Investigating Visual Imagery as a BCI Control Strategy: A Pilot Study

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***Abstract*—Brain-Computer Interface (BCI) technology may provide individuals with motor impairments or even the general population a new way to interact with the world around them. However, current BCI systems using electroencephalography (EEG) can be unreliable and produce large variations in performance. Most studies seek to improve performance by focusing on signal processing and classification techniques. However, it may also be beneficial to investigate different control strategies. For this reason, the main objective of this pilot study was to investigate the use of visual imagery, a control paradigm that has not been much tested for EEG BCI applications. Visual imagery may provide a more intuitive control strategy with a greater number of available classes than other popular imagery-based methods such as motor imagery. Using this paradigm, we have demonstrated above chance binary classification accuracy (59.9%, $p < 0.05$) during offline decoding of face and scene visual imagery. Furthermore, the participant in this study achieved significantly above chance performance during a three-class, closed-loop BCI interaction (47.2%, $p = 0.05$). The initial results of this pilot study demonstrate the feasibility of using visual imagery as an alternative EEG BCI control paradigm.**

Keywords*—*visual imagery, brain-computer interface, EEG

I. Introduction

A b ai -c e i e face (BCI) i a ech l g ha facili a e c ica i be ee he b ai a d a e e al de ice i h i f e i he al e e cle [1] [3]. The BCI i ead a la e ea ed b ai ac i i a c l ig al ha eflec he e i e ded ac i [4]. S ch a de ice c ld all a i di id al i h e e i ai e [5] e e he ge e al blic [6], [7] a e a i e ac i h he ld a d he . Elec e ce hal g a h (EEG) ha bee he la dali f ea i g b ai ac i i i BCI a lica i d e i high e al e l i , ea e f e, l c , a d abili [4]. H e e, he e a e c e l ai li i a i ha e e EEG BCI f achie i g e e da e [4]. T c ea e a BCI i able f dail e, a c l a adig fi be elec ed ha i ea e a d ide acc a e a d eliable edic i f he e i e .

A. External Stimulation Based Paradigms

Mea i g he e al e e e e al i la i i a la c l e h d ha ha ge e all ided high acc ac i dec di g e i e f EEG da a [4]. The i al P300 i e f he ell died c l a egie ha ca e he P300 e e - ela ed e ial (ERP) ha cc a a e e a i f e e l e e ed i al i l [4], [8]. The P300 i ide ified a a i i e eak ha all cc be ee 250 a d 500 af e he e f a e e [9]. O e a lica i f hi a adig i he la P300 elle hich all a ici a e d h a e b fi i g hei ga e a ke b a d h e le e ligh a diffe e i e al [10]. B i i g he cc e ce f he P300 ERP i h he cha gi g i e i f e f he le e , he BCI ca de e i e hich le e he e i e d e.

A i ila a adig k a he ead a e i al e ked e ial (SSVEP) e e a ici a i h a a a f a ge flicke i g a diffe e f e e cie [4]. T elec a ac i , he e i e i ed ai ai hei ga e e f he a ge . The i e ded a ge ca he be dec ded b a chi g he f e e c i he e EEG da a f he i al c e i h he f e e c f he flicke i g a ge [11], [12]. While he e f a e e al i la i ca ide a acc a e a d eliable c l a adig , i i fea ible f e i all a lica i . The e ech i e e i e he e ai ai f c a a ge i la i ha a be di ec l a cia ed i h he a k a ha d. F he e, he f e ca e g ea e fa ig e f a ici a d e he high le el f a e i a d i al f c e i ed e he e [4], a d he a e ell i ed f a ici a i h i al i ai e h e i i i [13].

