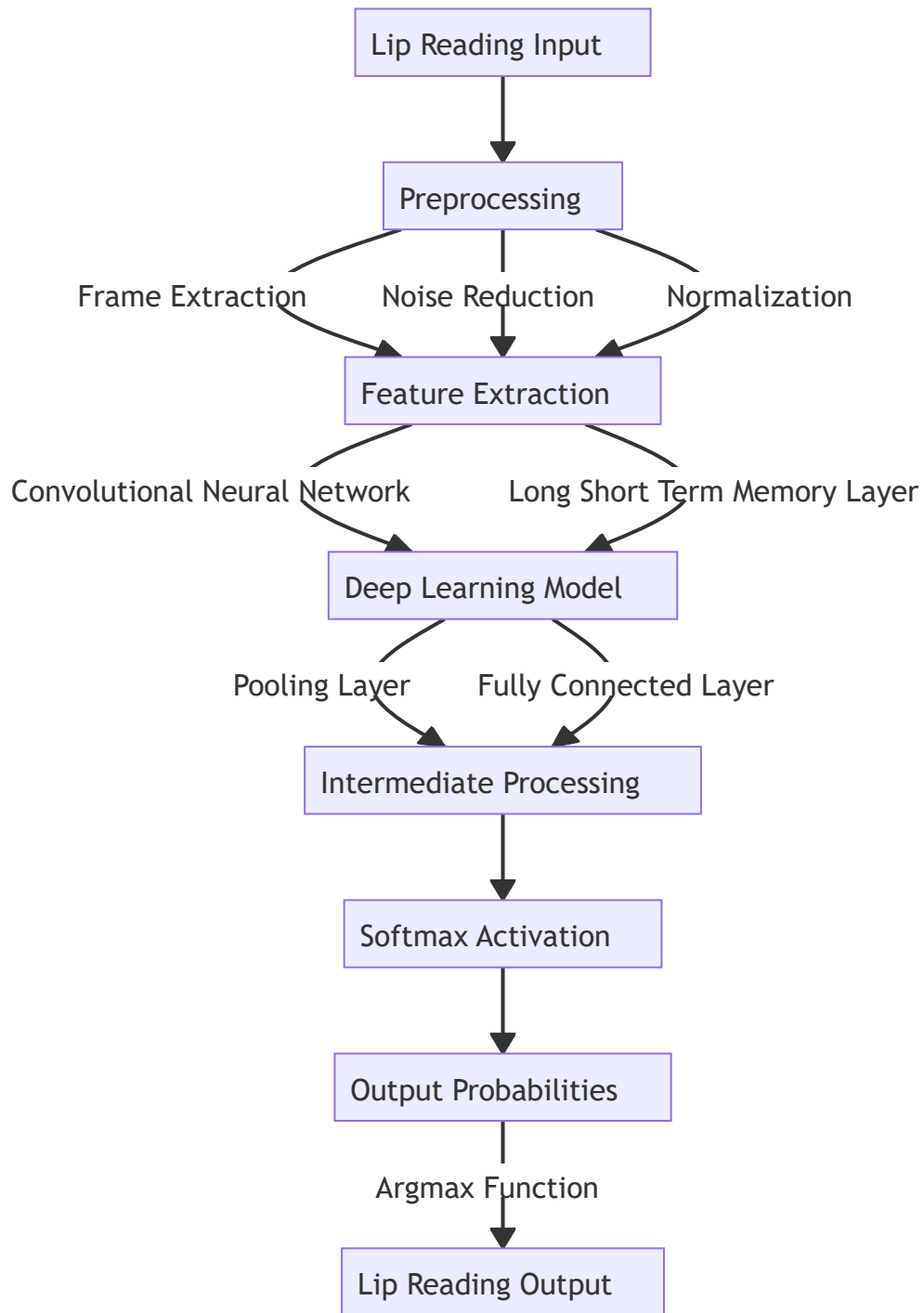
Accessible support channels for users requiring assistance or encountering issues with the system.

5. Project Design

5.1 Data Flow Diagram



5.2 Solution Architecture



1. *Lip Reading Input*: This section represents the source of data for the lip-reading system. It typically includes video or image frames containing a person's lips, which serve as the input for the lip-reading process.
2. *Preprocessing*: Preprocessing involves the initial data cleaning and enhancement steps. This can include tasks like noise reduction, image stabilization, and frame alignment to prepare the lip data for subsequent analysis.
3. *Feature Extraction*: In this stage, relevant features are extracted from the pre-processed lip data. These features might include lip shape, motion patterns, or other visual cues that are essential for lip reading.
4. *Deep Learning Model*: This section represents the core of the architecture. It outlines the neural network model used for lip reading. This model is typically a deep learning architecture, such as a convolutional neural network (CNN) or recurrent neural network (RNN), designed to learn and understand the extracted features.
5. *Intermediate Processing*: This stage refers to any additional data transformations or computations that occur within the deep learning model. It might include hidden layers, recurrent connections, or other processing steps within the neural network.
6. *Softmax Activation*: The softmax activation is often applied at the output layer of the neural network. It converts the model's raw predictions into probability distributions over different

classes or phonemes, which represent the likelihood of each phoneme being spoken based on the lip movements.

