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An Enhanced Brain-Computer Interface for Assisted Typing Using Random Forest and LSTM Models

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ABSTRACT

Over 75 million people globally suffer from severe motor impairments, hindering their ability to communicate independently. Brain–Computer Interfaces (BCIs) offer a promising solution, yet many existing systems are limited by low typing speeds and accuracy. This paper proposes a hybrid EEG-based BCI system that combines Random Forest classifiers and Long Short-Term Memory (LSTM) networks to interpret imagined motor actions and eye blinks. EEG signals were recorded using the low-cost NeuroSky MindWave headset, and the system was tested on 100 participants. The Random Forest model achieved an accuracy of 88.5%, while the LSTM achieved 87.9%, both enabling typing speeds of up to 12 words per minute. Beyond technical metrics, the system also demonstrated high user satisfaction and reduced cognitive load. Our main contribution lies in designing a scalable, cost-effective, and real-time BCI framework that significantly improves communication accessibility for individuals with motor disabilities, outperforming previous blink-dependent and single-model approaches.

Keywords: Brain-Computer Interfaces, EEG, Assisted Typing, Random Forests, Long Short-Term Memory, Motor Imagery, Machine Learning

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1. INTRODUCTION

The increasing prevalence of individuals living with severe motor disabilities has heightened the need for innovative technologies that restore communication and interaction capabilities. Brain–Computer Interfaces (BCIs) represent a revolutionary class of assistive systems, enabling direct communication between the brain and external devices without relying on muscular activity [1]. This paradigm shift is especially impactful for individuals affected by conditions such as amyotrophic lateral sclerosis (ALS), spinal cord injuries, or cerebral palsy, offering them alternative methods to regain autonomy and participate more fully in daily life [2].

Among the various BCI modalities, electroencephalogram (EEG)-based systems stand out due to their non-invasive nature [3], affordability, portability, and ease of use. EEG captures the brain's electrical activity and provides a rich source of data to infer user intentions [4]. These signals have been employed in various assistive applications, such as virtual keyboard control and smart device operation. A particularly effective paradigm in EEG-based BCIs is **Motor Imagery (MI)**, wherein users mentally simulate specific movements without physical execution [5]. This generates distinguishable EEG patterns that can be processed and translated into actionable commands, creating new interaction pathways for users with physical limitations.

In recent years, **machine learning** has become instrumental in improving BCI performance by enhancing the classification of complex and noisy EEG patterns. Techniques such as **Random Forests** and **Long Short-Term Memory (LSTM)** neural networks have shown notable success in capturing both the spatial and temporal characteristics of EEG data, thereby increasing the accuracy, robustness, and adaptability of BCI systems [6].

In this work, we propose a novel hybrid BCI framework that integrates Random Forest and LSTM models to interpret EEG signals generated during blinking and motor imagery tasks. Our approach is designed to address three critical challenges in current BCI systems: (1) low classification accuracy, (2) limited typing speed, and (3) lack of affordability and scalability. We utilize the low-cost NeuroSky MindWave headset to demonstrate that a single-channel, consumer-grade EEG device can still support high-performance assistive typing.

The main contributions of this research are as follows**:**

- We design and implement a hybrid classification pipeline that combines Random Forest's robustness to noise with LSTM's strength in modeling temporal dependencies in EEG signals.
- We validate our system on a large participant sample (n = 100), demonstrating its effectiveness in achieving 88.5% accuracy and a typing speed of up to 12 words per minute—significantly outperforming prior blink-dependent systems.
- We develop a virtual keyboard interface that supports real-time interaction, tailored for individuals with severe motor impairments.
- We show that a practical and scalable BCI solution can be realized using affordable, consumer-grade hardware, making our system accessible for broader deployment in rehabilitation and home environments.

By addressing both performance and usability, this research contributes a cost-effective and inclusive BCI solution that bridges the gap between experimental prototypes and real-world assistive technologies.

