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BlinkSpeller: Dynamic EAR-Based Eye Blink Morse Code Communication System with Predictive Text and Speech Synthesis

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Abstract: Assistive communication technologies are crucial to the communication of people who cannot use traditional input devices because of their severe motor impairments. In this paper, a low cost, web-based communication system is presented that uses eye blink detection to provide text and speech output in real time. The system uses MediaPipe Face Mesh for facial landmark detection and calculates the Eye Aspect Ratio (EAR) to detect blinks. A custom algorithm categorizes blinks into short and long blinks (Morse code) and adds noise filtering, head motion compensation and gaze stabilization to make it more robust. A special decoding engine is used to decode the generated Morse sequences into alphanumeric characters and control commands. The system is built on browser-based APIs such as the Webcam API, SpeechSynthesis API, and localStorage, allowing for real-time data processing, speech generation, and storage. A word prediction module increases the efficiency of input. The proposed system shows high reliability, low latency and high accessibility, which can provide an effective solution for hands-free human–computer interaction.

Keywords: Assistive Communication System, Eye Blink Detection, MediaPipe Face Mesh, Eye Aspect Ratio (EAR), Morse Code Communication, Speech Synthesis, Computer Vision, Human–Computer Interaction

I. INTRODUCTION

Assistive communication technologies are an important tool for facilitating communication for people with severe motor impairments who cannot use traditional input devices like a mouse, keyboard or touchscreen. Such people are likely to experience a lot of difficulties for communicating their thoughts and requirements, and thus cannot communicate effectively and independently. Therefore, there is an increasing need for alternative means of communication that do not require much human resource but are reliable and efficient in terms of communication. In this area, eye-based communications have been an enticing solution since eye movements and blinks are some of the few movements an individual can control even in the most constrained physical environment. There have been several studies that have investigated eye-based interaction systems and assistive communication frameworks that enhance accessibility and usability [7], [10], [12].

Eye blink detection is one of the many assistive communication methods that provides an easy and very effective means of creating an input signal. Blink patterns can be translated into meaningful output and designed systems can be created. Morse code is a binary encoding system consisting of a short and a long signal, which can be used for such applications effectively. The detection of eye blinks combined with the Morse code system can be used to develop an input system that can represent a large number of characters and controls. The use of facial landmarks and classification techniques for blink detection to enable human–computer interaction has been shown to be effective in previous studies [1, 11] and Morse code based assistive systems have been investigated for minimal input communication [2, 15]. But the accurate and real-time detection of blinks is still a challenge because of lighting conditions, head movement, facial variations, and environmental noise.

The growth in computer vision and web technologies have allowed real-time face processing systems to be implemented. Frameworks like MediaPipe Face Mesh can detect facial landmarks in real-time through web browsers with no need for additional hardware or software installations. Facial landmarks can be used to track transitions in eye state and count blinks using the Eye Aspect Ratio (EAR). Traditional computer vision methods and feature extraction techniques have been used to create effective visual processing systems [3]–[5]. Deep learning based methods have also been used to detect eye state and count blinks [13], [14]. Approaches using MediaPipe are able to run in real-time in web browsers and are lightweight [16].

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However, despite such innovations, many of the current systems are either only capable of detecting eye blinks or doing facial recognition without implementing an end-to-end communication solution. Additionally, some of the existing solutions require special hardware or a computationally intensive model that might make their application difficult and raise costs for their implementation. The majority of existing eye tracking/gaze detection systems require additional sensors and even calibration, which makes it difficult to deploy them effectively [8], [9]. Currently, there is a need for a unified system that not only detects eye blinks but also translates them into written and spoken words with minimum effort from the user's side.

In response to these issues, this project attempts to develop an Eye Blink Based Morse Code Text Generation and Voice Output System. It is a web-based platform for communication assistance that makes use of computer vision algorithms for real-time interaction. In particular, the MediaPipe Face Mesh is used for facial landmark detection, and Eye Aspect Ratio (EAR) is calculated for detecting blinks, which are further classified into either short or long blinks according to Morse code symbols. Subsequently, the symbols can be translated into alphanumeric letters or control commands that allow for text generation and voice generation through web-based APIs. Noise filtering, word prediction and persistence are some of the other features included in this project to make it more efficient. The key goals behind this project include the development of an eye blink detection algorithm, implementation of Morse code encoding and decoding, ability to generate texts and voices, design of an easy-to-use web interface and scalability to become hardware independent.

A ·—	J ·———	S ···	0 —————
B —···	K —·—	T —	1 ·————
C —·—·	L ·—··	U ··—	2 ··———
			3 ···——
D —··	M ——	V ···—	4 ····—
E ·	N —·	W ·——	5 ·····
F ··—·	O ———	X —··—	6 —····
G ——·	P ·——·	Y —·——	7 ——···
H ····	Q ——·—	Z ——··	8 ———··
I ··	R ·—·		9 ————·

Fig. 1 Morse code table

II. LITERATURE REVIEW

A. *Eye Blink Detection and Facial Landmark-Based Systems*

Blink detection is a crucial process in many human-computer interaction (HCI) systems and assistive communication applications. Soukupová and Čech [1] presented a method for real-time blink detection using facial landmarks and the Eye Aspect Ratio (EAR). This method has been widely used since then owing to its efficiency and simplicity. Soukupová and Čech [1] demonstrated accurate blink detection under controlled environment; yet, the fixed threshold EAR value makes the method unreliable for different head postures, lighting conditions and user-dependent facial structures. Further research in blink detection applications was done by Raj et al. [11], who proposed a new algorithm for real-time HCI applications, thus increasing its practicality. In addition, Sharma et al. [13] utilized deep learning to improve blink detection accuracy. Although deep learning can significantly increase blink detection accuracy, they often introduce increased computational overhead, making real-time deployment on low-resource systems challenging.

