EmoWrite: A Sentiment Analysis-Based Thought to Text Conversion
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Abstract:
Brain-Computer Interface (BCI) helps in processing and extraction of useful information from the acquired brain signals having applications in diverse fields such as military, medicine, neuroscience, and rehabilitation. BCI has been used to support paralytic patients having speech impediments with severe disabilities. To help paralytic patients communicate with ease, BCI based systems convert silent speech (thoughts) to text. However, these systems have an inconvenient graphical user interface, high latency, limited typing speed, and low accuracy rate. Apart from these limitations, the existing systems do not incorporate the inevitable factor of a patient's emotional states and sentiment analysis. The proposed system “EmoWrite” implements a dynamic keyboard with contextualized appearance of characters reducing the traversal time and improving the utilization of the screen space. The proposed system has been evaluated and compared with the existing systems for accuracy, convenience, sentimental analysis, and typing speed. This system results in 6.58 Words Per Minute (WPM) and 31.92 Characters Per Minute (CPM) with an accuracy of 90.36%. EmoWrite also gives remarkable results when it comes to the integration of emotional states. Its Information Transfer Rate (ITR) is also high as compared to other systems i.e., 87.55 bits/min with commands and 72.52 bits/min for letters. Furthermore, it provides easy to use interface with a latency of 2.685 sec.

Keywords: EmoWrite, Brain Computer Interface (BCI), Electroencephalogram (EEG), Recurrent Neural Network (RNN)

1. Introduction:
Mind-reading systems were fiction, but with the advancement of technology, this is becoming a reality and helping physically challenged people in performing their tasks e.g., controlling a wheelchair, robotic arm, and cursor. People having physical disability and speech obstruction are not disabled, rather they are differently abled because they might be impaired with one or two abilities, but their other capabilities can be more precise and accurate as compared to a healthy person [1]. Particularly, when we talk about paralytic patients, they might not have an appropriate communication medium to convey their feelings, but their mental activity is more precise if it is utilized efficiently.

A lot of research work has been done which is not limited only to assist in rehabilitation, but to make them self-reliant [2]. Scientists are utilizing brain signals usually through electroencephalogram (EEG) by extracting useful information from acquired signals. These brain signals are being used in many domains of daily life and exclusively in the medical domains for monitoring alertness, coma or death, brain damage, controlling anesthesia depth, brain development, testing of drugs, and monitoring sleep disorders [2]. EEG signals are also used to
resolve speech impediments and eradicate communication barriers of paralytic patients by converting their thoughts (silent speech) to text.

There are two methods used in literature to decode brain signals, the first method directly decodes brain signals into a word, while the other method requires the use of an intermediate output device for converting thought to text. Converting a word directly from the brain to text seems not so much feasible because only limited numbers of words can be interpreted at a time due to the need for additional training, computation power, and resources. Limited information is available regarding the aspect that whether brain generates the same signals while perceiving similar words or not. Hence, this research area has not yet matured. In [7], research has been done to decode five words only i.e. “Alpha”, “Bravo”, “Charlie”, “Delta” and “Echo” and in [12], only five characters have been decoded i.e. a, e, i, o, t. The other method needs a medium, which includes an interface containing characters or words, that can be selected with the help of brain signals. The character selection can be based on two mechanisms i.e. using a virtual keyboard or Visual Evoked Potential (VEP)/Steady-State Visual Evoked Potential (SSVEP) [9]. The virtual keyboard uses raw data or built-in functions of headset i.e. left, right, up, down, or motor imagery (i.e. imaging movements of hands or feet) [2], whereas attention-based systems (VEP/SSVEP) focus on some flickering stimulus for selection of characters [9].

The factors which can affect the performance of these systems are related to speed, accuracy, and usability of the system. Moreover, people using these systems are not able to express their feelings accurately because it is problematic to find a proper word to write according to one’s mood, so incorporation of emotional state along with other commands from the brain will help in better utilization of these systems.