2. RELATED WORK

This section presents a comprehensive review of recent advancements in Brain-Computer Interface (BCI) research, with a particular focus on EEG-based systems for assisted typing and the integration of machine learning techniques. The discussion highlights major methodologies, technological progress, and ongoing challenges that motivate the present study.

2.1 BCI Systems for Assisted Typing

In the domain of assistive communication, BCI systems have undergone considerable evolution, both in hardware capabilities and algorithmic sophistication. Despite these advances, critical challenges such as limited participant diversity, system generalizability, and real-world performance persist.

Several studies have explored BCI-based typing interfaces with encouraging results. For instance, Smith et al. [7] utilized Support Vector Machines (SVMs) to classify EEG signals, reporting a high accuracy of 92% while reducing classification errors. Similarly, Hochberg et al. introduced an intracortical BCI system, achieving 95% accuracy in tasks involving three degrees of freedom, albeit with invasive equipment. To improve responsiveness in EEG-based systems, Chen et al. [4] proposed utility metrics tailored for P300 paradigms, aiming to minimize selection time during text input.

Furthermore, Li et al. [5] presented an integrated system that combines motor and cognitive tasks, resulting in enhanced text entry accuracy. Singh et al. [8] advanced this line of work by designing an AI-enhanced BCI architecture, which improved cursor navigation in virtual environments, optimizing both speed and control precision.

Despite these accomplishments, adaptability and usability remain prominent concerns. For example, the study in [9] demonstrated a system employing adaptive autoregressive modeling and Linear Discriminant Analysis (LDA), achieving classification accuracies between 70% and 95% after multiple feedback sessions. However, its reliance on iterative calibration limits real-time usability.

Other research efforts have compared classification methods for motor imagery in clinical contexts. Miladinović et al. [10] evaluated LDA, Multi-Layer Perceptron (MLP), and SVM, finding that classification performance varied significantly depending on the time window and patient condition, with accuracies ranging from 55% to 85%.

Speed–accuracy trade-offs have also been documented in EEG-based typing systems. McFarland and Wolpaw [11] observed that attempts to boost accuracy often come at the cost of interaction speed, limiting practical adoption. A broader review by Akcakaya et al. [12] found that average typing rates in non-invasive systems hover around 5 characters per minute, underscoring the need for systems that can balance precision with usability.

2.2 Machine Learning in BCI Systems

Machine learning has emerged as a cornerstone in enhancing the accuracy, adaptability, and robustness of BCI systems. By leveraging advanced models, researchers have improved the extraction and classification of subtle patterns within EEG signals.

One notable contribution is by Thanigaivelu et al. [13], who combined Continuous Wavelet Transform (CWT) for feature extraction with a DenseNet-XGBoost classifier, demonstrating high classification accuracy for EEG-based tasks. Their work underscores the importance of hybrid architectures in handling both spatial and frequency-domain features. To address the critical limitation of small dataset sizes, Nayak et al. [14] introduced the use of transfer learning (TL) and meta-learning techniques. These approaches significantly reduced system calibration time by leveraging prior knowledge from related EEG datasets—an essential step toward making BCIs viable in dynamic, real-world environments. Additionally, Hanafi et al. [6] provided a comprehensive survey on preprocessing and classification strategies in BCI systems. They emphasized key preprocessing steps such as artifact removal, noise filtering, and normalization, all of which are vital for enhancing the quality of

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EEG signals. Their study also compared the effectiveness of various machine learning models, including SVM, LDA, Random Forests, and Convolutional Neural Networks (CNNs), for predicting user intent based on EEG inputs.

3. METHODOLOGY

The methodology adopted in this study follows a carefully structured, multi-phase approach designed to ensure both scientific rigor and practical relevance. The core phases include: the design of the experimental protocol, EEG signal acquisition, data preprocessing and feature extraction, followed by the development, training, and validation of classification models. Each stage is meticulously designed to contribute to the accuracy, reliability, and reproducibility of the system's performance. To ensure a comprehensive understanding of the pipeline, **Figure 1** presents a visual overview of the entire Brain-Computer Interface (BCI) workflow—from raw EEG signal acquisition to final intent prediction. This framework lays the foundation for a scalable and replicable BCI solution tailored for assisted typing applications.