Facial landmark detection techniques have recently been greatly refined to provide enhanced eye tracking results. For example, Li et al. [14] suggested an assistive communication interface that utilized facial landmarks for interaction with

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the system, whereas Zhang et al. [16] developed a lightweight solution known as MediaPipe Face Mesh that is able to detect dense facial landmarks in real-time in the browser environment. Compared to earlier techniques, MediaPipe Face Mesh demonstrates increased precision and lower delay in landmark detection, which makes it appropriate for assistive purposes. Unfortunately, existing approaches mainly pay attention to the accuracy of blink detection without expanding their approach for a full communication application.

B. Eye Tracking and Gaze-Based Assistive Communication Systems

A number of scientists have explored eye tracking technology as a possible communication technique for people who have very limited control over motor skills. In this regard, D'Orazio et al. [7] created a system of eye-tracking for assistive communication that allowed users to use computer interfaces through eye movements. In addition, Asadifard and Shanbezadeh [8] developed an adaptive eye-gaze tracking system based on gaze estimation to enhance user interaction efficiency. Al-Rahayfeh and Faezipour [9] offer a detailed overview of various eye-tracking and head gesture recognition technologies.

While eye-tracking systems provide more advanced forms of user interaction, they generally come with additional calibration steps or even involve special sensors or complicated tracking techniques that make their development difficult and expensive. Systems like the one developed by Barea et al. [10], which use an electrooculography technique, attain great levels of accuracy but need electrodes worn on the eyes and specific hardware. This hardware makes the system less portable and harder to implement cheaply for communication aid purposes.

C. Computer Vision Techniques for Face Detection and Recognition

The development of the current advanced communication technologies has greatly benefited from the rapid development of computer vision technology. The Viola-Jones detector [5] is an efficient algorithm based on the Haar-like feature that allows for the first-time implementation of an actual face detection system. Although this method greatly improves the computational efficiency of detecting a face, its accuracy is not sufficient to determine the eye state of a user. Dalal and Triggs [4] have developed the Histogram of Oriented Gradients (HOG), which has a proven ability to detect objects effectively. However, the computation of the feature vectors is too computationally expensive.

Szeliski [3] gave an elaborate account of computer vision algorithms such as feature detection, image segmentation, object recognition and motion estimation, laying the groundwork for the theories that make up the basis of today's facial recognition technology. The camera calibration method proposed by Zhang [6] contributed to improving the geometric precision within the field of vision-based systems. These laid the computational groundwork needed for visual interactive technologies. Nevertheless, classic approaches in computer vision have always emphasized detection and recognition tasks, not communication using visual cues generated by users.

D. Morse Code-Based Assistive Communication Approaches

Morse code has proven to be efficient in communicating for individuals with impaired motor skills because of its binary signal encoding. In particular, Smith and Brown [2] conducted research on Morse code-based assistive communications devices, where they made use of mechanical switches and special hardware interfaces in order to enable the formation of dots and dashes. The results obtained from this experiment showed that Morse code was capable of creating a dependable form of communication requiring minimal user input. Also, Islam et al. [15] developed a cost-effective eye tracking text generation system for patients with paralysis.

Even with the effectiveness of some Morse code communication systems, they have not been integrated into an internal mechanism that is free from hardware components or physical signal generation. Some of the existing solutions may concentrate more on the signal generation and decoding process without integrating other important modern-day computer vision techniques. In addition, some Morse code communication devices lack some interaction capabilities like speech generation, intelligent text assistance, and web browser support.

E. Comparative Analysis and Research Gap

From the literature review, it is clear that there have been remarkable advancements in areas of blink detection, gaze tracking, face landmark recognition and assistive communications. Methods using facial landmarks [1], [14], [16] offer fast and accurate detection of blinks and gaze tracking systems [7]–[10] enable better interactions. Although deep learning approaches [13] enhance recognition performance, they can lead to increased computation time. Morse code–based communication systems [2], [15] demonstrate effective low-input communication strategies but typically depend on specialized hardware or lack integration with modern vision-based frameworks.

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However, some of the following issues have yet to be solved. First, most studies focus on individual components such as blink detection, eye tracking or Morse decoding rather than providing an integrated end-to-end communication framework. Second, a dependence on specific hardware makes accessibility worse and costs more. Third, some current approaches lack real-time speech output, smart assistance in text input and browser accessibility. Finally, computational requirements might become an issue when implementing a communication solution with deep learning or gaze-tracking algorithms. All these observations prove that there is a need for an efficient, vision-based, and independent from hardware approach aimed at converting eye blink signals into text and speech output in real time.

III. METHODOLOGY

A. System Architecture

The proposed Eye Blink Based Morse Code Text Generation and Voice Output System is based on modular browser based architecture for real time assistive communication. The system can be divided into six key layers: Video Acquisition Layer, Facial Landmark Detection Layer, Optimization Layer, Blink Detection Layer, Morse Code Processing Layer, and Communication Layer. Using a regular webcam, video frames are captured and MediaPipe Face Mesh is used to extract facial landmarks from the video. Eye landmarks are identified and then the Eye Aspect Ratio (EAR) is calculated, and this is continuously tracked for blinks. Blink events detected are labelled as short or long duration events (dots or dashes) of morse code. The Morse sequences are then translated back into alphanumeric characters and control commands. The resulting text is shown to the user interface and converted into audible speech using browser-based speech synthesis. Other optimization modules enhance real-time performance, robustness, and prediction accuracy. The entire system architecture of the proposed system is shown in figure 2.

