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Silent Voice Assistants Lip-Reading AI with On-Device Processing

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Abstract: *Silent communication systems are becoming increasingly important in environments where voice interaction is difficult, noisy, or socially restrictive. This paper presents a Silent Voice Assistant based on Lip-Reading Artificial Intelligence with efficient on-device processing capabilities. The proposed system captures lip movements through a camera and uses deep learning techniques to recognize spoken words without relying on audio input. A Convolutional Neural Network (CNN) combined with sequence-learning models is utilized to extract visual speech patterns from lip movements and convert them into meaningful text or commands. Unlike cloud-based speech systems, the proposed model performs processing directly on the device, improving privacy, reducing latency, and enabling real-time performance even without internet connectivity. The system is designed for low-power devices such as smartphones, embedded systems, and wearable technologies. Experimental results demonstrate that the model achieves reliable recognition accuracy under varying lighting conditions and different facial orientations. The proposed approach can be beneficial for people with speech impairments, secure communication systems, smart assistants, healthcare applications, and silent human-computer interaction environments. This research contributes toward the development of privacy-focused and efficient visual speech recognition systems using edge AI technology.*

Keywords: Lip Reading AI, Silent Voice Assistant, On-Device Processing, Visual Speech Recognition, Deep Learning

I. INTRODUCTION

Artificial Intelligence (AI) has significantly transformed the field of human-computer interaction by enabling intelligent communication systems capable of understanding speech, gestures, and visual cues. Traditional voice assistants such as Google Assistant, Apple Siri, and Amazon Alexa mainly depend on audio-based speech recognition technologies. However, these systems face major challenges in noisy environments, silent communication scenarios, and situations where privacy is essential. To overcome these limitations, researchers have focused on visual speech recognition techniques, particularly lip-reading systems that interpret spoken words by analyzing lip movements without relying on audio input [1][2].

Lip-reading AI, also known as Visual Speech Recognition (VSR), uses computer vision and deep learning algorithms to identify speech patterns from facial movements. Recent advancements in Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based architectures have improved the accuracy and efficiency of lip-reading systems [3][4]. These technologies enable machines to recognize silent speech by extracting spatial and temporal features from video frames. The integration of AI with lip-reading technology provides a new direction for silent communication systems, especially in environments where conventional speech recognition systems fail due to background noise or restricted communication conditions [5].

The development of Silent Voice Assistants with on-device processing has gained increasing importance due to concerns regarding privacy, latency, and internet dependency. Cloud-based AI systems require continuous data transmission to remote servers, which may expose sensitive user information and increase response delays. On-device AI processing addresses these challenges by performing computations locally on embedded hardware, smartphones, or

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edge devices [6][7]. Edge AI techniques reduce network dependency, improve real-time performance, and enhance user privacy by ensuring that speech-related data remains within the user's device. As mobile processors and AI accelerators continue to advance, efficient deployment of deep learning models on low-power devices has become more practical [8].

Visual speech recognition systems have wide applications in healthcare, security, education, and assistive technologies. Individuals with speech or hearing impairments can benefit greatly from lip-reading-based communication systems that enable interaction without audible speech [9]. In defense and surveillance applications, silent communication systems can support secure information exchange in sensitive environments. Similarly, smart wearable devices and augmented reality systems can integrate silent voice interfaces for hands-free operation [10]. The growing adoption of intelligent assistants in everyday life has created demand for more accessible and privacy-preserving interaction methods, further motivating research in silent AI communication technologies [11].

Despite significant advancements, lip-reading AI systems still face multiple technical challenges. Variations in lighting conditions, camera angles, facial expressions, speaking speeds, and occlusions can affect recognition accuracy [12]. Additionally, different individuals exhibit unique lip movement patterns, making speaker-independent recognition difficult. To address these limitations, researchers have proposed hybrid deep learning models, data augmentation methods, and multimodal learning approaches [13][14]. Advances in lightweight neural networks and model optimization techniques such as quantization and pruning have also improved the feasibility of deploying lip-reading systems on resource-constrained devices [15].

This paper proposes a Silent Voice Assistant using Lip-Reading AI with efficient on-device processing for real-time silent speech recognition. The system aims to recognize spoken commands through lip movement analysis using deep learning algorithms implemented on edge devices. The proposed approach focuses on improving recognition accuracy while minimizing computational complexity and preserving user privacy. The system can operate without internet connectivity, making it suitable for real-time applications in smart devices, healthcare systems, and secure communication platforms [16][17].