7. Output Probabilities: This part shows the probabilities generated by the softmax activation layer. Each probability corresponds to the likelihood of a specific phoneme or word being spoken based on the lip movements observed in the input data.

8. Lip Reading Output: This is the final output of the lip-reading system. It typically involves selecting the phoneme or word with the highest probability from the softmax output as the recognized lip-reading result. The output can be in the form of text or phonetic transcription, representing what was spoken by the person based on their lip movements.

6. Project Planning and Scheduling

6.1 Technical Architecture

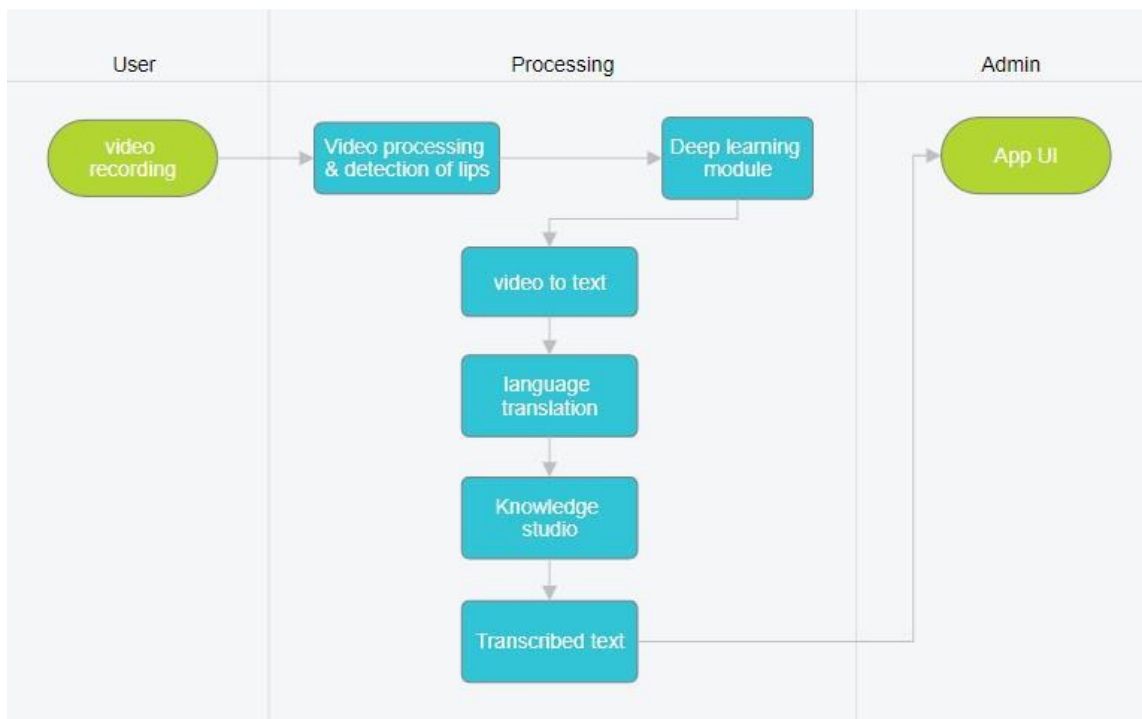


Table-1 : Components & Technologies

S.No	Characteristics	Description	Technology
1	Data Collection	Gather a dataset of video clips showing lip movements and corresponding transcriptions.	Video cameras, data labeling tools
2	Data Preprocessing	Prepare and clean the data for training. This involves video frame extraction, alignment, and cleaning of text data.	Python, OpenCV, Video processing libraries
3	Feature Extraction	Extract relevant features from lip movements and convert them into a format suitable for deep learning models.	Convolutional Neural Networks (CNN), PyTorch, TensorFlow
4	Model Development	Create and train deep learning models for lip reading. You may use various architectures like CNNs, RNNs, or Transformer-based models.	PyTorch, TensorFlow, Keras
5	Training Infrastructure	Utilize hardware resources for training, which can include GPUs or TPUs for faster model training.	NVIDIA GPUs, Google Colab, AWS, Azure
6	Model Evaluation	Assess model performance using evaluation metrics such as accuracy, Word Error Rate (WER), or Character Error Rate (CER).	Python, Evaluation libraries
7	Hyperparameter Tuning	Optimize hyperparameters to improve model performance.	Grid search, random search
8	Model Deployment	Deploy the lip-reading model in a production or application environment.	Web frameworks (e.g., Flask, Django), cloud platforms (e.g., AWS, Azure)
9	Real-time Lip Reading	Develop a real-time lip reading application that captures and processes video streams.	Webcam, OpenCV for real-time video processing
10	User Interface (UI)	Design a user-friendly interface for the lip reading application.	Front-end frameworks (e.g., React, Angular), HTML/CSS
11	Database (optional)	Store and manage data, such as user profiles and transcriptions, if required for the application.	Databases (e.g., PostgreSQL, MongoDB)
12	API Integration (optional)	If needed, integrate with external services or APIs for additional functionality.	API libraries, RESTful APIs
13	Monitoring and Logging	Implement monitoring and logging to track application usage and detect issues.	Logging tools (e.g., ELK stack)
14	Security	Implement security measures to protect data and user privacy.	Encryption, authentication, authorization
15	Documentation	Create thorough documentation for the project, including code, usage guides, and model documentation.	Markdown, documentation platforms (e.g., Read the Docs)