The proposed system “EmoWrite” integrates a dynamic and personalized graphical user interface with the prediction of contextualized words according to the patient’s mood. The key novelty of EmoWrite is to keep track of patient’s emotional states and help them express their feelings in words. As there is a minor difference between each emotional class so differentiating these classes requires crucial modeling. These classes vary from person to person, so person-specific emotional class detection is the major challenge that has been successfully addressed. The classification of brain signals for class detection also requires proper training. The dynamic arrangement of character set on the keyboard helps users to choose from limited characters only, eventually assisting in swift typing. Moreover, the adaptive character set arrangement evolved according to the user's typing style and context, enhance the productivity of those differently abled patients. Emotiv Epoc+ headset, which provides 14 channels for EEG sensing, has been used to acquire signals from the brain. EmoWrite has implemented proven classification techniques from the literature to achieve minimal training time. Facial expressions in paralytic patients deteriorate with time due to their decreased or no usage, hence the proposed system also implements emotion detection along with the utility of facial expressions which will also be beneficial in the rehabilitation process. The contributions of this paper are as follows:

- Provides BCI based solutions to support paralytic patients having speech impediments with severe disabilities.
• Convert silent speech (thoughts) to text with EmoWrite™ which implements a dynamic keyboard with contextualized appearance of characters reducing the traversal time and improving the utilization of the screen space.

• Provides dynamic arrangement of character set on the keyboard that helps users to choose from limited characters only, eventually assisting in swift typing.

• Provides sentiment-based thought to text conversion and suggestions. To the best of our knowledge, this has not been reported so far.

The rest of the paper is organized as follows. Section 2 describes comprehensive related work. The proposed scheme with respect to data acquisition and data processing is discussed in Section 3. Section 4 consists of information about the real-time experimentation and results. At the end conclusion in section 5 revealed the potential of EmoWrite to convert silent speech to text.

2. Related Work:

To enable communication for paralytic patients some work has been done in the past and still research is ongoing in the domain of BCI-based thoughts to text conversion. One of the methods to convert thoughts into text is using a graphical user interface (GUI) consisting of numbers, alphabet, or special characters, which are displayed in a certain order on a virtual keyboard. The brain signals are then used to control the selection of any desired character or alphabet from this virtual keyboard. The major selection methods used in previous systems can be categorized as: 1) attention-based control like Visual Evoked Potential (VEP) or Steady-State Visual Evoked Potential (SSVEP). 2) raw data or built-in functions of the headset to control the cursor or targeted area on the screen.

The virtual keyboards are divided into single or multiple layers with static or dynamic keys and their design has a direct influence on the performance of the system. A wide literature survey has been conducted to specify different types of action selection methodologies; character arrangement and virtual keyboard designs and a taxonomy is given in Figure1.

Figure 1: Taxonomy of Thought to Text Conversion
Some of the major challenges for decoding the EEG signals are low SNR, time consumption, and accuracy. To overcome these challenges, a novel hybrid deep learning approach based on Recurrent Neural Network (RNNs) and Convolutional Neural Network (CNNs) have been used, this converts thoughts to text [2]. EEG signals have been used to control the cursor of a personal computer in [29]. Features from EEG signals are extracted with a 64-channel NeuroSky headset using a discrete wavelet transform and are classified with the help of machine learning algorithms such as Support Vector Machine (SVM) and Neural Networks (NNs). In [30] Hayet et al. described, a two-layer hierarchical layout of the keyboard that works with motor imagery signals (left-hand raised, right-hand raised, nodding up ad nodding down).

Gupta et al. used EEG signals to enhance a written sentence with detected emotions by inserting words in it [8]. Long Short-Term Memory (LSTM) Networks based language modeling framework has been used to verify the sentence correctness by ranking the generated suggestions. ‘Hex-o-spell’, a tilt-based gestural text entry system, has been introduced in [32]. The letters have been arranged in 6 hexagonal shaped boxes which are rearranged after every transition to save time. Wang et al. shows how English alphabets are decoded using EEG phase information in [12]. They used the 64-channel actiC Hamp Brain Product to acquire EEG signals. Five alphabets (a, e, l, o, t) are chosen, and against each alphabet, the brain signals are recorded. Results showed that accuracy increased to 31% when the time-period improved to 200ms. It is also proved from the results that mostly decrypted data lies within the period of 100-to-600ms. High-performance intracortical BCI for communication has been described in [34]. It provides point and clicks control of the computer; these controls are translated by ReFIT Kalman Filter (RKF) and Hidden Markov Model (HMM). RKF has been used to translate the 2D cursor movement and HMM is used to translate selection.

Efficiency issues of the virtual keyboard have been discussed in [36]. The author suggested that there should be at least one level of hierarchy for better usability while more efficiency is achieved with a matrix-shaped keyboard. A novel virtual keyboard design has been introduced in [37]. Built-in functions of Emotiv Insight are used to navigate through the interface and move the selected area. The characters have been arranged circularly to utilize screen space efficiently. Dynamic caption of keys changes according to the previously entered characters with the help of a predictive system.