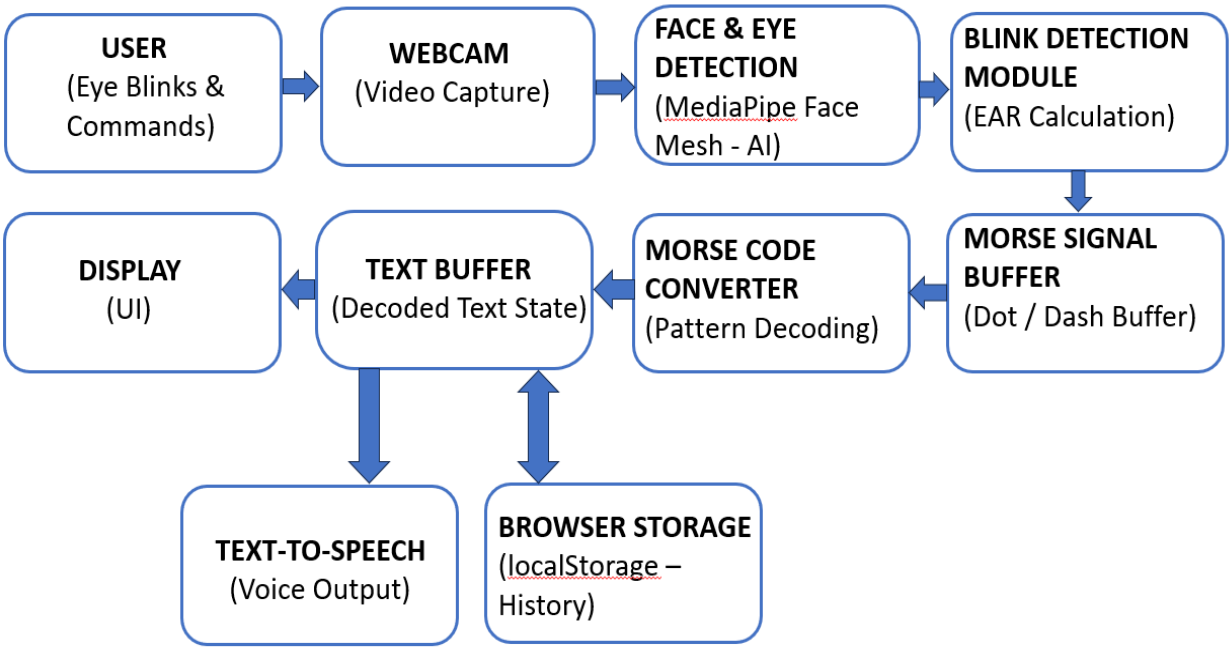

Fig. 2 System Architecture

The data flow of proposed Eye Blink Based Morse Code Text Generation and Voice Output System starts with the generation of eye blink signals in front of a webcam by the user. The video stream captured is analyzed to find the occurrence of short and long blinks and they are recognized as “dots” and “dashes” of Morse code. The resulting Morse sequences are converted to characters and put in a text buffer to make a message. The user interface displays the decoded text and at the same time, the text is translated into speech via a text-to-voice module. Moreover, generated messages are archived in the history for retrieval and communication process management. The entire data flow diagram of the proposed system is shown in figure 3.

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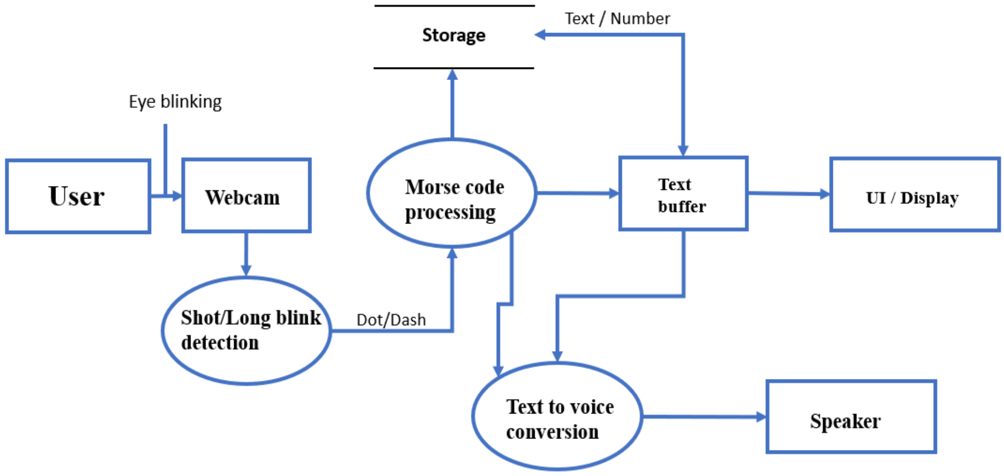

Fig. 3 Data Flow Diagram

B. *Video Acquisition and Facial Landmark Detection Layer*

The system acquires real-time video frames using the browser Webcam API. Each frame is processed by MediaPipe Face Mesh, which detects 468 facial landmarks. Eye-specific landmarks are extracted from the detected face mesh and used for eye state analysis.

MediaPipe Face Mesh performs dense facial landmark estimation using lightweight machine learning models optimized for real-time browser execution. The detected landmarks provide stable eye coordinates even under moderate head movement and lighting variations.

C. *Eye Aspect Ratio Computation Layer*

Blink detection is performed using the Eye Aspect Ratio (EAR), which measures the ratio between vertical and horizontal eye distances. For each eye, six landmark points are selected.