Table-2: Application Characteristics:

S.No	Characteristics	Description	Technology
1	Open-Source Frameworks	Utilizes open-source frameworks for model development and web application.	- Deep learning frameworks: PyTorch, TensorFlow - Web framework (for UI): Flask or Django
2	Security Implementations	Implements security measures to protect data and user privacy, including encryption and access controls.	- Encryption (e.g., TLS/SSL for data in transit), - Access controls (e.g., Role-Based Access Control, JWT) - Use of authentication libraries (e.g., OAuth2, JWT tokens)

3	Scalable Architecture	The application is designed for scalability. The architecture may be a combination of 3-tier or microservices.	<ul style="list-style-type: none"> - Microservices architecture for scalability - Use of containerization (e.g., Docker, Kubernetes)
4	Availability	Ensures high availability through load balancing and distributed servers.	<ul style="list-style-type: none"> - Use of load balancers (e.g., HAProxy, Nginx) - Distribution across multiple data centers or cloud regions
5	Performance	Designed for optimal performance, considering the number of requests per second, cache usage, and content delivery networks (CDNs).	<ul style="list-style-type: none"> - Caching mechanisms (e.g., Redis, Memcached) - Content Delivery Network (CDN) for static assets

6.2 Sprint Planning and Delivery

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-1	User Interface	USN-1	As a user with hearing difficulties, I want a user-friendly interface for real-time text transcription.	3	High	Siddharth Rashmi
Sprint-2	Data Collection and Preprocessing	USN-2	As a data engineer, I want to gather a diverse dataset of video clips with transcriptions.	5	High	Siddharth Rashmi
Sprint-2		USN-3	As a data scientist, I want to develop data preprocessing pipelines for video and audio data.	4	High	Siddharth Rashmi
Sprint-3	Model development	USN-4	As a machine learning engineer, I want to build the lip-reading module using a CNN-based architecture.	8	High	Siddharth Rashmi
Sprint-3		USN-5	As a data scientist, I want to train the lip-reading model on the diverse dataset for lip reading.	7	High	Siddharth Rashmi
Sprint-4	Model Development	USN-6	As a machine learning engineer, I want to develop the speech recognition module using an RNN-based architecture.	8	High	Siddharth Rashmi
		USN-7	As a data scientist, I want to train the speech recognition model on the diverse dataset for speech recognition.	7	High	

7. Coding and Solutions

This Python code imports essential libraries, including OpenCV for computer vision, TensorFlow for machine learning, NumPy for numerical operations, Matplotlib for plotting, and ImageIO for image and video input/output operations.

```
import os
import cv2
import tensorflow as tf
import numpy as np
from typing import List
from matplotlib import pyplot as plt
import imageio
```

The **load_video** function processes a video file specified by a given path. It reads each frame, converts it to grayscale, extracts a specific region of interest, and then normalizes the pixel values across all frames. The normalized frames are returned as a TensorFlow float32 tensor. This function is designed for video pre-processing, likely as part of a pipeline for tasks such as lip reading or video transcription.

```
def load_video(path:str) -> List[float]:
    cap=cv2.VideoCapture(path)
    frames=[]
    for _ in range(int(cap.get(cv2.CAP_PROP_FRAME_COUNT))):
        ret, frame = cap.read()
        frame=tf.image.rgb_to_grayscale(frame)
        frames.append(frame[190:236,80:220,:])
    cap.release()

    mean=tf.math.reduce_mean(frames)
    std=tf.math.reduce_std(tf.cast(frames,tf.float32))
    return tf.cast((frames-mean),tf.float32)/std
```

The code sets the video file path and calls the `load_video` function to preprocess the specified video, storing the normalized frames in the variable `value`.

```
path="/kaggle/input/lipreading/data/s1/bbaf2n.mpg"
value=load_video(path)
value
```