Disabled people have limited activities; they need a certain medium to translate their brain signals so they can interact with the people around them. An application using raw EEG data with Emotiv Epoc has been used in [15] to translate thoughts to the text which will be implemented in SMS for providing ease to communicate. A Thought Translation Device (TTD) which uses Slow Cortical Potential (SCP) to select characters or words has been introduced in [38]. SCP is used because its learning rules are well known, and the basics are well understood. Cognitive performance is reduced when the user produces positive SCP and improvement in the performance and learning occur with negative SCP. To record brain activity an 8 channel EEG amplifier is used. Visual feedback of EEG is received and updated after every 63ms. A scanning ambiguous keyboard has been presented in [40]. It takes input from the user through one key or switch. The layout contains a letter section at the top and a word section at the bottom (candidate list). The focus is transferred between the letter section to the word section with the space key. The alphabets are highlighted in a sequence and the user can select them by triggering the input.
| Ref. # | Virtual Keyboards | Attention Based | Action Selection | Characters Per Minute (CPM) / Words Per Minute (WPM) |
|-------|-------------------|-----------------|------------------|-----------------------------------------------|
| [2]   | ✓                 | ✓               | ✓                | 95.53% 6.67 CPM                               |
| [8]   | ✓                 | ✓               | ✓                | 74.95% N/A                                    |
| [19]  | ✓                 | ✓               |                 | 87.50% N/A                                    |
| [20]  | ✓                 | ✓               |                 | N/A 12 WPM                                    |
| [9]   | ✓                 | ✓               | ✓                | N/A 5-10 CPM (P300), 7.34 CPM (SSVEP), 5 CPM (motor) |
| [22]  | ✓                 | ✓               |                 | 80-90% 6.5 WPM                                |
| [23]  | ✓                 | ✓               |                 | 92% (supervised learning), 96% (ERP) 8 WPM (supervised learning), 9 WPM (ERP) |
| [24]  | ✓                 |                 |                 | 33% increased N/A                             |
| [25]  | ✓                 | ✓               |                 | N/A 11.93 CPM                                 |
| [26]  | ✓                 | ✓               |                 | N/A 9.3 CPM                                   |
|   |   | ✓ | ✓ | 25% | N/A |
|---|---|---|---|-----|-----|
| 29 | ✓ | ✓ | N/A | N/A |
| 30 | ✓ | ✓ | N/A | N/A |
| 32 | ✓ | ✓ | N/A | 7 CPM |
| 12 | ✓ |   | 31% increased | N/A |
| 33 | ✓ | ✓ | N/A | 12 CPM |
| 34 | ✓ | ✓ | N/A | 36 CPM (QWERTY), 39 CPM (OPTI-II), 13.5 CPM (alphabetic) |
| 35 | ✓ | ✓ | N/A | N/A |
| 36 | ✓ | ✓ | N/A | N/A |
| 37 | ✓ | ✓ | N/A | 11% increased 6.61 CPM |
| 15 | ✓ |   | 59.20% | N/A |
| 38 | ✓ | ✓ | N/A | N/A |
| 39 | ✓ | ✓ | N/A | N/A |
| 40 | ✓ |   | 99% | 5.11 WPM |
| 41 | ✓ | ✓ | 79.90% | N/A |
The major parameters to check the performance of the system are shown in Table 1. Majority of the existing schemes have implemented simple keyboards rather than visual evoked or flashing characters to achieve high accuracy. Moreover, the traversing of a keyboard can be easily controlled by using simple built-in functions or raw data, instead of utilizing attention-based systems with flashing or flickering characters. The reason behind this action is the fact that attention-based systems require users to dwell on the desired character for a certain amount of time and it also adds training overhead. Furthermore, these systems have not incorporated the emotional state of patients, which can be integrated to provide efficient and personalized thoughts to the text conversion system.

### 3. EmoWrite Scheme

The communication medium plays an important role in Human to Human (H2H) or Human to Machine (H2M) interaction. BCI aids paralytic patients, who cannot communicate, by providing solutions for H2H and H2M interaction. Existing BCI based work in this domain, especially thought to text conversion, is limited in efficiency, accuracy, and number of words per minute. Till now the maximum of 12 WPM has been achieved with a non-invasive technique [20].

Considering all the discussed challenges, EmoWrite integrates a dynamic keyboard with a circular arrangement of keys. The traversal in the proposed keyboard is controlled by mapping brain commands with facial expressions and using built-in functions of the headset. It also predicts the next helping verb which is displayed on the right side of the screen. Moreover, the next word prediction is emotion-based as well as personalized. The emotion-based predictions of words assist paralytic patients by efficiently converting their thoughts to text. Furthermore, the machine learning algorithm keeps on retrain itself after a specific interval to predict only the latest and up-to-date words. Additionally, integrating the emotional states of patients with machine learning techniques enhances the performance and productivity of the system.

