Visual Speech Recognition for Seamless Communication with Hearing Impaired Persons

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May 14, 2025

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What is Lip Reading:

fig no - 1: https://livingwithhearingloss.com/2016/04/19/lipreading-in-paradise/

Why Lip Reading is important?

Communication aid for the deaf and hard-of-hearing

- Primary Communication Tool
- Complement to hearing aids and cochlear implants

https://www.inc.com/john-boitnott/this-entrepreneur-is-solving-one-of-the-biggest-problems-all-deaf-people-face.html

https://www.connecthear.org/post/all-about-cochlear-implants

cont...

Laryngeal cancer

- laryngeal cancer can result in loss of speech or changes in the voice, especially if the cancer or its treatment affects the vocal cords or requires the removal of parts of the larynx. In such case speaker can only move their lips to communicate.

https://utswmed.org/medblog/cold-flu-allergy-hurt-your-voice/

Research Advancement

Time Period	Advancement
Early 20th century	The concept of lip reading as a skill for the deaf and hard-of-hearing began to be formally studied and taught. Schools for the deaf often included lip reading in their curricula.
1970s	Early research in automated lip reading began. Initial efforts focused on understanding the visual aspects of speech and how they could be captured and analyzed by computers.
1980s and 1990s	Advances in computer vision and pattern recognition led to more sophisticated experiments with automated lip reading systems. Algorithms to recognize visual speech elements were developed.
2000s	Deep learning and AI started to significantly improve automated lip reading accuracy. Researchers used statistical models like Hidden Markov Models (HMMs) to analyze visual speech data.
2010s	Deep learning techniques, especially CNNs and RNNs, began to be applied to lip reading, leading to substantial improvements. Large datasets and improved computational power also contributed to advancements.
2016	Google DeepMind's LipNet model demonstrated high accuracy in lip reading by leveraging deep learning techniques.
2020s	Ongoing research continues to refine and improve lip reading technologies, which are now applied in fields such as assistive technology for the deaf and hard-of-hearing, security, and human-computer interaction.

Motivation

- Accessibility for Hearing-Impaired Individuals
- Speech Enhancement in Noisy Environments
- Multimodal Systems
- Advances in AI and Machine Learning

Author, year	Methodology	Dataset Used	Findings
Freitas *et al.*, 2016 [1]	LipNet model: spatiotemporal convolutional neural networks (STCNNs) to extract spatial and temporal features, followed by Bidirectional Gated Recurrent Units (Bi-GRUs) to capture temporal dependencies, and employs Connectionist Temporal Classification (CTC) loss for end-to-end training without the need for pre-segmented data	GRID corpus	• Achieving a 95.2% sentence-level accuracy on the GRID corpus. • The study highlights the effectiveness of combining spatiotemporal convolutions, recurrent networks, and Connectionist Temporal Classification (CTC) for sentence-level prediction, marking a major improvement in automated lipreading

Author, year	Methodology	Dataset Used	Findings
Zimmermann *et al.*, 2020[2]	The paper employs two methodsTemporal Conditional GANs (TC-GANs) to generate lip movement videos for unseen utterances and a viseme-concatenation approach to synthesize videos by mapping phonemes to visemesto enable zero-shot learning in visual speech recognition.	OuluVS2 dataset	Using GANs for zero-shot learning significantly improves visual speech recognition accuracy for unseen utterances, effectively addresses the cold-start problem, and generalizes to new languages, with GANs outperforming the viseme-concatenation approach.

Author, year	Methodology	Dataset Used	Findings
XIAO *et al.*, 2020[3]	The methodology involves preprocessing video frames to extract lip regions, using a spatial-temporal CNN to generate features, applying a transformer-based model to classify visemes, and converting visemes to words through perplexity analysis for sentence prediction.	BBC LRS2 dataset.	The paper finds that the proposed viseme-based lip reading system significantly improves word accuracy with a 15% reduction in Word Error Rate (WER), achieves a Viseme Error Rate (VER) of 4.6%, and demonstrates robustness to varying lighting conditions, though further optimization is needed in converting visemes to words

Author, year	Methodology	Dataset Used	Findings
Xie *et al.*, 2024[4]	The methodology involves multi-scale lip motion video extraction, dynamic augmentation, and an end-to-end VSR system with multi-system fusion using diverse encoders for optimal visual speech recognition performance.	The paper uses the CN-CVS dataset for training, along with the development sets of CNVSRC-Single/Multi datasets from the Chinese Continuous Visual Speech Recognition Challenge (CNVSRC) 2023.	The paper finds that the proposed multi-system VSR approach with E-Branchformer encoder and ROVER fusion achieves leading performance with 34.76% CER in the Single-Speaker Task and 41.06% CER in the Multi-Speaker Task, securing first place in all three CNVSRC 2023 tracks.