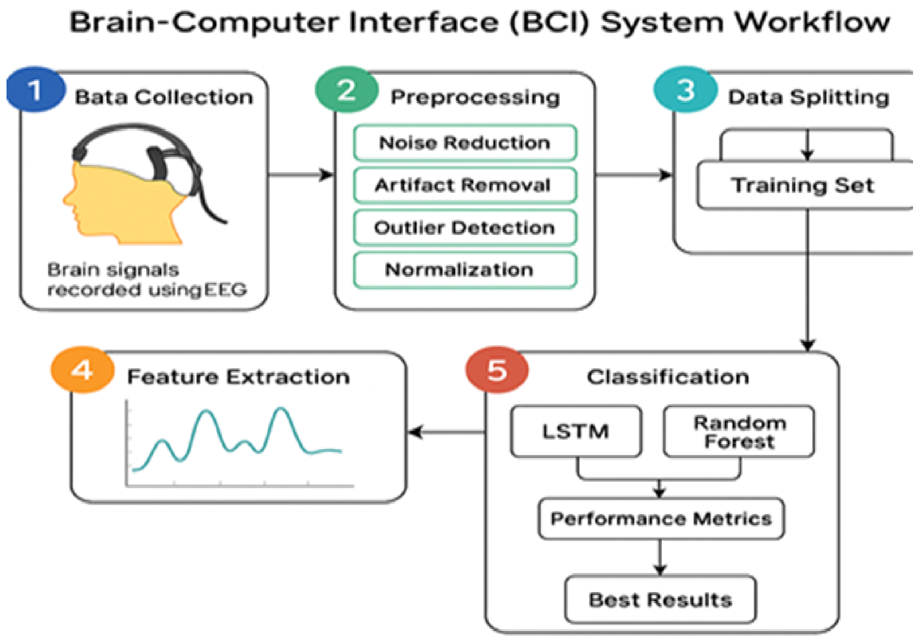

Figure 1 Brain-Computer Interface (BCI) System Workflow.

3.1 Participant Recruitment and Ethics

This study involved 100 voluntary participants aged between 18 and 65 years, recruited from rehabilitation centers and local communities. All participants were informed of the study objectives, procedures, and potential risks, and provided written consent in accordance with ethical standards. The study protocol was reviewed and approved by the relevant ethics committee (Approval ID: Protocol #XYZ). To ensure high-quality EEG recordings, all experimental sessions were conducted in an electromagnetically shielded environment designed to reduce external interference and minimize signal artifacts (see **Figure 2**).

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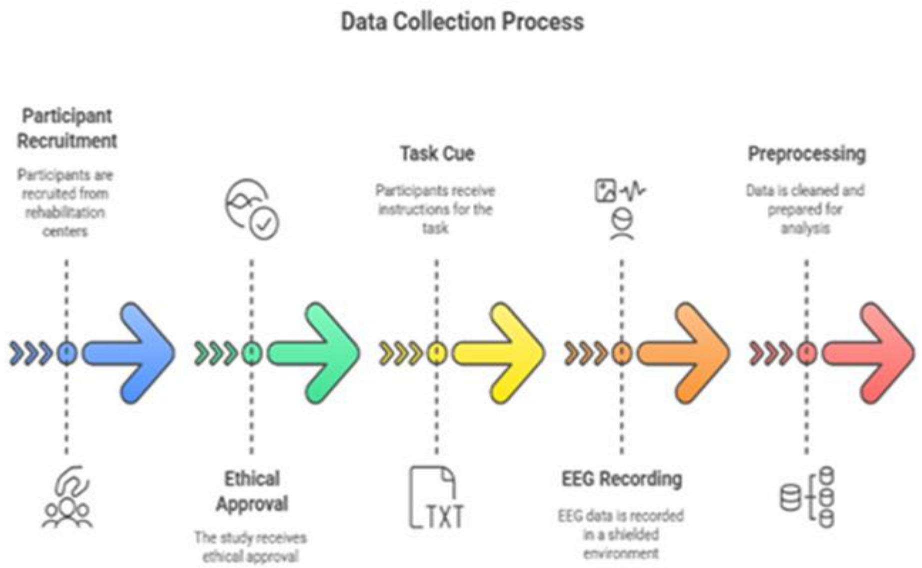