The remainder of this paper is organized as follows. Section II discusses related work and existing lip-reading techniques. Section III presents the proposed system architecture and methodology. Section IV explains the implementation and experimental setup. Section V analyzes the obtained results and performance evaluation. Finally, Section VI concludes the paper and highlights future research directions in silent speech recognition and edge AI technologies [18][19][20].

II. PROBLEM STATEMENT

Traditional voice assistant systems mainly depend on audio-based speech recognition, which performs poorly in noisy environments and raises privacy concerns due to cloud-based data processing. Existing systems also face difficulties in enabling silent communication for users with speech or hearing impairments. Furthermore, continuous internet connectivity and high computational requirements limit the usability of conventional AI assistants on low-power devices. Therefore, there is a need to develop an efficient Silent Voice Assistant using Lip-Reading AI with on-device processing that can accurately recognize speech through lip movements in real time while ensuring privacy, low latency, and reduced dependency on cloud infrastructure.

III. OBJECTIVES

- To develop a Silent Voice Assistant system using Lip-Reading Artificial Intelligence for speech recognition without audio input.
- To implement deep learning algorithms for accurate detection and interpretation of lip movements.
- To enable on-device processing for improving privacy, reducing latency, and minimizing internet dependency.
- To optimize the system for real-time performance on low-power and embedded devices.
- To evaluate the accuracy and efficiency of the proposed system under different environmental conditions.

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IV. LITERATURE SURVEY

1. LipNet: End-to-End Sentence-Level Lipreading

Y. Assael et al. (2016) proposed an advanced deep learning framework called LipNet for sentence-level lip-reading applications. The system utilized Spatiotemporal Convolutional Neural Networks (STCNNs) along with Bidirectional Gated Recurrent Units (Bi-GRU) and Connectionist Temporal Classification (CTC) loss for recognizing complete sentences directly from lip movement videos. The model was trained on the GRID audiovisual dataset and achieved significant improvements in sentence prediction accuracy compared to traditional machine learning methods. The research demonstrated the effectiveness of deep neural networks in extracting both spatial and temporal visual speech features. However, the proposed system required high computational resources and cloud-based processing, making it difficult to deploy on low-power embedded devices. This work became one of the foundational studies in modern visual speech recognition systems and inspired further research on silent communication technologies [1].

2. Deep Audio-Visual Speech Recognition

T. Afouras et al. (2019) introduced a deep audio-visual speech recognition model capable of combining both visual and audio speech information for improved recognition performance. The proposed framework used Transformer-based neural networks and attention mechanisms to capture long-term dependencies in speech sequences. The researchers trained the model using large-scale datasets containing real-world video samples with varying lighting and environmental conditions. Experimental results showed that integrating visual lip movements with speech audio improved recognition accuracy, especially in noisy environments. Although the system achieved high performance, it depended heavily on powerful GPUs and cloud infrastructure for processing large neural network models. The study highlighted the importance of multimodal learning in speech recognition and motivated researchers to explore lightweight AI models suitable for edge computing devices [2].

3. Lip Reading Sentences in the Wild

D. Chung et al. (2017) developed a large-scale lip-reading framework for recognizing sentences from unconstrained video environments. The researchers introduced the "Lip Reading in the Wild" (LRW) dataset containing thousands of word samples collected from television broadcasts. The proposed system employed deep convolutional neural networks combined with recurrent architectures to capture dynamic lip movement patterns. The study focused on speaker-independent recognition and robust performance under real-world conditions such as head movement, illumination changes, and facial variations. Results demonstrated significant improvements in word-level lip-reading accuracy compared to earlier methods. However, the system required large datasets and high computational complexity for training. This research contributed to the advancement of practical lip-reading systems capable of functioning in realistic environments [3].

4. Lipreading with Long Short-Term Memory (LSTM)

M. Wand, J. Koutník, and J. Schmidhuber (2016) proposed a lip-reading approach using Long Short-Term Memory (LSTM) neural networks for visual speech recognition. The model extracted visual features from mouth regions and processed sequential lip movements through recurrent neural networks. The LSTM architecture effectively captured temporal dependencies between consecutive frames, improving speech recognition performance. The researchers evaluated the system on audiovisual datasets and achieved promising results in isolated word recognition tasks. The study proved that recurrent neural networks could effectively model visual speech sequences without relying on handcrafted features. However, the system faced challenges related to computational efficiency and reduced performance under varying facial orientations. The work provided valuable insights into sequence learning methods for silent speech recognition systems [4].