Author, year	Methodology	Dataset Used	Findings
Pingchuan *et al.*, 2022[5]	The methodology involves enhancing VSR performance through prediction-based auxiliary tasks, hyperparameter optimization, data augmentation (like time-masking), and pre-training/fine-tuning across multiple languages.	The paper uses the LRS2, LRS3, CMLR (Mandarin), and CMU-MOSEAS (Spanish) datasets for training and evaluation, with a focus on publicly available datasets for achieving state-of-the-art VSR performance across multiple languages. Additionally, the LRW and AVSpeech datasets are used in some experiments for further improvements.	The paper finds that careful model design, including prediction-based auxiliary tasks, data augmentation, and hyperparameter optimization, can significantly improve visual speech recognition performance, even surpassing models trained on much larger datasets.

Author, year	Methodology	Dataset Used	Findings
GUO *et al.*, 2020[6]	The methodology involves using a viseme-to-word conversion system with perplexity analysis, where visual speech input is processed through word lookup, chunkification, and iterative beam search to identify the most likely word sequences based on a pre-trained language model.	The paper uses two datasets for experimentation: • OuluVS Dataset: This consists of short phrases like "hello," "excuse me," "I am sorry," etc. • BBC LRS2 Dataset: This contains longer and more varied sentences from BBC videos, making it more challenging due to a wide range of speakers and vocabulary	The findings show that the model effectively predicts short phrases with 100% accuracy and performs reasonably well on longer sentences using perplexity analysis, though it struggles with increased errors when word boundaries are unknown.

Author, year	Methodology	Dataset Used	Findings
Ro *et al.*, 2024[7]	The proposed methodology adapts a pre-trained lip reading model to individual speakers by incorporating speaker-specific visual prompts and low-rank adaptation in the visual encoder, along with input prompt tuning in the language decoder to capture both visual and linguistic speaker-specific traits.	VoxLRS–SA , which is specifically designed for speaker-adaptive lip reading in real-world, sentence-level scenarios.	The study finds that combining vision- and language-level adaptations using lightweight methods like LoRA and prompt tuning significantly improves sentence-level lip reading accuracy for unseen speakers, even with limited speaker-specific data.

Author, year	Methodology	Dataset Used	Findings
Pantic *et al.*, 2022[8]	The methodology combines advanced temporal models (like DC-TCN), effective data augmentations (Time Masking, mixup), and training strategies (self-distillation, word boundary indicators) to systematically enhance lip-reading performance.	LRW dataset	The paper finds that combining advanced temporal models (DC-TCN), Time Masking augmentation, and training strategies like self-distillation and word boundary indicators achieves state-of-the-art performance in lip-reading, particularly improving recognition of difficult words.

Author, year	Methodology	Dataset Used	Findings
Jakob Uszkoreiti *et al.*, 2017[9]	The paper introduces the Transformer, a sequence transduction model based entirely on self-attention mechanismswithout recurrence or convolutionusing an encoder-decoder architecture to efficiently capture long-range dependencies in data.	WMT 2014 English-German, WMT 2014 English-French	The paper demonstrates that the Transformer model, relying solely on self-attention, achieves state-of-the-art results on translation tasks with significantly faster training and better parallelization compared to RNN- or CNN-based models.

Research Gap

- Accuracy is not very high for word prediction.
- No dataset available for different accents.
- Viseme-based Challenges
- Cross-lingual Transfer Learning

Despite significant progress, visual speech recognition faces challenges such as variability in lip movements, diverse speaking styles, and need for large and labeled datasets for training. Ongoing research aims to address these challenges and further refine technology making it more accurate, reliable and widely applicable.

Objectives

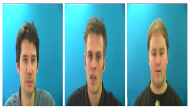
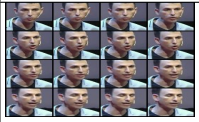
- To create a dataset of different accents.
- To develop an algorithm that can recognize words correctly independent of accents.