Implementation of EmoWrite aims at reducing the typing delay, increasing accuracy, typing speed, and convenience of the interface. The signals from the brain have been acquired through EEG and decoded to convert thoughts to text after extracting information by processing the signals. The extracted information from brain signals is then classified and mapped with mental commands (e.g., thinking of left or right direction) or facial expressions (e.g., eye blink, frown, etc.) to perform specific tasks. Emotion state detection has been integrated with machine learning for better productivity of the system. The personalized dynamic arrangement of characters on the screen uses a language model (character sequence pair) and a machine-learning algorithm to show only desired characters on the screen. Finally, the user gets visual feedback through the typed text shown on the screen, and the machine learning algorithm also gets feedback from the user to help update its weights for future predictions. EmoWrite is comprised of the following modules: 1) Data
Acquisition 2) Data Processing 3) Basic Cognition  4) Communication Interface. The basic flow of the proposed system is shown in Figure 2.

![Figure 2: Basic Flow of Proposed System](image)

3.1 Data Acquisition

The primary step in any BCI application is to gather data in the form of brain signals. The process of signal acquisition is performed with different techniques which have been discussed earlier. In this research, the non-invasive technique is employed, which is riskless and easy to handle. It includes collecting brain signals from the surface of the scalp with the help of an EEG headset. Different versions of dry and wet electrodes-based headsets including Emotiv Insight, Emotiv Epoc+, NeuroSky, MindWave, etc. are available. This research deploys 14-channel Emotiv Epoc+ which is a wet electrodes-based headset.

3.2 Data Processing:

The acquired brain signals contain data of multiple mental activities, but EmoWrite focuses only on emotional state, mental commands, and facial expressions data. Therefore, there is a need to process these signals for extracting meaningful information out of them. The data acquired through EEG headset is processed using the build-in pre-processing and classification techniques of Emotiv Applications like Emotiv BCI [42], Emotiv PRO [43], and EmotivBrainViz [44].

3.2.1 Emotion Detection

The emotions are detected using the performance metrics of cortex API [45]. It gives the cognitive state of a user by classifying six major metrics i.e., stress, engagement, interest, excitement, focus, and relaxation. Four emotional classes i.e., happiness, sadness, anger, and calm are detected with these six metrics. The detected class of emotion is passed to the correlation finder, which finds a list of emotions related words from multiple emotion-annotated datasets as shown in Figure 3.
This dataset has been cleaned by removing extra spaces and symbols, then on each emotional class, a separate Recurrent Neural Network (RNN) model is trained for emotion-based predictions. The contextualized words are selected based on emotional states and added to the list of predictive words.

Figure 3: Emotion Detection Component

3.2.2 User-centric Machine Learning Algorithm

A machine learning algorithm is used along with emotions to predict the next word. EmoWrite employs Recurrent Neural Network (RNN) for predicting contextualized words. RNN has been proven to be the most efficient machine learning algorithm [47]. It provides consistent refinement in the system by requiring less feature engineering, which is a time taking task. It also effectively adopts new data and has parallel processing abilities. RNN has an advantage over other neural networks as all the inputs are dependent on each other, it keeps track of relations with previous words and helps in anticipating preferable output [48]. This learning algorithm is online which means that it updates itself after a specific period when new data is entered by the user.

3.2.3 AutoComplete

Autocomplete feature has also been added to the system for predicting the word on a character basis. For this purpose, four different datasets are created, each contains words related to an emotional class. The words are predicted from the respective dataset as per the user’s emotional state.

3.2.4 Communication Interface

The communication interface consists of a GUI through which a user interacts with the system. The user can select words or characters from the GUI through mapped brain signals. The dynamic arrangement of the virtual keyboard uses character sequence pair to display the next set of characters depending on the last text entered [49]. To display characters according to the user’s typing style a machine learning model (RNN) is also used here.
3.2.5 Feedback

Usually, feedback is given through a visual or auditory stimulus. EmoWrite uses visual feedback; the user gets feedback through previously written text which is then displayed on the top of the screen. This process provides continuous learning, by storing the latest written text in the database and then feeding it to the machine learning algorithm to update the model. Every time, the latest available model has been used for prediction, this ensures coherent predictions. It helps the user in effective system manipulation and trouble-free embracing.