The EAR is calculated as:

$$EAR = \frac{\|P_2 - P_6\| + \|P_3 - P_5\|}{2\|P_1 - P_4\|} \qquad (1)$$

where:

- P_1 and P_4 represent horizontal eye corner points.
- P_2, P_3, P_5 and P_6 represent vertical eye landmarks.
- $\|\cdot\|$ denotes Euclidean distance.

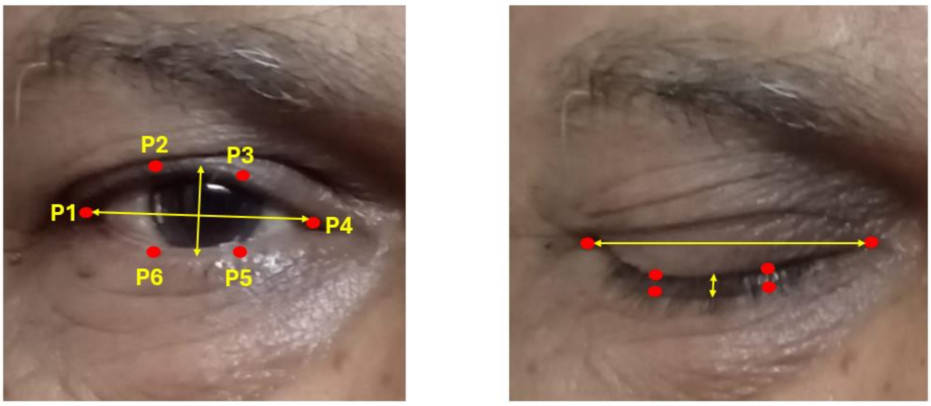

Fig. 4 Eye landmarks used for Eye Aspect Ratio (EAR) computation. Left: Eye in open state with landmark points $(P1 - P6)$. Right: Eye in closed state showing reduced vertical distance.

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The Euclidean distance between two points is computed as:

$$D = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \quad (2)$$

When the eye is open, EAR remains relatively constant. During a blink, the vertical distances decrease significantly, causing EAR to drop below a predefined threshold.

D. Blink Detection and Classification Layer

The blink detection module continuously monitors EAR values. A blink event is detected when:

$$EAR < T_{ear} \quad (3)$$

where T_{ear} the blink threshold.

The duration of the detected blink is then measured:

$$t_{blink} = t_{end} - t_{start} \quad (4)$$

where:

- t_{start} = blink initiation time
- t_{end} =blink completion time

The blink is classified according to its duration:

Short Blink (Dot):

$$t_{blink} < T_{dash} \quad (5)$$

Long Blink (Dash):

$$t_{blink} \geq T_{dash} \quad (6)$$

where T_{dash} represents the duration threshold separating dots and dashes.

E. Morse Code Encoding and Decoding Layer

Each classified blink is converted into a Morse symbol.

Short Blink → Dot (.)

Long Blink → Dash (-)

The generated Morse sequence is stored in a buffer:

$$M = \{m_1, m_2, m_3, \ldots, m_n\} \quad (7)$$

where $m_i \in \{., -\}$

The Morse decoding engine compares the generated sequence with a predefined Morse lookup table:

$$\text{Character} = \text{Decode}(M) \quad (8)$$

The decoder supports alphabetic characters, numeric symbols, and control commands for text editing, message management, prediction selection, and speech synthesis.

F. Text Generation and Speech Synthesis Layer

After decoding, characters are appended to the generated text string:

$$T_{new} = T_{old} + C \quad (9)$$

where:

- T_{old} = existing text
- C = decoded character

The generated text is converted into speech using the browser SpeechSynthesis API:

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$$\text{Voice Output} = \text{Speak}(T_{new}) \qquad (10)$$

This enables real-time auditory communication for users with severe motor impairments.

G. *Word Prediction Module*

To reduce user effort and improve communication speed, a prefix-based prediction mechanism is incorporated.

Let P represent the current text prefix:

$$P = \{c_1, c_2, c_3, \ldots, c_n\} \qquad (11)$$

Predicted words are selected using:

$$\text{Suggestions} = \{w \in D \mid w \text{ startsWith } P\} \qquad (12)$$

where:

- D = prediction dictionary
- w = candidate word

The prediction engine dynamically updates suggestions as additional characters are generated.

H. *Data Persistence and History Management*

Generated messages are stored locally using browser localStorage.

The storage operation is represented as:

$$\text{History}(n) = \text{History}(n-1) \oplus \text{Message}_n \qquad (13)$$

Previously stored messages can be retrieved using:

$$\text{Retrieve} = \text{Fetch}(\text{History}) \qquad (14)$$

This allows users to access previously generated communication records without requiring external databases.

I. *Optimization Layer*

To improve blink detection accuracy, communication reliability, and system robustness, several optimization techniques are incorporated within the proposed system.

1) Dynamic EAR Threshold Optimization:

A fixed Eye Aspect Ratio (EAR) threshold may result in inaccurate blink detection when the user's head orientation changes. Therefore, the proposed system dynamically adjusts the blink threshold based on the head pitch ratio:

$$T_{EAR} = f(P) \qquad (15)$$

where:

- T_{EAR} = active EAR threshold
- P = head pitch ratio

The threshold is modified according to the user's head position, improving blink detection under varying viewing angles. This optimization reduces missed detections and improves system adaptability for different head orientations.

2) Motion Compensation Optimization:

Rapid head movement may generate false blink detections due to facial landmark displacement. To address this issue, head movement velocity is computed using nose landmark displacement:

$$V = \sqrt{(\Delta x)^2 + (\Delta y)^2} \qquad (16)$$

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where:

- V = head movement velocity
- Δx = horizontal displacement
- Δy = vertical displacement

Blink detection is temporarily suppressed when:

$$V > V_{th} \qquad (17)$$

where V_{th} represents the motion threshold.