This additional function, named `get_vocab`, retrieves the vocabulary used for the

`CHAR_TO_NUM` function. It iterates through alignment files in a specified directory, extracts the third element of each line, representing the characters, and adds them to the `vocab` list. The resulting list of characters is returned as the vocabulary for the subsequent `CHAR_TO_NUM` function.

```
def get_vocab():
    vocab=[]
    directory="/kaggle/input/lipreading/data/alignments/s1"
    for file in os.listdir(directory):
        file_path = os.path.join(directory, file)
        with open(file_path, 'r') as f:
            lines=f.readlines()
            for line in lines:
                line=line.split()
                vocab.append(line[2])
    return vocab
```

The code defines two TensorFlow StringLookup layers, `char_to_num` and `num_to_char`.

`char_to_num` maps characters to numerical indices using a specified vocabulary, and

`num_to_char` performs the reverse mapping, converting numerical indices back to characters.

Both layers handle out-of-vocabulary cases with an empty string as the out-of-vocabulary token. These layers are commonly used in natural language processing tasks for converting text data between characters and numerical representations.

```
char_to_num= tf.keras.layers.StringLookup(vocabulary=vocab, oov_token="")
num_to_char=tf.keras.layers.StringLookup(vocabulary=char_to_num.get_vocabulary(), oov_token="",invert=True)
```

The `load_alignments` function reads the content of a specified file and processes the lines to extract non-'sil' tokens. It converts these tokens into numerical indices using the `char_to_num` StringLookup layer. The resulting list represents the non-silence tokens as numerical indices. Note: There's a small correction in the code for appending elements to the `tokens` list.

```
def load_alignments(path:str) -> List[str]:
    with open(path, 'r') as f:
        lines=f.readlines()

    tokens=[]
    for line in lines:
        line=line.split()
        if line[2]!='sil':
            tokens= [*tokens, ' ',line[2]]

    return char_to_num(tf.reshape(tf.strings.unicode_split(tokens,input_encoding='UTF-8'),(-1)))[:,1:]
```

The `load_data` function takes a file path, decodes it, extracts the file name, and constructs paths for the corresponding

video and alignment files. It then calls the `load_video` and `load_alignments` functions to load and process the video frames and alignments, respectively. The function returns the loaded frames and alignments as a tuple. This function is likely part of a data loading pipeline for a lip-reading project, where video frames and corresponding alignments are loaded for further processing or training a machine learning model.

```
def load_data(path:str):  
    path=bytes.decode(path.numpy())  
    file_name=path.split('/')[-1].split('.')[0]  
    video_path=os.path.join('/kaggle/input/lipreading/data','s1',f'{file_name}.mpg')  
    alignment_path=os.path.join('/kaggle/input/lipreading/data','alignments','s1',f'{file_name}.align')  
    frames=load_video(video_path)  
    alignments=load_alignments(alignment_path)  
  
    return frames,alignments
```

The code tests the `load_data` function by providing a sample file path

("/kaggle/input/lipreading/data/s1/bbaf2n.mpg") and printing the resulting frames and alignments. It converts the file path to a TensorFlow tensor before passing it to the function. The output will show the loaded frames and corresponding alignments for the specified file.

```
#TESTING THE OUTPUT FOR A SAMPLE FILE  
path="/kaggle/input/lipreading/data/s1/bbaf2n.mpg"  
frames, alignments=load_data(tf.convert_to_tensor(path))  
print("frames:",frames)  
print("alignments:",alignments)
```

This code prepares a TensorFlow dataset for training, testing, and validation by utilizing the **tf.data.Dataset** API. Here's a summary of the key steps:

1. **Mapping Function:**

- The **mappable_function** is defined to use the **load_data** function, converting the file path to frames and alignments.

2. **Dataset Creation:**

- **tf.data.Dataset.list_files** is used to create a dataset of file paths.
- The dataset is shuffled with a buffer size of 500, and **reshuffle_each_iteration** is set to False to maintain the same shuffling order across epochs.
- The **mappable_function** is applied to each element in the dataset using **map**.

3. **Batching and Padding:**

- The dataset is batched with a batch size of 2 using **padded_batch**.
- Padding is applied to ensure uniform shapes within each batch.

4. **Prefetching:**

- **tf.data.Dataset.prefetch** is used to prefetch data for better performance.

5. **Splitting into Train, Test, and Validation Sets:**

- The **take** and **skip** operations are used to split the dataset into training (450 samples) and testing sets.

- A sample from the dataset is extracted to create a validation set.

6. **Output:**

- The **val** variable contains a sample from the validation set.