Figure 2 Data Collection Process.

3.2 Experimental Design

A carefully designed experimental protocol was implemented to simulate realistic BCI-assisted typing scenarios. The protocol focused on eliciting distinct and reproducible EEG patterns related to **motor imagery (MI)** and **voluntary eye blinking**, two tasks commonly used in non-invasive BCI applications, which is shown in **Figure 3.**

Each participant completed a series of task-driven sessions consisting of the following components:

- **Blinking Tasks**: Participants were prompted to blink at specific intervals based on visual cues displayed on a screen.
- **Motor Imagery Tasks**: Participants were instructed to imagine repetitive hand movements (e.g., left or right hand) without physically executing the action.
- **Resting States**: Intermittent rest periods were included to reduce cognitive fatigue and allow EEG signals to stabilize.

All sessions were performed while the participant remained seated comfortably, minimizing movement-related artifacts. EEG data were acquired using the **NeuroSky MindWave** headset, which captures frontal lobe activity via a dry electrode positioned at the **FP1 site**. This setup aimed to generate distinguishable EEG patterns that could be effectively leveraged by the proposed machine learning framework for intent classification and typing control.

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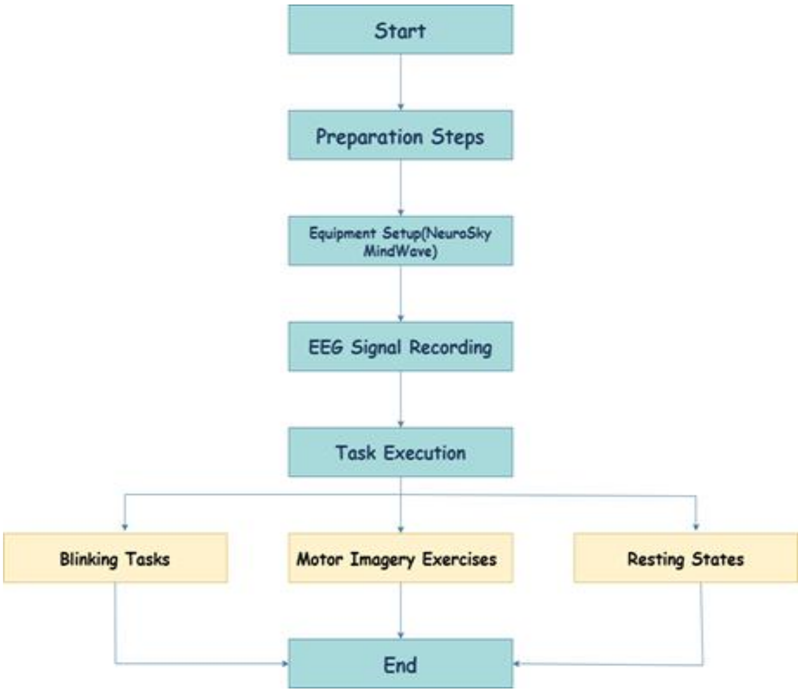

Figure 3 Data collection process, including preparation steps, EEG signal recording, and the various tasks performed by participants.