This optimization prevents false Morse code inputs caused by sudden head movements.

3) Head Tilt Compensation Optimization:

Changes in head tilt can affect the appearance of the eyes and influence EAR measurements. Therefore, the proposed system monitors the head pitch ratio:

$$P = \frac{D_{top}}{D_{bottom}} \qquad (18)$$

where:

- D_{top} = distance between forehead and nose landmarks
- D_{bottom} = distance between nose and chin landmarks

The variation in pitch ratio is calculated as:

$$\Delta P = | P_t - P_{t-1} | \qquad (19)$$

where:

- ΔP= change in head pitch ratio between consecutive frames
- P_t= current frame pitch ratio
- P_{t-1}= previous frame pitch ratio

The value of ΔP represents the magnitude of head tilt variation between two successive frames. If ΔP exceeds a predefined threshold, blink detection is temporarily suppressed to prevent false Morse code generation caused by rapid head movements.

4) Gaze-Based False Positive Filtering:

Extreme eye movements may artificially reduce EAR values and produce incorrect blink detections. Therefore, iris position is used to compute a gaze ratio:

$$G = \frac{D_{iris}}{D_{eye}} \qquad (20)$$

where:

- G = gaze ratio
- D_{iris} = distance between iris center and eye corner
- D_{eye} = eye width

Valid gaze positions satisfy:

$$0.25 \leq G \leq 0.75 \qquad (21)$$

Blink detection is temporarily suppressed when the gaze ratio falls outside the valid range. This optimization reduces false detections caused by extreme side-eye movements.

J. Communication Output Layer:

The output of the final communication is the decoded text, predicted words, synthesized speech, and messages stored in the history. The integration of computer vision, Morse code translation, speech synthesis, and browser-based optimization techniques enables the system to be a lightweight, real-time, and hardware independent assistive communication system for people with severe motor impairments.

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IV. RESULT AND DISSCUSSION

A. Results and Performance Evaluation

The proposed Eye Blink Based Morse Code Text Generation and Voice Output System was tested in controlled real-time conditions to test the effectiveness of eye blink detection, generation of Morse code, and reliability of communication. The system used MediaPipe Face Mesh and the Eye Aspect Ratio (EAR) method to detect whether the eyes were short-blinking, long-blinking or not blinking. A typical webcam was used in the normal indoor lighting for experimental testing. The results showed that the system performed well in detecting the blink and mapping it to the corresponding Morse code symbol. The combination of motion suppression, head-tilt-based suppression, and gaze-based suppression techniques significantly reduced false blink detections arising from facial movements and gaze variations, thereby enhancing the robustness and accuracy of the proposed communication system.

For the quantitative assessment of blink classification accuracy, a test set of 150 samples was collected under real-time operating conditions. The dataset consisted of 50 short blinks (Dot), 50 long blinks (Dash), and 50 non-blink eye states. The non-blink samples were obtained by instructing participants to maintain a normal and comfortable head position while keeping their eyes naturally open. A time interval of 3 seconds was considered for each non-blink observation. If no blink event was detected and no Morse symbol was generated during the 3-second interval, the sample was labelled as a No-Blink instance. All samples were manually verified and compared with the corresponding system predictions. The confusion matrix obtained is shown in Table I. The proposed system achieved an overall classification accuracy of approximately 90.6%, demonstrating effective discrimination among Dot, Dash, and No-Blink classes. Most classifications were concentrated along the main diagonal of the confusion matrix, indicating reliable recognition performance and low inter-class confusion.

TABLE I CONFUISON MATRIX FOR BLINK CLASSIFICATION

Actual / Predicted	Dot	Dash	No Blink
Dot (50)	46	2	2
Dash (50)	3	46	1
No Blink (50)	3	3	44

From the confusion matrix:

$$\text{Accuracy} = \frac{46 + 46 + 44}{150} \times 100$$

$$\text{Accuracy} = \frac{136}{150} \times 100 = 90.6\%$$

The results obtained show that the main misclassification errors were between the short and long blink categories when the blink duration was near to the predefined value of the blink duration. However, the adopted duration-based classification scheme was able to classify most of the blink events. All the precision and recall values calculated for each class were above 88%, showing a balance between the detection capability and robustness. The geometric approach using EAR was also computationally inexpensive, with lower complexity than deep learning-based methods, allowing for real-time processing without the need for dedicated GPU acceleration.

In addition to blink classification, the complete communication pipeline was successfully validated through practical testing. Blink patterns were translated into morse code sequences which were successfully translated back into alphanumeric characters and pre-defined control commands like Space, Backspace, Clear, Save, Lock/Unlock. The word prediction module enhanced the efficiency of text entry by offering suggestions for words that are contextually appropriate, generated from prefixes of the text, and the Speech Synthesis API gave instant voice output for generated messages. Local history management module allowed text to be stored and retrieved from previous instances to further improve usability. The findings overall support the reliability, low cost, and hardware-independence of the proposed assistive communication solution implemented in a browser-based framework, which can be used for real-time hands-free interaction for people with severe motor impairments.