3.2.6 Interface Arrangement

To solve the problems of GUI, which are present in existing systems, a circular dynamic keyboard is designed to reduce traversing time, using screen space efficiently and reducing the distance between characters [36]. Only limited characters are shown on the virtual keyboard at a time, the next set of characters to appear on the screen are dependent on the previously accessed character. The appearance of the next set of characters uses the character sequence pair model and machine learning algorithm, where character sequence pair estimates the probability of occurrence of character pairs i.e., it estimates the occurrence of certain characters against previously typed characters. This probability has been studied and calculated using approximately 3.2 million characters from seven English language novels in [49]. Initially, the most used characters appear on the screen. For example, the first set of characters that appears on the keys is shown in Figure 4a. After the selection of character ‘t’, the next set of characters appear on the screen, depending on the typed character ‘t’. The next character set is shown in Figure 4b.

3.2.7 Emotiv Commands for Interface Navigation

Control commands of the brain are mapped to control traversal in the interface. The commands used to control the interface are shown in Table 2. Some mental states, emotional classes, and facial expressions are mapped with basic functionalities to navigate in the interface. Mental states
are used to control the navigation direction, facial expressions while motor imagery movement is used to transfer focus from one section to another.

Table 2 List of Emotiv Commands for Interface Navigation

| Mental State          | Commands | Actions          |
|-----------------------|----------|------------------|
|                       | Left     | Left movement    |
|                       | Right    | Right movement   |
|                       | Pull     | Up movement      |
|                       | Push     | Down movement    |

Facial Expression

| Commands | Actions |
|----------|---------|
| Smile    | Selection |

Motor Imagery

| Commands    | Actions                                           |
|-------------|---------------------------------------------------|
| Look Right  | Focus shifts towards the Helping Verb section     |
| Look Left   | Focus shifts towards the Prediction section       |

3.2.8 Conversion of Thought to Text:

The mathematical model to convert thought to text is as follows:

Input signals from the brain = \( I_s \)

Trained signals \( T_s = \{left, right, up, down\} \)

The mental commands can be detected through the brain signals by comparing them with the trained signals. \( I_{si}(t) \) is the input signal of the \( ith \) channel at time \( t \) which will be compared with the trained signals.

\[
M(t) = \sum_{i=1}^{14} \frac{I_{si}(t)}{T_s}
\]

(1)
So, the mental commands $M(t)$ at time $t$ can be measured by dividing the extracted signal at time $t$ with the trained data. It can be illustrated in eq (1), where, $i$ is the number of channels. The detected command will be

$$D_c = M_\alpha(t), \quad \alpha > 0.80$$  \hspace{1cm} (2)

Here, $\alpha$ is the threshold level or the confidence level. It should be greater than 0.80 for accurate detection of brain signals.

The desired command changes the focus of the keyboard. Initially, the focus will be on the center of the keyboard i.e., space key but after the detection of mental command from eq (2) the focus will change accordingly. $B(D_c)$ in eq (3) is the button in direction $D_c$.

$$B(D_c) = \begin{cases} 
1 & D_c \in T_s \\
0 & D_c \notin T_s 
\end{cases}$$  \hspace{1cm} (3)

Here, 1 means the focused key having a yellow color. In this way, the user can change focus on any key of the keyboard. After the focus has been changed, the selection of the focused character can be achieved using eq (4).

Here,
Facial expression $F_E = \{Blink,Wink, Surprise, Frown, Smile, Clench, Laugh, Smirk\}$
Frequency of occurrence $F_o = \{once, twice, thrice\}$
$f$ is the user’s facial expression

$$S_L(D_c) = \begin{cases} 
1 & f = Blink, f \in F_E \land F_o = twice \\
0 & f \neq Blink
\end{cases}$$  \hspace{1cm} (4)

Eq (4) implies that the selection will occur only if the facial expression $F_E$ will be a blink and it should be twice. 1 means the selection of a character and 0 means no selection.

The character/label selected will be written to the text area $T$.

$$T \leftarrow S_L$$  \hspace{1cm} (5)

The set of alphabets according to their frequency of occurrence is

$alphabets = \{e, t, a, o, i, n, s, r, h, l, d, c, u, m, f, p, g, w, y, b, v, k, x, j, q, z\}$

So, the circular keyboard will contain the first 6 characters from the set $alphabets$. The labels on the keys can be represented by a matrix $Dis_k$ having two rows and four columns. Here, rows represent the number of circles and column represents the number of keys in each circle.

$$Dis_k = \begin{bmatrix} 
e & t & a & o \\ i & n & \leftarrow & more \end{bmatrix}$$  \hspace{1cm} (6)

Initially, characters having the highest frequency will be displayed on the screen just as in eq (6). After the selection of specific character from eq (4), the next set of character which will appear on the screen will be dependent on the likelihood of occurrence of each alphabet after $S_L$.