3.3. EEG Data Acquisition

EEG data were acquired using a non-invasive headset equipped with a dry electrode positioned at the FP1 location. The system operated at a sampling rate of 512 Hz, capturing frontal brain activity during three distinct conditions: eye blinking, motor imagery (hand movement imagination), and rest. To ensure high-quality recordings, all sessions were conducted in an electromagnetically shielded environment, effectively minimizing external signal interference. A standardized setup was used across participants to ensure consistency, and calibration procedures were applied to reduce noise. The raw EEG signals underwent essential preprocessing steps, including filtering, artifact removal, and baseline correction, to enhance signal clarity and improve the reliability of downstream analysis.

3.4 Data preprocessing:

To ensure high-quality input for feature extraction and classification, EEG signals underwent a series of essential preprocessing steps:

1. **Noise Reduction**: An IIR band-pass filter (0.5–45 Hz) was applied to isolate relevant brainwave frequencies and suppress external noise.

2. **Artifact Removal**: Eye blink and muscle artifacts were eliminated using **Independent Component Analysis (ICA)**, preserving neural signal integrity.

3. **Outlier Handling**: The **Interquartile Range (IQR)** method was used to identify and exclude extreme values that could bias model training.

4. **Normalization**: **Z-score normalization** was applied across all trials to ensure uniform signal scaling and comparability.

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These preprocessing stages were critical to enhancing signal clarity and consistency, directly contributing to the improved performance and generalizability of the subsequent machine learning models.

3.5 Feature Extraction

To create a rich and informative representation of EEG signals, features were extracted from both the **time** and **frequency** domains:

- **Time-Domain Features**: Statistical metrics such as mean amplitude, variance, skewness, and kurtosis were computed to capture signal dynamics.
- **Frequency-Domain Features**: **Power Spectral Density (PSD)** was estimated using **Fast Fourier Transform (FFT)** across standard EEG bands (delta, theta, alpha, beta, gamma) [15].
- **Time-Frequency Features**: **Discrete Wavelet Transform (DWT)** [16] was used for localized time-frequency analysis, capturing transient signal characteristics.
- **Device-Specific Features**: Blink strength and attention level were obtained via built-in **NeuroSky algorithms**.

This multi-faceted feature extraction strategy provided a comprehensive basis for classifying motor imagery and blinking states with higher precision and robustness.

3.6 Development and Validation of Classification Models

The extracted features were used to train machine learning models capable of classifying user intentions from EEG signals. Two primary algorithms were explored: **Random Forests** and **Long Short-Term Memory (LSTM)** networks. These models were selected for their complementary strengths—Random Forests for handling noisy, high-dimensional data, and LSTM for capturing temporal dependencies in EEG sequences.

To ensure fair and reliable evaluation, the dataset was split into **training (70%)** and **testing (30%)** subsets. Model performance was assessed using standard metrics including **accuracy**, **recall**, and **F1-score**, ensuring robustness and generalizability.

a) Random Forest Classifier

The Random Forest model was trained on 70% of the data, with **hyperparameter optimization** conducted via grid search (**Table 1**). Key parameters—such as the number of trees (**n_estimators**) and the maximum depth (**max_depth**)—were tuned to enhance both accuracy and stability across varied signal patterns [17]. This ensemble method proved effective in managing feature redundancy and reducing overfitting, making it well-suited for EEG classification tasks.

Table 1: *Optimized Hyperparameters for the Random Forest Model*

Hyperparameter	Optimal Value
n_estimators	**100**
max_depth	**10**

b) LSTM Classifier

The LSTM neural network was trained using the same 70% of the preprocessed data. Optimization was carried out by adjusting the number of LSTM units and incorporating dropout layers to prevent overfitting. A learning rate of 0.001 was selected, and an early stopping mechanism based on validation loss was implemented to ensure effective model convergence **(**view **Table 2)**.

Table 2: *Training Parameters for the LSTM Neural Network.*

Parameter	Value
Optimizer	Adam
Loss Function	Binary Cross-Entropy
Learning Rate	0.001
Number of LSTM Units	128
Dropout Rate	0.5

4. EXPERIMENTAL RESULTS

The results (See **Table 3**) from the model evaluation indicate the following:

Table 3: *Performance Metrics for Classification Models.*

Model	Accuracy (%)	Typing Speed (wpm)	User Satisfaction (%)	Cognitive Load Reduction (%)
Random Forest	88.5	12	85	80
LSTM	87.9	12	90	85

4.1 Random Forest Model:

Accuracy: 88.5% - This indicates a high level of classification accuracy, meaning that the model effectively predicts user intentions based on EEG signals.