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B. System Working Demonstration

1) Blink-Based Text Generation (Initial Input Stage):

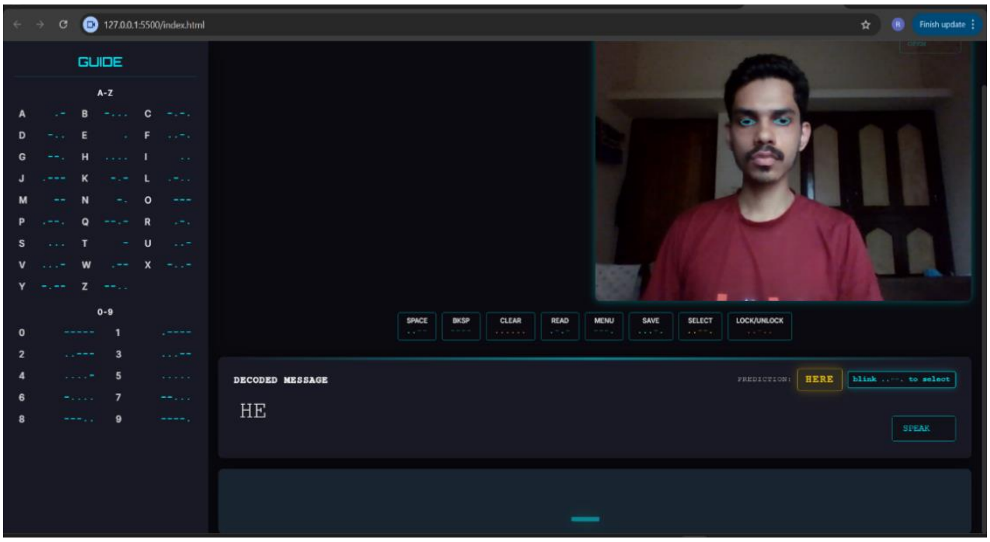

Fig. 5 Initial blink-based text generation with partial decoded output

The communication process begins with the real-time acquisition of video frames through the webcam interface. MediaPipe Face Mesh continuously detects facial landmarks and extracts eye coordinates required for Eye Aspect Ratio (EAR) computation. As the user generates blink signals, the system identifies short and long blink durations and converts them into Morse code symbols. The generated symbols are decoded into characters and displayed within the message area. At this stage, the partial text “HE” has been successfully generated, while the word prediction module simultaneously suggests relevant word completions based on the current text prefix. This demonstrates the integration of blink detection, Morse decoding, text generation and predictive assistance within a unified interface.

2) Word Prediction and Selection Mechanism:

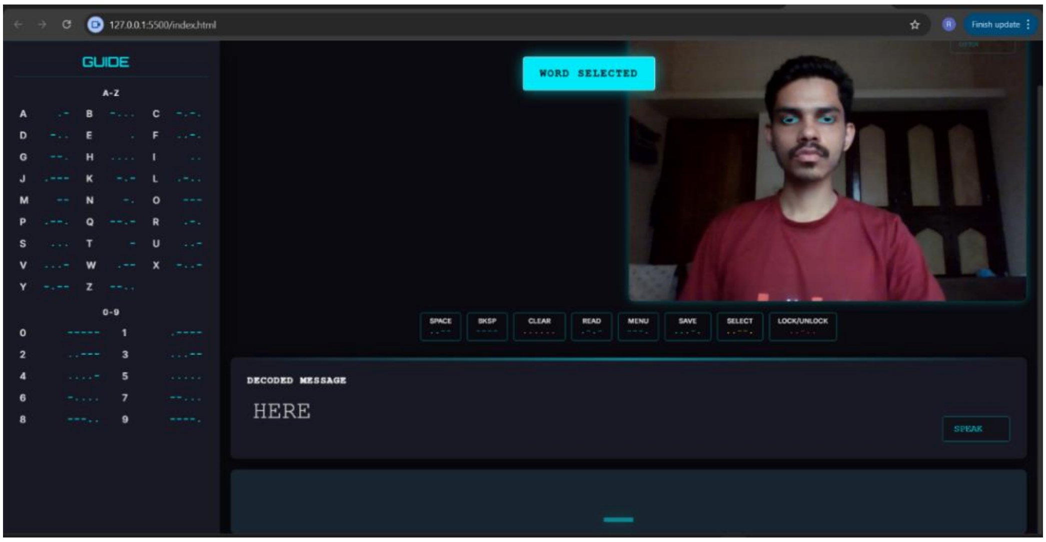

Fig. 6 Word prediction and selection using blink-based commands

After generating a sufficient character prefix, the prediction engine dynamically provides context-relevant word suggestions to reduce user effort during text entry. The displayed prediction “HERE” is selected through a predefined Morse command without requiring additional character input. Once selected, the suggested word is automatically appended to the decoded message buffer, resulting in the complete word being displayed in the communication area. This functionality significantly improves communication speed by reducing the number of blink sequences required to construct frequently used words and phrases.

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3) System Lock and Input Protection Feature:

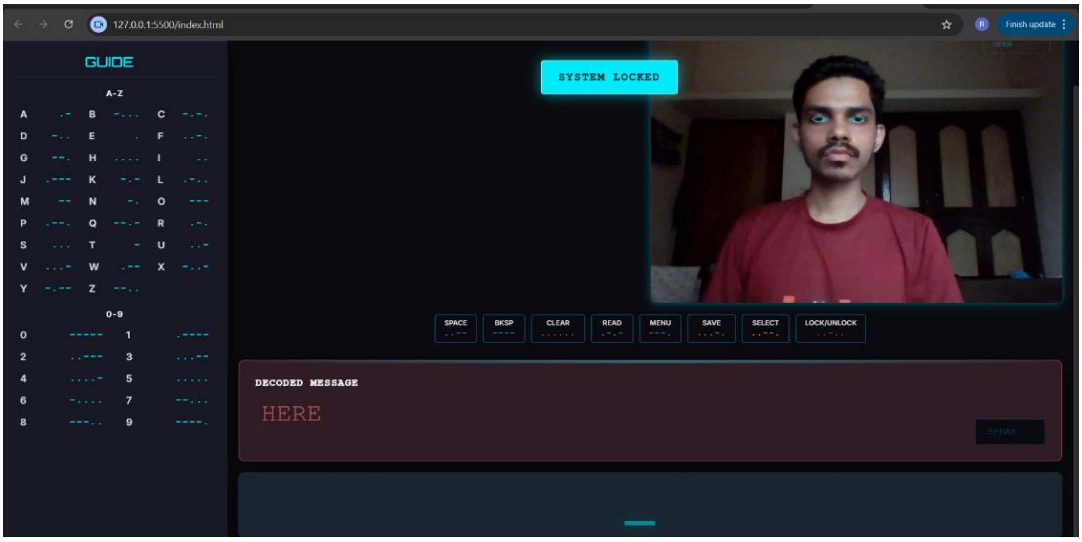

Fig. 7 System lock state preventing unintended inputs

To prevent unintended text generation during temporary pauses or user inactivity, the system incorporates a lock mechanism controlled entirely through Morse code commands. Upon receiving the corresponding blink sequence, the interface enters a protected state and displays a visual confirmation indicating that input processing has been suspended. During this period, blink events are ignored until the unlock command is received. This feature enhances operational reliability and prevents accidental character generation caused by involuntary eye movements or environmental disturbances.

4) Message Archiving and Data Persistence:

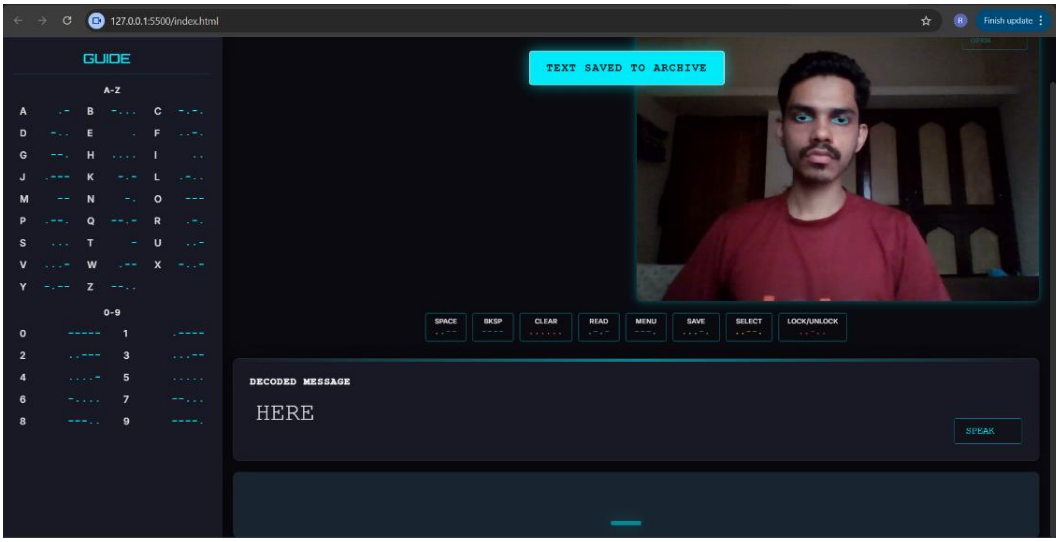

Fig. 8 Text saving confirmation using blink command

The generated communication output can be permanently stored using the archive functionality integrated within the browser environment. When the save command is executed through Morse input, the current text message is preserved using localStorage and a confirmation notification is displayed to the user. The storage mechanism enables long-term retention of generated communication records without requiring external databases or cloud services. This functionality improves usability by allowing frequently used messages to be preserved for future access and communication sessions.

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5) History Management and Message Retrieval Interface:

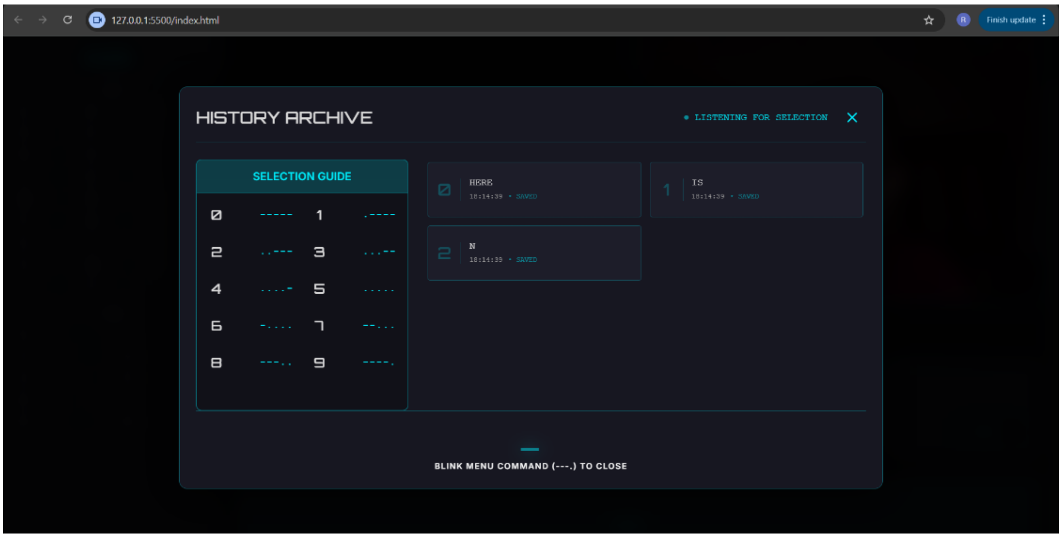

Fig. 9 History archive displaying saved messages with indexed selection guide

The history archive module enables users to access previously stored communication records through a fully blink-controlled interface. Upon opening the archive, all saved messages are displayed together with their timestamps and a numerical selection identifier ranging from 0 to 9. Each number is mapped to a corresponding Morse code sequence shown in the selection guide, allowing users to retrieve messages without the use of conventional input devices. By generating the Morse pattern associated with a particular number, the user can select and load the desired archived message directly into the communication buffer. This mechanism provides an efficient method for reusing frequently generated phrases, reducing the need to repeatedly construct common messages through blink sequences and thereby improving communication speed and overall user convenience.