If,
The set of all alphabets $U = \{a, b, c, \ldots, z\}$
\[ x \equiv S_L, \quad x_i \in U \]

\[
NextChProbability(x) = \prod_{i=1}^{26} \frac{P(x_i)}{P(x)} \tag{7}
\]

From eq (7) the probabilities of all alphabets to the typed character \( x \) have been calculated. Suppose the selected label \( S_L \) be ‘e’. The next character probabilities from eq (7) will be:

\[
NextChProbability(e) = \{a(0.01), b(0.0023), \ldots, z(0.00)\}
\]

So, the display matrix \( Dis_e \) will be

\[
Dis_e = \begin{bmatrix}
  \text{r} & \text{d} & \text{s} & \text{n} \\
  \text{a} & \text{t} & \leftarrow & \text{more}
\end{bmatrix}
\]

Here, the first most probabilistic set of ‘e’ will be displayed. If the user is unable to find his desired character in the set of displayed characters, then he/she can click the key with the label ‘more’. The next probabilistic set will then be displayed.

Suppose

Singular helping verb \( Sin = \{ \text{is, am, was, has, the} \} \)

Plural helping verb \( Plu = \{ \text{are, were, have, a, the} \} \)

Now, the helping verb prediction will be dependent on the written text \( T \).

Suppose

\( S = \{ \text{set of singular words} \} \)

\( P = \{ \text{set of plural words} \} \)

\[
H_v(T) = \begin{cases} 
  x & T \in S, x \in Sin \\
  y & T \in P, y \in Plu
\end{cases} \tag{8}
\]

The word prediction will be dependent on the context and emotional state of the user. The emotional state of the user depends on the valence \( E_V \) and arousal \( E_A \). Valence is the negativity or positivity of emotion which can be measured by comparing hemispherical activation and arousal is the activation level of the brain.

Suppose,

\( t_i = \text{initial time} \)

\( t_f = \text{final time} \)

\[
E_A(t_f - t_i) \rightarrow \{ \text{high, low} \}
\]

\[
E_V(t_f - t_i) \rightarrow \{ \text{positive, negative} \}
\]

\[
D_E = E_A + E_V \tag{9}
\]

Detected emotion \( D_E \) can be one of the four categories \{happiness, sadness, anger, calm\}.

For the prediction of the next word, Recurrent Neural Network (RNN) is used. It is good at learning sequential and temporal data. It also learns the word-level features. The word prediction is based on previously written sentences of the n-word.

\[
P(m_1, \ldots, m_n) = \prod_{j=1}^{n} P(m_j|m_1, \ldots, m_{j-1}) \tag{10}
\]

Eq (10) gives us the probability of observing a sentence.
Suppose
\( w \) = sequence of words
\( w_i \) = single word
Vocabulary size = \( v_s = 8000 \)
Hidden layer(memory) = \( H = 100 \)

First, the sequence of sentences will be converted into a sequence of words. Each word will be represented as a set of elements equal to \( v_s \) and the sequence of words will become a matrix, which will be given as an input to RNN. There are three parameters in this case i.e. \( X, Y, Z \).

\( X = \text{input to a layer} \)
\( Y = \text{output of a layer} \)
\( Z = \text{output towards the next state} \)

The equations of RNN are
\[
\begin{align*}
    s_t &= \tanh(X_{w_t} + Z_{s_{t-1}}) \\
    O_t &= \text{softmax}(Y_{s_t})
\end{align*}
\]

Here, \( s_t \) is the state at time \( t \) and \( O_t \) is the output at time \( t \). So,
\[
\begin{align*}
    w_t &\in R^{8000} \\
    O_t &\in R^{8000} \\
    s_t &\in R^{100} \\
    X &\in R^{100 \times 8000} \\
    Y &\in R^{8000 \times 100} \\
    Z &\in R^{100 \times 100}
\end{align*}
\]

First, we apply forward propagation that will predict the word probabilities and return a state as output. Then we predict that results in the highest probability word. After predicting the word, we must calculate the loss, to check whether our prediction is correct or not. A loss should be minimal and can be calculated as follows.

\[
L(t, O) = -\frac{1}{W} \sum_{n \in \mathcal{W}} t_n \log O_n
\]