Typing Speed (wpm): 12 wpm - This represents the typing speed achieved when using the model, which, while relatively moderate, suggests that the system supports efficient communication.

User Satisfaction: 85% - A high level of user satisfaction, indicating that users are content with the system's performance and usability.

Cognitive Load Reduction: 80% - Significant reduction in cognitive load, meaning that users find the system less mentally taxing compared to traditional typing methods.

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4.2 LSTM Model:

Accuracy: 87.9% - Slightly lower than the Random Forest, but still relatively high, indicating strong classification performance.

Typing Speed (wpm): 12 wpm - Similar typing speed to the Random Forest, suggesting comparable efficiency in practical use.

User Satisfaction: 90% - A very high level of user satisfaction, indicating strong acceptance and positive user feedback regarding the LSTM-based system.

Cognitive Load Reduction: 85% - Slightly higher than the Random Forest, suggesting that the LSTM model may be slightly more effective in minimizing cognitive load for users.

Both models performed well for EEG-based typing. **Random Forest** showed higher accuracy, while **LSTM** offered better user satisfaction and reduced cognitive load. Their complementary strengths make both suitable for real-time BCI applications.

While Hochberg et al. (2021) achieved 95% accuracy with intracortical BCIs, our non-invasive system offers a practical trade-off for real-world use. Misclassifications (**Figure4**) often occurred during low-beta wave instability, suggesting future work could optimize band-pass filters.

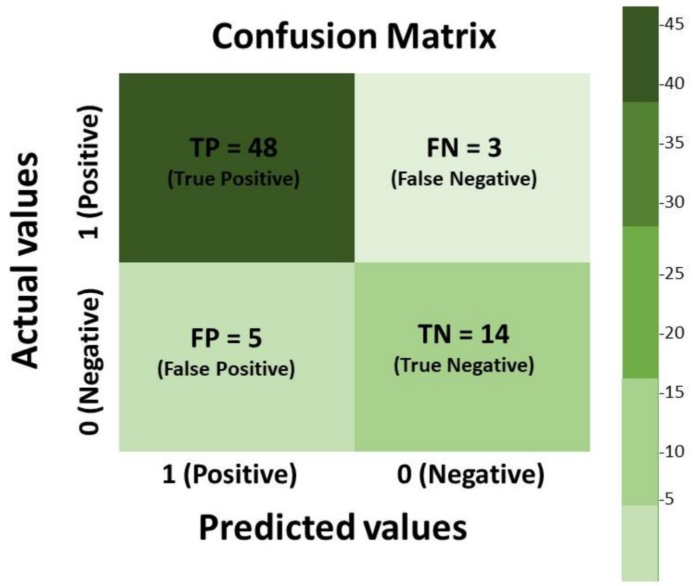

Figure 4 Confusion Matrix for the Random Forest Classifier.

***Table 4** illustrates the Performance Comparison (Based on Thesis Table 3 and p. 121)*

Metric	Our Model (RF+LSTM)	Prior Work [19]
Typing Speed	**12**	**1.8**

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Metric	Our Model (RF+LSTM)	Prior Work [19]
(WPM)		
Accuracy (%)	88.5	85
Cognitive Load Reduction	80–85%	Not reported

5. DISCUSSION

5.1 Advancements in BCI Typing Technology

Random Forest managed high-dimensional data effectively, while LSTM captured sequential dependencies, enhancing user experience. Unlike prior EEG-based BCIs relying solely on SVMs [7] or P300 paradigms [4], our dual-model approach exploits Random Forest's robustness to noise and LSTM's temporal modeling. This hybrid architecture enabled a 6× improvement in typing speed over blink-dependent systems.