6) Context-Aware Word Prediction During Continuous Communication:

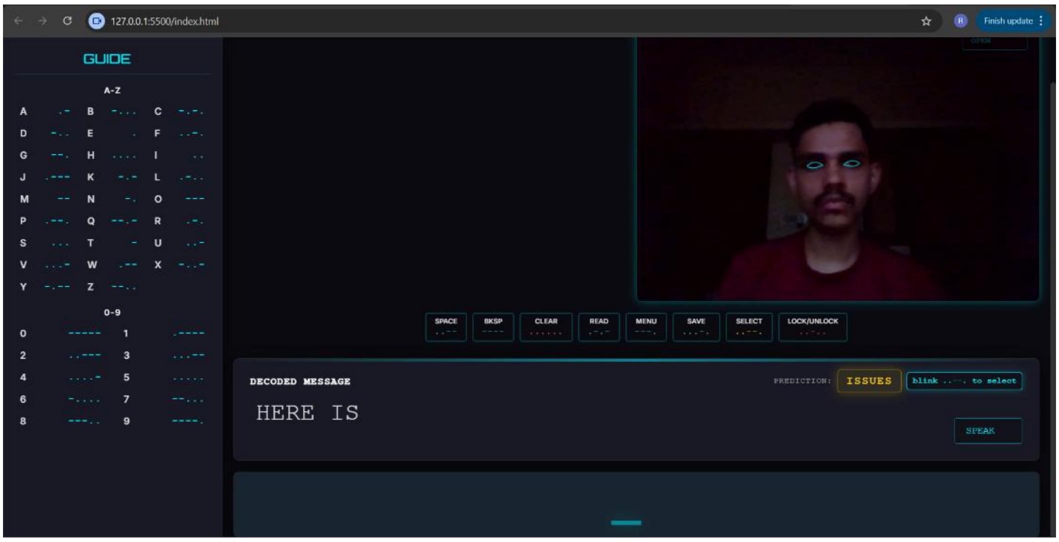

Fig. 10 Retrieval of saved message and continuation of communication

Following the retrieval process, the selected archived message is automatically inserted into the active communication buffer and becomes available for further message construction. In the illustrated example, the archived word “IS” has been successfully selected and appended to the existing text, resulting in the phrase “HERE IS.” After updating the communication buffer, the prediction engine immediately analyses the newly formed text context and generates relevant continuation suggestions, such as “ISSUES,” which can be accepted using the predefined Morse-based selection command. This seamless integration of archive retrieval and context-aware word prediction minimizes user effort,

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reduces the number of required blink operations, and significantly enhances the efficiency of prolonged communication sessions.

V. CONCLUSION

Assistive communication is still a major problem for users with severe motor impairments who cannot use a keyboard, mouse or touch-based input device. Current communication systems may depend on specialized hardware or installation methods, can be costly and complicated to use, thus making it difficult to access and implement. To overcome these issues, a web-based Eye Blink Based Morse Code Text Generation and Voice Output System that enables users to communicate through voluntary eye blinks captured with a standard webcam to communicate. By leveraging MediaPipe Face Mesh and Eye Aspect Ratio (EAR)-based blink detection, the system successfully transforms eye blink patterns into Morse code signals that are subsequently decoded into meaningful text and speech output.

The solution to the problems of low cost and hands-free communication was achieved by designing a framework that could be implemented in a web browser and did not require any specific hardware or external sensors. The real-time facial landmark detection, blink classification, Morse code decoding, text generation, speech synthesis, word prediction, and message archiving were all integrated to form a complete end-to-end communication platform. Experimental evaluation demonstrated that the system can reliably detect short and long blink patterns, generate alphanumeric text in real time, execute predefined control commands, and provide immediate voice feedback. Other features like predictive text generation and history-based message retrieval further enhanced the efficiency and ease of communication in prolonged interactions.

Despite its effectiveness, the proposed system has certain limitations. Blink detection performance may be influenced by variations in illumination, camera quality, excessive head movement, and partial facial occlusions. Although the system employs a pitch-ratio-based dynamic EAR threshold selection mechanism, the threshold values are selected from a predefined set and are not individually calibrated for different users. Consequently, detection accuracy may still vary across users and environmental conditions. Furthermore, the blink-duration threshold remains fixed, which may not be equally suitable for all users. The current word prediction module relies on lightweight prefix-based matching and does not incorporate advanced contextual language understanding. The system also depends on the continuous visibility of facial landmarks generated by MediaPipe Face Mesh, which may be affected by extreme viewing angles, rapid movements, or unstable lighting conditions.

Future work can focus on improving robustness, intelligence and accessibility of the communication framework. Adaptive thresholding techniques and personalized calibration mechanisms can be incorporated to enhance blink detection accuracy across diverse users and operating conditions. Advanced Natural Language Processing (NLP) models and transformer-based language prediction techniques can be integrated to provide more accurate context-aware suggestions and accelerate text generation. Additional enhancements may include multilingual communication support, adaptive user profiling, cloud-based synchronization of communication history, advanced gaze-assisted navigation, and liveness verification mechanisms for improved reliability and security. These improvements have the potential to further expand the applicability of browser-based assistive communication systems and contribute to the development of more inclusive and accessible human–computer interaction technologies.

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