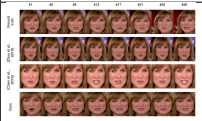
Available Dataset

Dataset	Type	Description
GRID Corpus	Sentence-level	Contains 34 speakers uttering structured sentences with fixed vocabulary (1000 unique sentences).
LRS2 (Lip Reading Sentences 2)	Sentence-level	Contains over 224 hours of data from BBC programs with spoken sentences for audio-visual speech recognition.
LRS3 (Lip Reading Sentences 3)	Sentence-level	Larger version of LRS2 with over 475 hours of videos for lip reading in challenging conditions.
TCD-TIMIT	Continuous Speech	Phonetically balanced dataset with 59 speakers reading 98 sentences, suitable for continuous speech recognition.
AVLetters	Alphabet-level	Dataset with speakers uttering letters A-Z multiple times for isolated letter recognition.
LRW (Lip Reading in the Wild)	Word-level	Contains over 500 different words spoken by various speakers extracted from TV broadcasts.
OuluVS2	Phrase-level	Contains 53 speakers saying 10 phrases, repeated 6 times per phrase, for small-scale phrase recognition.

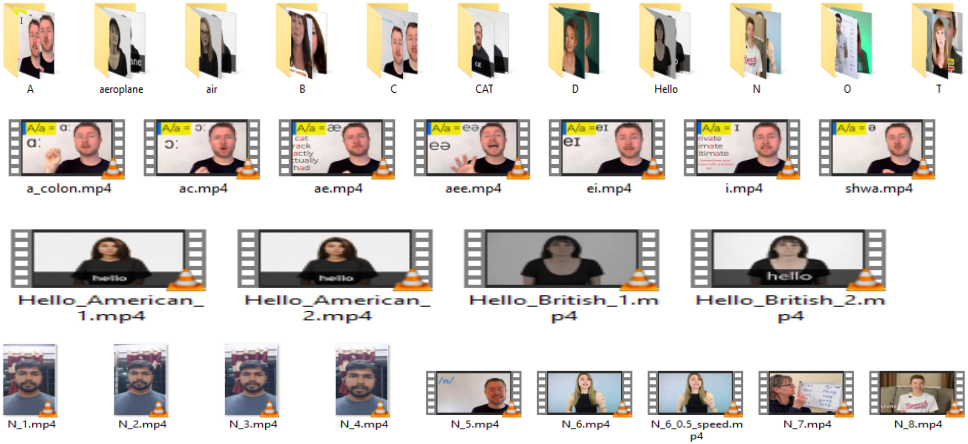
Table 1: Available Datasets for Visual Speech Recognition by Lip Reading

Dataset Names and Images for Visual Speech Recognition

Dataset	Image
GRID Corpus	
LRS2 (Lip Reading Sentences 2)	
LRS3 (Lip Reading Sentences 3)	
TCD-TIMIT	