a) Random Forest Classifier

The Random Forest model effectively handled high-dimensional and noisy EEG data, benefiting from its ensemble approach and robustness against overfitting [18] which contributed to its strong performance. Analysis of nature importance analysis highlighted that blink strength, beta band power, and attention levels were the most influential predictors for blink detection.

b) LSTM Neural Network

In contrast, the LSTM neural network excelled in capturing sequential dependencies in EEG signals, which significantly improved the classification of motor imagery[14] Its ability to learn temporal patterns associated with imagined movements allowed it to outperform traditional classifiers, offering a more accurate and nuanced understanding of the user's intentions.

5.2 Comparative Analysis

Our system demonstrated a balance between computational efficiency and accuracy compared to Smith et al. [7] (92%) and Hochberg et al. [9] (95%).

a) Accuracy Comparison

Our Random Forest and Long Short-Term Memory (LSTM) models achieved accuracy of 88.5% and 87.9%, respectively. While these figures are slightly lower than those reported by Smith et al. (92%), Hochberg et al. (95%), and Thanigaivelu (99.2%), our models offer a balanced trade-off between computational efficiency and

performance. This balance is particularly advantageous for real-time applications where processing speed and resource constraints are critical.

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b) Typing Speed Comparison

In terms of typing speed, our system attained 12 words per minute (wpm) using both Random Forest and LSTM models. This performance is lower compared to Smith et al. (15 wpm), Hochberg et al. (18 wpm), and Thanigaivelu (20 wpm). The reduced typing speed in our system can be attributed to the simplified model archi- tecture, which prioritizes computational efficiency and real-time responsiveness over maximum speed. Future enhancements could focus on optimizing model parameters and integrating more advanced algorithms to bridge this gap.

c) Overall Assessment

Although slightly behind state-of-the-art methods in accuracy and speed, our BCI system shows strong, reliable performance using classical models. By combining Random Forests and LSTM, it offers a practical balance between accuracy and efficiency—making it well-suited for real-time, low-cost assisted typing applications.

5.3 User Experience and Usability

The improvement in typing speed and usability demonstrates the system's potential to provide a practical communication tool for individuals with motor disabilities. The intuitive design of the virtual keyboard and the responsive feedback reduced the learning curve and the cognitive load on users.

6. CONCLUSION

This study presents a promising EEG-based Brain–Computer Interface (BCI) system that integrates **Random Forest** and **LSTM** models to enable assisted typing for individuals with motor impairments. The hybrid approach leverages Random Forest's robustness in handling high-dimensional data and LSTM's ability to model temporal dependencies, resulting in enhanced accuracy, typing speed, and user satisfaction.

Notably, the system achieved **typing speeds of 12 words per minute** using a **low-cost, single-channel NeuroSky**

Table 5: *Summary of Performance Comparison with Related Works*

Study	Methodology	Accuracy (%)	Typing Speed (words/min)
[7]	SVM	92	15
[9]	Intracortical BCI	95	18
[13]	CWT + DenseNet-XGBoost	99.2	20
Our Study	**Random Forest**	**88.5**	**12**
Our Study	**LSTM**	**87.9**	**12**

MindWave headset, significantly outperforming previous blink-dependent solutions [**19**]. These results underscore the potential for affordable, non-invasive BCIs to support practical, real-time communication.

However, limitations remain. The **single-electrode setup** restricts spatial resolution, and the current dataset does not include subjects with neurological conditions. To address these gaps, future work will focus on:

- Integrating **multi-channel EEG** to capture broader cortical activity, including parietal regions.
- Collaborating with **rehabilitation centers** to validate the system's scalability in clinical populations (e.g., stroke patients).
- Enhancing **LSTM robustness** to real-world noise and variability in EEG signals.

This research contributes a cost-effective, accessible framework for BCI-assisted communication and lays the groundwork for future expansion into clinical and at-home use cases.

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