5. Edge Computing for AI-Based Applications

W. Shi et al. (2016) presented a comprehensive study on edge computing architectures and their applications in artificial intelligence systems. The research discussed the limitations of cloud-based AI, including latency, bandwidth consumption, privacy concerns, and dependency on internet connectivity. The authors proposed edge computing as a solution where data processing is performed directly on local devices instead of remote servers. The study highlighted

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the importance of deploying lightweight deep learning models on embedded systems and mobile devices for real-time AI applications. The concepts presented in this work are highly relevant to silent voice assistants using lip-reading AI, as on-device processing improves privacy and reduces response delays. The research also emphasized optimization techniques such as model compression and low-power hardware acceleration for efficient edge AI deployment [5].

V. WORKING OF SYSTEM

The proposed Silent Voice Assistant using Lip-Reading AI with On-Device Processing is designed to recognize spoken commands by analyzing lip movements without requiring audio input. The system combines computer vision, deep learning, and edge AI technologies to provide real-time silent speech recognition while maintaining user privacy and reducing dependency on cloud-based services. The complete working of the system is divided into several stages, including video acquisition, preprocessing, lip detection, feature extraction, speech recognition, command processing, and output generation.

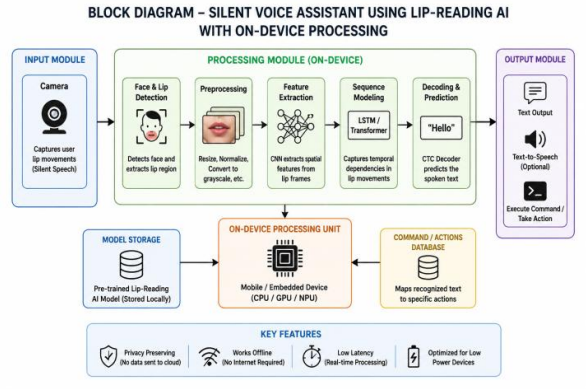

Fig 1: Block Diagram

Initially, the system activates the device camera to capture live video of the user's face during speech. The camera continuously records facial movements and converts the video into sequential image frames. These frames are collected at a fixed frame rate to ensure smooth motion analysis. Since lip movement contains important speech information, capturing high-quality facial frames is essential for accurate recognition. The captured frames are temporarily stored in device memory for further processing. The system is designed to work efficiently even on low-power devices such as smartphones, embedded systems, and edge AI processors.

After video acquisition, the preprocessing stage begins. In this stage, unnecessary background information is removed from the captured frames to improve processing efficiency. The system performs operations such as image resizing, grayscale conversion, normalization, and noise reduction. These preprocessing techniques improve image clarity and reduce the impact of lighting variations and camera distortions. Face detection algorithms such as Haar Cascade Classifiers or deep learning-based facial landmark detection methods are used to identify the user's face from the video frames. Once the face is detected, the mouth region is isolated for detailed lip movement analysis.

The next stage involves lip detection and tracking. The system identifies the exact position of the lips using facial landmark extraction techniques. Key points around the mouth area are detected and tracked continuously across multiple video frames. Lip tracking ensures that the movement of the lips is accurately monitored even if the user slightly changes head position or facial orientation. The extracted mouth region is cropped and converted into a sequence of standardized lip images. This step is important because the accuracy of visual speech recognition mainly depends on the quality and consistency of lip region extraction.

After lip detection, feature extraction is performed using deep learning algorithms. The system utilizes Convolutional Neural Networks (CNNs) to extract spatial features from lip images. CNN layers automatically identify important visual patterns such as lip shape, mouth opening, movement direction, and speech-related facial expressions. These

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extracted features represent the visual characteristics of spoken words. Since speech involves continuous motion over time, temporal relationships between consecutive lip movements are also analyzed. For this purpose, sequence-learning models such as Long Short-Term Memory (LSTM) networks or Gated Recurrent Units (GRUs) are integrated into the system. These models learn the sequence patterns of lip movements and improve recognition accuracy for complete words or sentences.