Splitting data into train and test and validation sets

```
def mappable_function(path:str) ->List[str]:
    result = tf.py_function(load_data, [path], (tf.float32, tf.int64))
    return result

data = tf.data.Dataset.list_files('/kaggle/input/lipreading/data/s1/*.mpg')
data = data.shuffle(500,reshuffle_each_iteration=False)
data = data.map(mappable_function)
data = data.padded_batch(2, padded_shapes=([75,None,None,None],[40]))
data = data.prefetch(tf.data.AUTOTUNE)
## ADDED DOR SPLIT
train = data.take(450)
test = data.skip(450)

frames, alignments = data.as_numpy_iterator().next()

sample = data.as_numpy_iterator()

val = sample.next();val[0]
```

The provided code defines a deep learning model using TensorFlow/Keras for lip-reading. It also includes custom callbacks for learning rate scheduling, saving model architecture, and producing predictions after each epoch.

Callbacks:

1. **Learning Rate Scheduler (scheduler):**

- Adjusts the learning rate using exponential decay after the 30th epoch.

2. **SaveModelArchitecture (SaveModelArchitecture):**

- Saves the model architecture in JSON format every 5 epochs.

3. **ProduceExample (ProduceExample):**

- Produces predictions after each epoch using a sample from the dataset.
- Prints the original and predicted sequences.

Notes:

- The model architecture assumes input shapes of (75, None, None, 1) for 3D convolutional layers.
- The number of output units in the Dense layer is set to 29, assuming 29 classes for characters.
- The provided callbacks offer learning rate scheduling, periodic model architecture saving, and prediction production for monitoring during training.

MODEL BUILDING

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv3D, LSTM, Dense, Dropout, Bidirectional, MaxPool3D, Activation, Re
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import ModelCheckpoint, LearningRateScheduler, Callback
```

Defining callbacks

```
def scheduler(epoch,lr):
    if epoch < 30:
        return lr
    else:
        return lr * tf.math.exp(-0.1)
```

```
class SaveModelArchitecture(Callback):
    def __init__(self, save_path):
        super(SaveModelArchitecture, self).__init__()
        self.save_path = save_path

    def on_epoch_end(self, epoch, logs=None):
        if epoch % 5 == 0: # Adjust the frequency of saving architecture as needed
            model_json = self.model.to_json()
            with open(os.path.join(self.save_path, f"model_architecture_epoch_{epoch}.json"), "w") as json_file:
                json_file.write(model_json)
```

```
class ProduceExample(tf.keras.callbacks.Callback):
    def __init__(self, dataset) -> None:
        self.dataset = dataset.as_numpy_iterator()
    def on_epoch_end(self, epoch, logs=None) -> None:
        data = self.dataset.next()
        yhat = self.model.predict(data[0])
        decoded = tf.keras.backend.ctc_decode(yhat, [75,75], greedy=False)[0][0].numpy()
        for x in range(len(yhat)):
            print('Original:', tf.strings.reduce_join(num_to_char(data[1][x])).numpy().decode('utf-8'))
            print('Prediction:', tf.strings.reduce_join(num_to_char(decoded[x])).numpy().decode('utf-8'))
            print('~'*100)
```

The `CTCLoss` function is a custom loss designed for Connectionist Temporal Classification (CTC) in sequence-to-sequence tasks. It computes the CTC loss between true labels (`y_true`) and predicted labels (`y_pred`). The function involves casting, reshaping, and replicating input and label lengths before utilizing the `tf.keras.backend.ctc_batch_cost` to calculate the loss. This loss function is particularly useful for training models on tasks such as speech or lip reading, where

the alignment between input and output sequences is not predefined.

Defining Loss function

```
def CTCLoss(y_true,y_pred):  
    batch_len = tf.cast(tf.shape(y_true)[0], dtype="int64")  
    input_length = tf.cast(tf.shape(y_pred)[1],dtype="int64")  
    label_length = tf.cast(tf.shape(y_true)[1],dtype="int64")  
    input_length = input_length * tf.ones(shape=(batch_len, 1), dtype="int64")  
    label_length = label_length * tf.ones(shape=(batch_len, 1), dtype="int64")  
    loss = tf.keras.backend.ctc_batch_cost(y_true, y_pred, input_length, label_length)  
    return loss
```

The provided code defines a lip-reading model using a combination of 3D convolutional layers, Bidirectional LSTM layers, and a dense output layer. The architecture processes 3D spatiotemporal data from video frames. Key components include convolutional layers with maxpooling, a time-distributed flattening operation, two Bidirectional LSTM layers with dropout, and a dense output layer for character classification using softmax activation. This model is designed for lip-reading tasks, where the goal is to interpret and classify sequences of lip movements. Ensure compatibility with your data and adjust hyperparameters as needed.

Model building