Dataset	Image
AVLetters	
LRW (Lip Reading in the Wild)	
OuluVS2	

Dataset Preparation for Visual Speech Recognition System



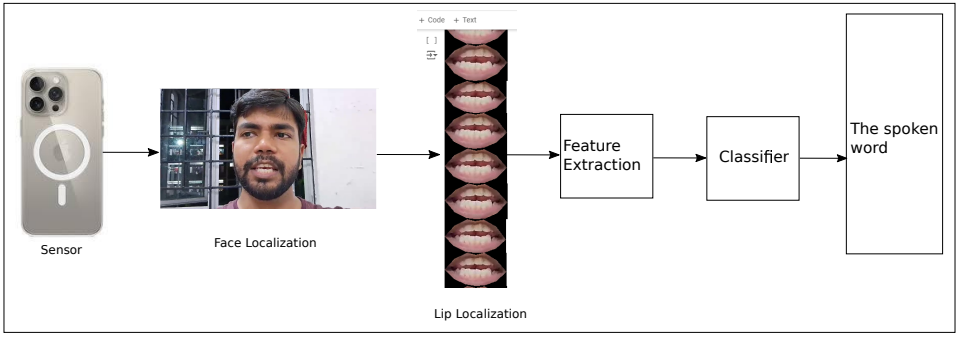


Figure 1: Generalized block diagram of visual speech recognition system

Figure 2: lip feature extraction

Deep Learning & Geometrical-based Approach

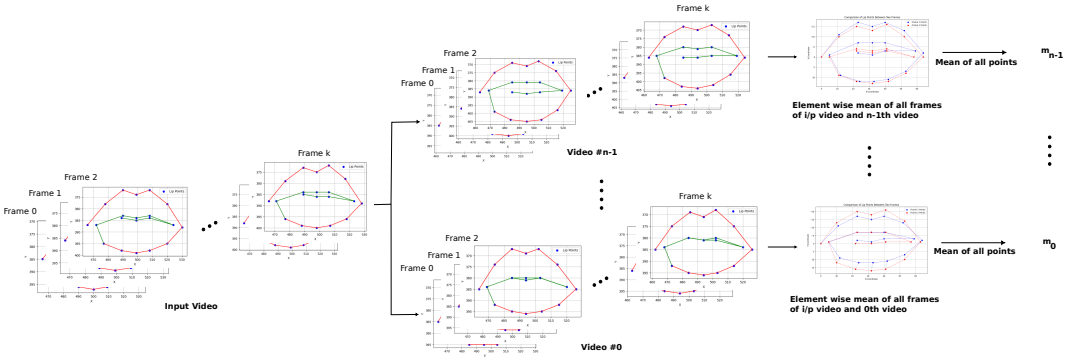


Figure 3: Calculating Euclidean Distance for the entire Dataset

$$\text{Predicted Word} = \min\{m_0, m_1, m_3, \ldots, m_{n-1}\}$$

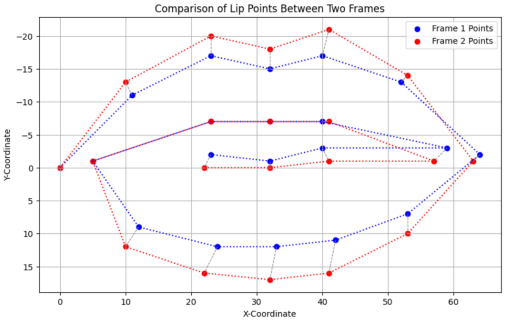


Figure 4: lip comparision

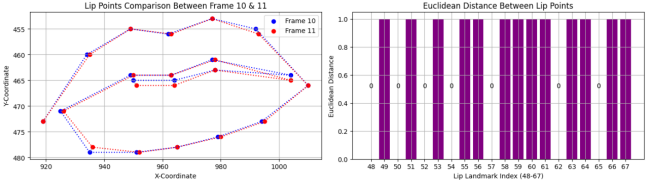


Figure 5: frame 10 and 11 lip comparision

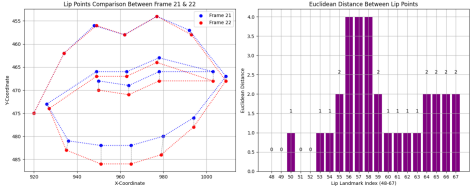


Figure 6: Beginning of Speaking Frame frame 21 and 22

Current Frame	Next Frame	Average Euclidean Distance
1	2	0.41
2	3	0.42
3	4	0.40
4	5	0.44
5	6	0.53
6	7	0.55
7	8	0.67
8	9	0.30
9	10	0.42
10	11	0.71
11	12	0.70
12	13	0.65
13	14	0.39
14	15	0.87
15	16	0.57
16	17	0.71
17	18	1.06
18	19	0.79
19	20	1.38
20	21	0.54
21	22	1.65
22	23	2.49
23	24	3.11
24	25	2.15
25	26	1.40
26	27	1.62
27	28	1.93
28	29	2.30
29	30	2.11
30	31	1.17
31	32	4.54
32	33	2.40
33	34	3.88
34	35	2.79
35	36	2.12
36	37	1.60
37	38	4.02
38	39	0.85
39	40	4.80
40	41	2.04
41	42	0.44
42	43	2.21
43	44	2.41
44	45	0.74
45	46	1.49
46	47	0.57
47	48	0.88
48	49	1.21
49	50	1.29
50	51	0.49
51	52	0.87
52	53	1.42
53	54	1.02
54	55	0.32
55	56	1.10
56	57	0.15
57	58	0.48
58	59	0.35
59	60	0.20

Figure 7: Detection of Speech Activity

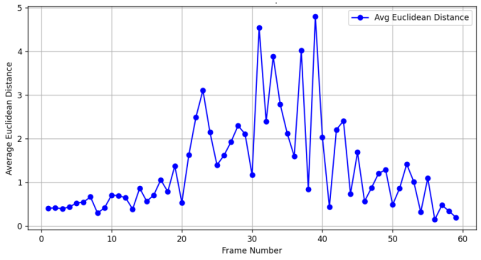


Figure 8: Detection of Speech Activity Graph

Given a set of lip landmark points, we normalize them such that point 48 becomes the origin $(0,0)$.

$$\text{If } 48 \in \text{lip\_points:} \quad \begin{cases} \text{origin} = \text{lip\_points}[48] \\ \text{normalized\_points}[i] = (x_i - x_{48},\ y_i - y_{48}) \quad \forall i \in \text{lip\_points} \end{cases}$$

Otherwise, return the original points.