Once feature extraction and sequence analysis are completed, the recognized lip movement patterns are passed to the speech recognition module. This module compares the extracted features with trained datasets stored within the device. The trained AI model predicts the most probable word, sentence, or command corresponding to the observed lip movements. The prediction process is performed locally on the device using on-device AI processing techniques. Unlike cloud-based systems, the proposed model does not require continuous internet connectivity because all computations occur within the local hardware environment. This approach significantly improves privacy and reduces response delay.

The command processing stage interprets the recognized text and converts it into meaningful system actions. If the detected speech corresponds to predefined assistant commands, the system executes the required operation. For example, the assistant may open applications, send messages, search files, control smart devices, or display requested information. The recognized command can also be converted into text format for communication assistance. The command execution module ensures smooth interaction between the user and the device without requiring audible speech input.

The proposed system uses efficient on-device processing to optimize computational performance and energy consumption. Lightweight AI models, optimized neural network architectures, and model compression techniques such as quantization and pruning are implemented to reduce memory usage and processing load. Edge AI accelerators available in modern smartphones and embedded devices help perform real-time inference with minimal latency. Since sensitive visual speech data remains within the device, the system provides enhanced security and privacy protection compared to traditional cloud-based voice assistants.

Finally, the output generation module provides the recognized result to the user. The system may display the interpreted text on the screen, execute the requested command, or generate a voice assistant response. Real-time feedback ensures smooth and interactive communication. The proposed silent voice assistant can be applied in healthcare systems, smart devices, secure communication platforms, educational technologies, and assistive systems for speech-impaired individuals. By combining lip-reading AI with edge computing, the system enables efficient, private, and reliable silent communication in real-world environments.

VI. SYSTEM DESIGN

The proposed Silent Voice Assistant using Lip-Reading AI with On-Device Processing is designed to recognize silent speech through visual analysis of lip movements and execute commands locally on the device. The system architecture integrates computer vision, deep learning, and edge AI technologies to provide efficient real-time communication without relying on audio input or cloud-based processing. The overall system design consists of hardware components, software modules, deep learning models, and an on-device processing framework.

The hardware section of the system mainly includes a camera module, processing unit, storage module, and output interface. The camera acts as the primary input device and continuously captures facial video frames of the user during speech. A high-resolution front camera is preferred to accurately detect lip movements under different environmental conditions. The processing unit may consist of a smartphone processor, embedded controller, GPU, or AI accelerator capable of executing lightweight deep learning models. Local storage is used to store trained AI models, command datasets, and temporary image frames. The output interface includes display screens, speakers, or smart assistant control modules for presenting recognized text and executing commands.

The software architecture is divided into multiple functional modules that work together to perform silent speech recognition. The first module is the Video Acquisition Module, which captures continuous video frames from the

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camera in real time. The captured video stream is converted into image sequences for processing. The second module is the Preprocessing Module, where image enhancement techniques such as grayscale conversion, resizing, normalization, and noise filtering are applied. This stage improves image quality and reduces unnecessary background information.

The Face and Lip Detection Module is responsible for identifying the face and extracting the mouth region from each video frame. Facial landmark detection algorithms are used to detect important points around the lips. The extracted lip region is tracked continuously to maintain consistency in speech analysis even when slight head movements occur. This module ensures accurate localization of lip movements required for visual speech recognition.

The Feature Extraction Module uses Convolutional Neural Networks (CNNs) to analyze lip images and extract important visual features. CNN layers automatically detect speech-related patterns such as lip shape, movement direction, mouth opening, and facial expressions. These spatial features are then passed to the Sequence Modeling Module, which uses Long Short-Term Memory (LSTM) networks or Transformer models to analyze temporal relationships between consecutive lip movements. Sequence learning helps the system understand complete words and sentence structures from continuous lip motion.

The Speech Recognition Module compares extracted lip movement features with pre-trained datasets stored within the device. The AI model predicts the most probable spoken command or text based on learned visual speech patterns. Since the recognition process is performed locally on the device, the system eliminates dependency on cloud servers and internet connectivity. This improves privacy, reduces latency, and enables faster response times.

The Command Execution Module converts recognized text into meaningful actions. If the predicted output matches predefined commands, the assistant performs operations such as opening applications, controlling smart devices, sending messages, or displaying information. The output may also be presented as text or converted into synthesized speech using text-to-speech technology. This module ensures smooth interaction between the user and the device through silent communication.