```
model = Sequential()
model.add(Conv3D(128, 3, input_shape=(75,46,140,1), padding='same'))
model.add(Activation('relu'))
model.add(MaxPool3D((1,2,2)))

model.add(Conv3D(256, 3, padding='same'))
model.add(Activation('relu'))
model.add(MaxPool3D((1,2,2)))

model.add(Conv3D(75, 3, padding='same'))
model.add(Activation('relu'))
model.add(MaxPool3D((1,2,2)))

model.add(TimeDistributed(Flatten()))

model.add(Bidirectional(LSTM(128, kernel_initializer='Orthogonal', return_sequences=True)))
model.add(Dropout(.5))

model.add(Bidirectional(LSTM(128, kernel_initializer='Orthogonal', return_sequences=True)))
model.add(Dropout(.5))

model.add(Dense(char_to_num.vocabulary_size()+1, kernel_initializer='he_normal', activation='softmax'))
```

The code trains a lip-reading model using TensorFlow/Keras with custom callbacks for saving weights, adjusting learning rate, producing predictions, and saving model architecture. The model is compiled with Adam optimizer and a custom CTC loss function, trained for 100 epochs on a training dataset, and validated on a test dataset. Ensure dataset compatibility and adjust hyperparameters as needed for your lip-reading task.

TRAINING THE MODELS

```
checkpoint_callback = ModelCheckpoint(os.path.join('models', 'checkpoint'),
                                     monitor='loss',
                                     save_weights_only=True,
                                     save_best_only=False) # Save at the end of each epoch

schedule_callback = LearningRateScheduler(scheduler)
example_callback = ProduceExample(test)
save_architecture_callback = SaveModelArchitecture('models')

model.compile(optimizer=Adam(learning_rate=0.0001), loss=CTCLoss)

model.fit(train,
          validation_data=test,
          epochs=100,
          callbacks=[checkpoint_callback, schedule_callback, example_callback, save_architecture_callback])
```

The code extracts a sample from the test dataset, uses the trained lip-reading model (`model`) to predict character sequences (`yhat`), and prints the real text by converting numerical indices to characters using the `num_to_char` function.

LOADING THE MODEL AND MAKING PREDICTIONS

```
[ ] test_data=test.as_numpy_iterator()

[ ] sample=test_data.next()

[ ] yhat=model.predict(sample[0])

1/1 [=====] - 0s 121ms/step

[ ] print('~'*100, 'REAL TEXT')
    [tf.strings.reduce_join([num_to_char(word) for word in sentence]) for sentence in [sample[1]]]

~~~~~ REAL TEXT
[<tf.Tensor: shape=(), dtype=string, numpy=b'bin green at u one againplace green ith 1 zero no'>]

[ ] decoded=tf.keras.backend.ctc_decode(yhat, input_length=[75,75], greedy=True)[0][0].numpy()
```

This code decodes predictions from the trained lip-reading model and compares them with the real text for a specific video. It first decodes the model predictions using the CTC

decoding method, prints the decoded predictions, loads the real text from the test dataset, and prints the actual text.

```
[ ] decoded=tf.keras.backend.ctc_decode(yhat,input_length=[75,75],greedy=True)[0][0].numpy()

[ ] print('~'*100, 'PREDICTIONS')
    [tf.strings.reduce_join([num_to_char(word) for word in sentence]) for sentence in decoded]

~~~~~ PREDICTIONS
[<tf.Tensor: shape=(), dtype=string, numpy=b'bin ren it ne again'>,
 <tf.Tensor: shape=(), dtype=string, numpy=b'place green ith fo no'>]

[ ] sample=load_data(tf.convert_to_tensor('/kaggle/input/lipreading/data/s1/bba95a.mpg'))

[ ] print('~'*100, 'REAL TEXT')
    [tf.strings.reduce_join([num_to_char(word) for word in sentence]) for sentence in [sample[1]]]

~~~~~ REAL TEXT
[<tf.Tensor: shape=(), dtype=string, numpy=b'bin blue at f five again'>]

[ ] yhat=model.predict(tf.expand_dims(sample[0],axis=0))
```

8. Performance Testing

Model Performance Testing:

S.No.	Parameter	Values
1.	Metrics	Classification Model:
2.	Tune the Model	Hyperparameter Tuning

```
[10]: from sklearn.metrics import confusion_matrix, accuracy_score, classification_report

# Assuming you have ground truth values (y_true) and predicted values (y_pred) for classification
y_true = ...
y_pred = ...

# Compute the confusion matrix
conf_matrix = confusion_matrix(y_true, y_pred)

# Compute the accuracy score
accuracy = accuracy_score(y_true, y_pred)

# Generate the classification report
class_report = classification_report(y_true, y_pred)

# Print and display the results
print("Confusion Matrix:")
print(conf_matrix)

print("\nAccuracy Score:", accuracy)

print("\nClassification Report:")
print(class_report)
```

```

# Assuming you have a function for creating and compiling the model named create_model()

# Hyperparameter tuning
learning_rates = [0.001, 0.0001, 0.00001]
batch_sizes = [16, 32, 64]

best_accuracy = 0
best_hyperparameters = None

for lr in learning_rates:
    for batch_size in batch_sizes:
        model = create_model() # Make sure to define this function
        model.compile(optimizer=Adam(learning_rate=lr), loss=CTCLoss) # Assuming Adam optimizer and CTC Loss

        # Train the model on the training set
        model.fit(train, epochs=50, batch_size=batch_size, callbacks=[checkpoint_callback, schedule_callback])

        # Evaluate on the validation set
        val_accuracy = model.evaluate(val)

        # Update best hyperparameters if the current model performs better
        if val_accuracy > best_accuracy:
            best_accuracy = val_accuracy
            best_hyperparameters = {'learning_rate': lr, 'batch_size': batch_size}

print("Best Hyperparameters:", best_hyperparameters)

```

9. Results

Output Screenshots

This code decodes predictions from the lip-reading model using a CTC decoding method with greedy decoding strategy for a specific video. It then prints the decoded predictions.

```
[39]: decoded=tf.keras.backend.ctc_decode(yhat,input_length=[75],greedy=True)[0][0].numpy()
```

```
[40]: print('~'*100,'PREDICTIONS')
      prediction=[tf.strings.reduce_join([num_to_char(word) for word in sentence]) for sentence in decoded]
      print(prediction)
```

```
~~~~~ PREDICTIONS
[<tf.Tensor: shape=(), dtype=string, numpy=b'binblueatfiveagain'>]
```

SPPLITTING THE PREDICTION INTO SEPERATE WORDS

```
[41]: print(vocab)

['a' 'again' 'at' 'b' 'bin' 'blue' 'by' 'c' 'd' 'e' 'eight' 'f' 'five'
 'four' 'g' 'green' 'h' 'i' 'in' 'j' 'k' 'l' 'lay' 'n' 'nine' 'now'
 'o' 'one' 'p' 'place' 'please' 'q' 'r' 'red' 's' 'set' 'seven' 'sil'
 'six' 'soon' 'sp' 't' 'three' 'two' 'u' 'v' 'white' 'with' 'x' 'y' 'z'
 'zero']
```

[+ Code](#) [+ Markdown](#)

```
[42]: vocab_words=[]
      for i in vocab:
          if len(i)>=2:
              vocab_words.append(i)
```

```
[43]: print(vocab_words)

['again', 'at', 'bin', 'blue', 'by', 'eight', 'five', 'four', 'green', 'in', 'lay', 'nine', 'now', 'one', 'place', 'please', 'red', 'set', 'seven', 'sil', 'six', 'soon', 'sp', 'three', 'two', 'white', 'with', 'zero']
```




```
[44]: prediction_str = prediction[0].numpy().decode('utf-8')
```


```
[45]: predicted_words=[]
current_word=''
for char in prediction_str:
    current_word+=char
    if current_word in vocab_words:
        predicted_words.append(current_word)
        current_word=''
predicted_sentence= ' '.join(predicted_words)
print(predicted_sentence)
```

bin blue at five again

After Integrating with web framework



making a prediction



This is the output of the machine learning model as tokens