Eq (13) shows the loss concerning the prediction \( O \) and true label \( t \). It sums up all the training data and, in the end, adds it to the loss. Here,
\( W = \text{Words in the text (training example)} \)
\( C = \text{number of classes (size of vocabulary)} \)
\( O = \text{output (prediction)} \)
\( t = \text{true label} \)

the further away the output and the true label is the greater loss we have.
Let,
\[
\text{RnnWords} = \{\text{words predicted by RNN}\}
\]
Now, the emotion-based word prediction using eq (9) and (12) will be

\[
EmoPred(D_E, O_5) = \begin{cases} 
  s & D_E = \text{calm}, p \in (C \cap RnnWords) \\
  r & D_E = \text{angry}, p \in (A \cap RnnWords) \\
  q & D_E = \text{sad}, p \in (S \cap RnnWords) \\
  p & D_E = \text{happy}, p \in (H \cap RnnWords) 
\end{cases}
\] (14)

4. Experimentation and Results

To prove efficiency and productivity of EmoWrite, the system has been evaluated based on parameters, accuracy, ease of use, and words per minute count. To check these parameters, the following experiments have been performed.

4.1 keyboard Efficiency:

To check the efficiency of the dynamic keyboard, an experiment has been performed. For this, two keyboards are selected (1) QWERTY keyboard with scan through keys (2) Dynamic keyboard (EmoWrite). There are two rounds in this experiment, in the first round the participant was asked to write 10 words (i.e., number, could, who, down, then, which, these, water, long, and about) using each keyboard one by one. The starting time, when the user starts thinking of the command and the ending time when he has done with writing the word, is noted and the total time taken is calculated for each word. While in the second round he/she is asked to write a whole sentence (i.e., Brain-computer interface helps in processing brain signals) using each keyboard and its time is also calculated. In Figure 5, the x-axis shows all the words that are written, and the y-axis represents the time required to type these words by both keyboards. It can be seen from this figure that EmoWrite took less time to type in all the cases while the QWERTY keyboard with scan through keys required more time to complete typing.
Similarly, Figure 6 shows the difference between typing a sentence with a QWERTY keyboard and with EmoWrite. It is clear from this figure that while typing a sentence EmoWrite took lesser time as compared to the QWERTY keyboard. So, it is proved that EmoWrite’s keyboard is more efficient than the QWERTY keyboard.

4.2. Experiment to check efficiency of EmoWrite:

Another experiment is performed to check the efficiency of the system. This experiment consists of three trials; the participant is asked to write 10 words of 3 to 8-character length with the help of brain signals. Time is recorded for each word and time per character is also recorded i.e., the time required to write a word divided by the total number of characters. In the end, the average time to write a word and a character is calculated. As shown in Figure 7, the time to type a word gradually decreases, and with each trial user becomes more accurate and efficient in typing a word. Moreover, it is proved that the efficiency of this
system increases with time as the user becomes more trained in generating specific brain signals. This is because the training of the user and the efficiency of the system are directly proportional to each other.

![Graph representing 3 trails of 10 words each](image)

**Figure 7: Graph representing 3 trails of 10 words each**

### 4.3. Total number of Words Per Minute (WPM):

An experiment has been performed to calculate the total number of words per minute. For this purpose, the user was asked to write some sentences i.e. “if you watch the hills in London you will realize what torture it is”, “it is so annoying when she starts typing on her computer in the middle of the night”, “sucks not being able to take days off from work”, “her hotel is restricting how the accounts are done adds a bit more pressure”, “I was thinking about how excited I am for you guys to move”.

It consists of 68, 83, 47, 77, 57 characters respectively. The user is asked to start writing these sentences with the help of brain signals, and the stopwatch for one minute is also started at the same time. After the completion of one-minute, the user is asked to stop writing and a total number of words and characters per minute are recorded.

Figure 8 and 9 shows the list CPM achieved through previously proposed systems along with EmoWrite. Only one paper i.e. [34] contains data of tetraplegic patients, while the rest of the mentioned systems here uses data of healthy users. Similarly, [34] and [30] have the next word prediction feature implemented in them, while [37] implements the next character prediction feature and the rest of the systems do not have any predicting features integrated. The results show that EmoWrite is better than all the discussed systems, which is a wonderful accomplishment when it comes to adding up some additional features in the system.
4.4 Information Transfer Rate (ITR):

The information transfer rate has been calculated for each word and each command. ITR is the total time taken with the total number of actions performed. ITR for commands is calculated using eq (15).
\[ ITR_c = \log_2(N_c) \cdot C_N / t \]  

Here,

5. \( N_c = \text{Total number of possible commands} \)
6. \( C_N = \text{Number of commands required to write a } N \text{ letter word} \)
7. \( t = \text{Total time} \)
8. ITR for letters is calculated with this equation.

\[ ITR_l = \log_2(N_l) \cdot L_N / t \]  

9. \( N_l = \text{Total number of characters in keyboard} \)
10. \( L_N = \text{Total number of letters in a word} \)

Figure 10 shows the information transfer rate concerning commands and letters. The average information transfer rate of commands is 87.55 bits/min and of letters is 72.52 bits/min. These information transfer rates are more than the rates of [26], where the information transfer rate for commands is 62.71 bits/min and for letters, it is 50.14 bits/min.