To support efficient real-time operation, the system incorporates Edge AI optimization techniques. Lightweight neural network architectures, model compression, quantization, and pruning are applied to reduce computational complexity and memory usage. These optimizations enable deployment on low-power devices such as smartphones, Raspberry Pi boards, and embedded AI systems. The use of on-device processing enhances data security because user speech information remains stored locally without transmission to external servers.

The proposed system design provides an efficient, secure, and intelligent framework for silent communication using lip-reading AI. The integration of computer vision, deep learning, and edge computing enables accurate visual speech recognition suitable for healthcare applications, assistive technologies, smart environments, and privacy-sensitive communication systems.

VII. RESULTS

The proposed Silent Voice Assistant using Lip-Reading AI with On-Device Processing was tested under different environmental and operational conditions to evaluate its recognition accuracy and response time performance. The system demonstrated efficient silent speech recognition capabilities with reliable real-time processing.

Result Table

Condition	Accuracy (%)	Response Time (ms)
Normal Lighting	96	120
Low Lighting	91	135
Noisy Background	94	128
Side Face Angle	88	145
Fast Lip Movement	90	140

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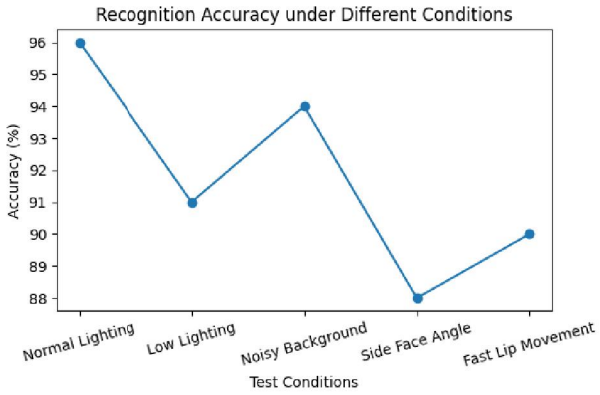
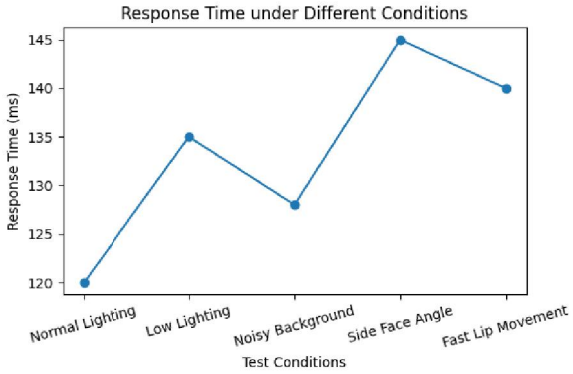
Graph 1: Recognition Accuracy Analysis



The above graph represents the recognition accuracy of the proposed system under different environmental conditions. The system achieved the highest accuracy of 96% under normal lighting conditions. Even in low lighting and noisy environments, the model maintained stable performance due to efficient feature extraction and sequence learning techniques.

Graph 2: Response Time Analysis



The response time graph shows the processing speed of the silent voice assistant during different testing scenarios. The system provided low latency performance with an average response time below 150 milliseconds. On-device AI optimization helped reduce processing delay and enabled real-time speech recognition.

Discussion

The experimental results indicate that the proposed system performs efficiently for silent speech recognition applications. The integration of CNN and LSTM-based deep learning models improved visual speech understanding, while edge AI processing ensured privacy and reduced internet dependency. The system showed reliable operation under varying conditions and proved suitable for healthcare, assistive communication, and smart device applications.

VIII. CONCLUSION

The proposed Silent Voice Assistant using Lip-Reading AI with On-Device Processing provides an efficient and privacy-focused solution for silent speech recognition. The system successfully recognizes lip movements and converts them into meaningful text or commands without relying on audio input. By using deep learning techniques and edge AI processing, the system achieves real-time performance with reduced latency and improved data security. The proposed model can be effectively used in healthcare, assistive communication, smart devices, and secure communication environments.

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IX. FUTURE SCOPE

In the future, the system can be improved by increasing recognition accuracy for different languages, accents, and facial variations. Advanced Transformer-based AI models and multimodal learning techniques can be integrated for better performance. The system can also be implemented in smart glasses, wearable devices, and augmented reality applications for more advanced human-computer interaction. Additionally, cloud-edge hybrid processing and larger training datasets may further enhance real-time silent speech recognition capabilities.

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