```
[[ 5 19 26  1  5 35  5 11  1 52  1 26 29  1 3:
-1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -:
-1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -1 -:
-1 -1 -1]]
```

Decode the raw tokens into words

aagainatbbinbluebycdeeightffivefourgreenhiin;

Lip Reading

This application helps us to convert video into text.

10. Advantages and Disadvantages

Advantages

1. *Accessibility*: Enables individuals with hearing impairments to communicate more effectively through visual cues, fostering inclusivity and accessibility.
2. *Noise Robustness*: Visual-based recognition is less affected by background noise, making it useful in noisy environments where audio-based systems struggle.
3. *Cross-Lingual Potential*: Language-agnostic nature allows potential application across different languages without specific language training data, facilitating cross-lingual communication.
4. *Privacy Consideration*: Relies on visual information rather than audio data, potentially mitigating privacy concerns associated with audio-based systems.
5. *Enhanced Communication in Multiple Contexts*: Aids communication not only for individuals with hearing impairments but also in scenarios where traditional audio-based systems face limitations.

Disadvantages and Challenges

1. *Complexity of Lip Movements*: Interpreting precise lip movements accurately can be challenging due to the variability in human speech and facial expressions, impacting system accuracy.
2. *Data Requirements*: Developing robust models necessitates extensive and diverse datasets, which may be challenging to collect and annotate comprehensively.
3. *Performance in Varied Environments*: System accuracy might decline in varying lighting conditions, different angles, occlusions, or when dealing with individuals with atypical lip movements.
4. *Dependency on Visual Information*: Limited effectiveness in scenarios where visual information is compromised or unavailable, restricting its applicability in certain settings.
5. *Ethical Considerations*: Potential ethical concerns related to privacy, especially if capturing and processing video data, necessitating stringent data protection measures.
6. *Technological Accessibility*: Requires technological infrastructure, potentially excluding individuals or regions with limited access to advanced technology.

11. Future Scope

Technological Advancements

1. *Improved Accuracy and Robustness*: Further refinement of neural network architectures and training methodologies to enhance accuracy and robustness, especially in handling diverse speech patterns and varying environmental conditions.
2. *Multimodal Integration*: Exploring enhanced models that seamlessly integrate visual lip reading with other modalities like audio or contextual information to improve accuracy and context comprehension.
3. *Adaptability to Real-World Scenarios*: Developing models capable of handling real-world challenges such as partial occlusions, varying lighting conditions, and diverse speaking styles, ensuring applicability in diverse environments.

Diverse Applications

1. *Assistive Technologies*: Advancing lip reading systems to serve as assistive tools not only for individuals with hearing impairments but also in healthcare, education, and customer service domains.
2. *Human-Computer Interaction*: Integrating lip reading capabilities into human-computer interfaces, enhancing

natural and intuitive interactions for diverse applications, from smart assistants to virtual reality.

3. *Cross-Domain Collaboration*: Collaborating with experts in linguistics, psychology, and other fields to deepen understanding and improve models based on insights from diverse disciplines.

Ethical Considerations and Accessibility

1. *Privacy Preservation*: Innovating methods to ensure privacy and data protection while utilizing video data for lip reading, adhering to ethical guidelines and regulations.
2. *Accessible Technology*: Designing user-friendly interfaces and models that cater to diverse user groups, ensuring inclusivity and accessibility for individuals with varying technical expertise and needs.

Research and Development

1. *Dataset Expansion*: Continual efforts in curating and expanding diverse and comprehensive datasets to train more robust and inclusive models.
2. *Novel Architectures and Techniques*: Exploring novel neural network architectures, attention mechanisms, and fusion strategies to improve accuracy and efficiency in lip reading systems.
3. *Interdisciplinary Collaboration*: Collaboration between researchers from diverse fields to leverage insights and

advancements for enhancing the efficacy and applicability of lip reading technologies.

The future scope for deep learning-based lip reading systems is vast, encompassing technological advancements, diverse applications across domains, ethical considerations, and ongoing research and development. As these systems evolve, they have the potential to transform communication paradigms, foster inclusivity, and facilitate seamless interactions in various real-world scenarios.

12. Conclusion

Achievements and Contributions

1. *Innovative Technological Development*: This project represents a pioneering effort in harnessing deep learning methodologies to create a system capable of accurately translating lip movements into spoken words, catering not only to individuals with hearing impairments but also augmenting communication in diverse settings.
2. *Addressing Communication Barriers*: The developed system serves as a bridge, addressing communication barriers faced by individuals with hearing impairments, offering them a reliable and accessible means of understanding spoken language solely through visual cues.
3. *Advancements in Accessibility*: By emphasizing inclusivity and accessibility, this project contributes to the technological landscape, striving to create communication tools that cater to diverse user needs and abilities.

Reflections and Future Directions

1. *Continuous Innovation*: While this project marks a significant achievement, the journey towards perfecting deep learning-based lip reading systems is an ongoing endeavor. Continued innovation, technological refinement,

and interdisciplinary collaboration will pave the way for future advancements.

2. *Ethical Considerations*: The project underscores the importance of ethical considerations, especially regarding privacy and data protection. Future developments should continue to prioritize ethical standards and regulatory compliance.
3. *Broader Applications*: The success of this project opens doors for broader applications in various domains, including healthcare, education, human-computer interaction, and beyond. Future research can explore these diverse applications to maximize the technology's impact.

Impact and Significance

In conclusion, this project represents a crucial step forward in leveraging technology for social good, fostering inclusivity, and redefining communication paradigms. The developed lip reading system stands as a testament to the potential of deep learning in addressing real-world challenges and enhancing the quality of life for individuals with hearing impairments.

The project's impact extends beyond technological innovation; it embodies a commitment to creating a more inclusive society, where communication barriers are dismantled, and individuals

of all abilities can engage and interact seamlessly. As the journey continues, the collective efforts in advancing deep learning-based lip reading systems will pave the way for a more connected and inclusive future.

13. APPENDIX

Git Repo:

<https://github.com/smartinternz02/Sl-GuidedProject-591413-1697563179>

Project Demo:

[https://drive.google.com/drive/folders/1K9kYAjVlzNoBLPQpujcxzZOtYp3HC8F ?usp=drive link](https://drive.google.com/drive/folders/1K9kYAjVlzNoBLPQpujcxzZOtYp3HC8F?usp=drive_link)

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