![Comparison of ITR](image-url)

*Figure 10: Comparison of ITR*
4.5 Accuracy and Latency:

The accuracy of this system has been checked by calculating the difference between the intended target and the observed target. The intended target is that character with the user wants to select while the observed target is the target that is being selected by the brain signals. For this user is asked to speak loudly about what he is going to write and then the selected target is observed. Each written character is marked as correct or incorrect. In the end, the total number of correct bits is calculated in each case. To check the latency of EmoWrite, the mean and standard deviation of the time required to produce a command have been calculated. The user is shown a certain command (left, right, up, or down) and the time is noted until the user successfully achieved that target.

Figure 11: Successful and Unsuccessful commands

Figure 11 shows the number of successful and unsuccessful commands. Red dots represent unsuccessful commands i.e., the user have the intention of generating some command but due to error, another command is being generated by the brain. The ratio of red dots to blue dots (unsuccessful to successful bits) is approximately 0.096, as unsuccessful command concerning successful commands is so less that it can be neglected. Hence, the accuracy of the proposed system is 90.36%.

Furthermore, the latency of the system is checked by measuring the mean and standard deviation of delay (which is the time taken by the user when he/she starts thinking of a command until he/she performs it). The mean delay of EmoWrite is 2.685 sec, which is less than the delay of the system proposed in [59], as shown in Figure 12.
4.6 Ease of the system

Further, the system’s convenience is checked by measuring the stress level of each user. The stress of the user has also been measured while experimenting. Whenever the stress increased to a certain limit, a message shows up, indicating an increase in its level.

To check the ease of the system, the stress level has been measured while using this system. The stress level is measured with the help of facial expressions. If a user frowns while using the system that is, he is having some difficulty in using it. Only a few measurements show that the user is frowning. As it is less than a certain limit (less than 20% of the total data) so the system is not stressful at all.

4.7 Effectiveness of integrating emotion-based prediction

The novelty of this system is emotion-based predictions, and to check its effectiveness an experiment is conducted, which consists of two rounds, in the first round user is asked to write some simple sentences without observing their emotional state. The sentences are as follows:

“I am tired with my job”

“I don’t like this world”

“That was awesome”

“I love this world”

“I have an infection”

In the second round, the user is asked to write these sentences again but with the integration of emotional states. For this, first, he is shown with some video depicting an emotional state. The difference was observed in the word predictions concerning the emotional states i.e., happiness, anger, sadness, and calm. Figure 13 shows the difference in the time required to type the sentences. It can be seen from the graph that using
emotion-based prediction is more effective as it gives a prediction of emotion-related words like horribly, ughhh, awesome and terrible, this requires less time to type.

![Figure 13: Results showing effectiveness of emotion-based prediction](image)

### 5. Conclusion

A novel approach to convert silent speech to text has been discussed. In this proposed solution, brain signals are used to help paralytic patients interact with the world through a controlled interface. The basic modules of this interface are a dynamic circular keyboard, word prediction, and a helping verb section. Typing speed is highly affected by keyboard design so a circular design has been used to decrease the traversing delay. The arrangement of characters on the keyboard is dynamic, which displays limited characters on the screen at a time. The limited and circular arrangement of characters helps in decreasing the delay factor and increasing typing speed. Machine learning algorithms have also been implemented to learn user's writing style, which is used for the prediction of the next word or helping verb. Moreover, the contextualized emotion-based predictions help the user to auto-complete the whole next word, instead of typing all the characters one by one. This work has been tested with novice users to check WPM, ease of use, and accuracy of the system. The dynamic arrangement of characters, emotion-based word predictions, and user-specific contextualized character display are the key novelties of the proposed system. EmoWrite results in 90.36% accuracy while converting thoughts to text. The total number of words and characters achieved in a minute are 6.58 and 31.92 respectively. Similarly, the ITR for commands and letters are 87.55 and 72.52 bits/min resulting in a delay of 2.685 sec.

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