Frame-wise Euclidean Distance

$$\mathrm{ED} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}, \tag{1}$$

Where (x_1, y_1) and (x_2, y_2) are the coordinates of a corresponding lip point in the input video and the reference video, respectively.

$$d_{ij} = \frac{\sum_{j=48}^{67} ED_{ij}}{20}, \tag{2}$$

d_{ij} is the average distance for reference frame i. ED_{ij} is the Euclidean Distance between tow landmarks point. Where j is the lip landmark number and i is the ith frame of a reference video

Video-wise Euclidean Distance

$$m_i = \frac{\sum_{j=1}^{N} d_{ij}}{N}, \tag{3}$$

- m_i is the average distance for reference video i.
- d_{ij} is the frame-wise average distance for frame j in reference video i.
- N is the total number of frames in the video.

$$\text{predicted word} = \min(m_0, m_1, m_2, \ldots, m_{n-1})$$

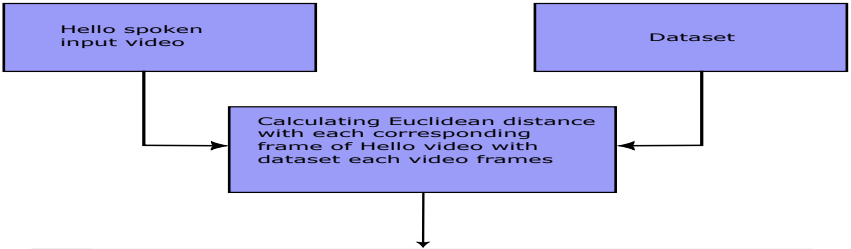


Figure 9: Calculating Euclidean Distance for the Entire Dataset

Confusion Matrix

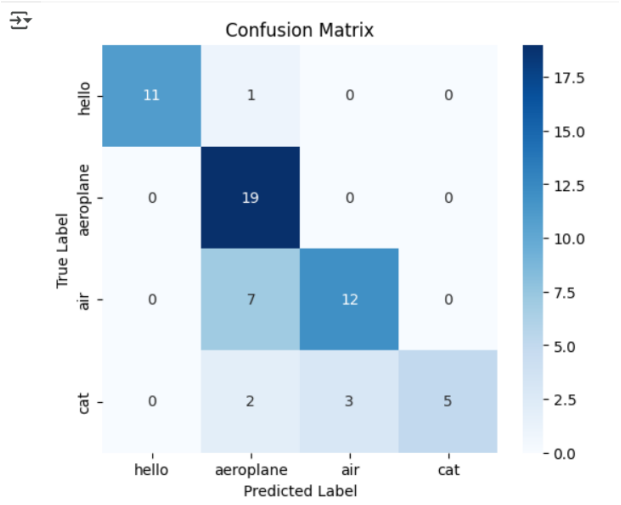


Figure 10: confusion matrix

Conclusion

- Successfully developed an algorithm which can recognize the spoken words by reading lips with partial use of Deep Learning.
- Our algorithm is only applied on Collins word dictionary and a custom dataset, which is created by me and accurately predicts 78.33% of words correctly. However, the accuracy is falling due to similar lip movements of different words(homophones).
- This algorithm can reduce the computational overhead as only deep learning is used for lip extraction from video, not for prediction. For word prediction, we are using our own developed algorithm.

Future Work and Proposed Improvements

- Acquire videos of the same word with different accents.
- Extract 3D lip feature so that accuracy can be achieved more easily
- Apply our algorithm to our dataset as well as publicly available datasets.
- Reading lips by using Deep Learning and comparing the result with Our Algorithm
- Finding the solution for Homophones
- Compare the results with the state-of-the-art.

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Project Timeline

- **Aug 2024 - Sep 27, 2024:** Read research papers.
- **Sep 28 - Dec 13, 2024:** Created block diagram and prepared custom dataset.
- **Jan 2025 - Mar 13, 2025:** Developed the Methodology for the project.
- **Mar 13 - May 14, 2025:** Wrote and prepared paper for submission.

Communicated

Visual Speech Recognition For Seamless Communication with hearing impaired persons
Md. Laraib Ahmad, Dr. Debbrota Paul Chowdhury,
Multimedia Tools and Applications, 2025.

Thank you for listening !

Md. Laraib Ahmad

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