B. Motor Imagery Based Paradigms

I age ba ed a adig ide a al e a i e a eg ha d e e i e he e f e e al i la i . B fa he c i age ech i e f BCI a lica i i i age [4]. The e i h h (SMR) a adig i e i age ech i e ha i defi ed a he i agi ed e e f la ge b d a ch a he ha d , fee , g e [4]. Thi i agi ed e e ca e e e - ela ed de ch i a i i he (8-12 H) a d be a (18-26 H) ba d f b ai ac i i i he e i c e [14]. O e aj li i a i f SMR ba ed a adig i he le g h ai i g i e e i ed f a ici a lea d la e he ecific f e e c ba d f b ai ac i i [4]. Addi i all , SMR e i e a i g a ac i he i agi ed e e f a b d a i a a ha i al a i i i e [15], i i li i ed b he a ie f a ailable cla e [16], a d i i bjec la ge i e - a d i a- bjec a iabili i a ici a e f a ce [17].

I agi ed b d ki e a ic (IBK) i a he i age a adig ha e he i agi ed e e f a i gle b d a i a l idi e i al ace [4]. F e a le, a e ca i agi e i g hei d i a ha d e a c a c e c ee a if he e e i g a c e e. The ki e a ic i f a i f hi a adig i e ac ed f he l f e e c (le ha 1 H) c e f he ec ded b ai ac i i [18]. The e f IBK i BCI a lica i i li i ed, b hi a adig a ide a e i i i e c l che e ha SMR. H e e , he e i age a ache a e ce ible a he e k a BCI illi e ac i hich 15-30% f a ici a a e able achie e e BCI c l de i e ade a e ai i g i e [19]. The ca e f BCI illi e ac i ill k , b i c ld ibl be d e a a ici a i abili d la e he ecific c e f b ai ac i i ece a c l he BCI. A al e a i e ibili i ha a ici a ha e diffic l a i i i g f he ai i g e i he li e c l e i d e he a i a i ie i he EEG ig al. EEG BCI a e ce ible la ge e f a ce a ia i be ee e i d e fac ch a fa ig e, f a i , i a i , cha ge i elec de i i [17].

C. Visual Imagery Paradigm

Ma e i die ha e f c ed i i g BCI e f a ce h gh ad a ced ig al ce i g cla ifica i ech i e [20]. H e e , a f e - e l ked l i i i e iga e e c l a egie [21], [22]. Vi al i age , he a i la i f i al i f a i f e [23], c ld be a ef l BCI c l a adig ha ha e bee ela i el e ed [24]. The h a b ai i i al b a e: 90% f he i f a i a i ed b he b ai i i al [25], a d i ca ce i age 60,000 i e fa e ha e [24], [26]. Vi al i age a al be a e i i i e c l a eg ha a f he a adig li ed ab e [16]. F e a le, if a e ld like e a BCI e c l a ligh i hei h e, he e c ld di ec l i agi e he la he ld like i ead f ga i g a flicke i g a ge e e be i g hich i agi ed e e f a li b c e d ha ligh . F he e, i al i age c ld e iall ide a ea i fi i e be f a ailable cla e he ea igh be li i ed l f fi e ible cla e i h i age [16].

Se e al die ha e h ha a i ca eg ie f i age (e.g., face , a i al , i a i a e bjec) ca be eliabl di i g i hed i g EEG he a ici a a e i all b e i g (VO) a e e ed i age [24], [27], [28]. H e e , e fe die ha e a e ed ea e i al i age i g EEG, a d h e ha d ha e h i ed cce [16], [24], [29]. B b e al. [29] ide he fi i e iga i i he e f i al i age a a BCI c l a adig . I hi d , he e e able eliabl di i g i h be ee i age f face , i age f h e , a d e i g a e i h a a e age f 56% cla ifica i acc ac (cha ce 33%) ac e e a ici a . I K a e al. [24], e ea che e f ed ffli e cla ifica i be ee cla e ffl e . ha e d i g i al b e ai a d i age . The e e able achie e ab e cha ce acc ac be ee he cla e d i g i age (a e age cla ifica i acc ac 52%, cha ce 50%), b he e e able di i g i h a diffe e ce be ee he ial he a ici a e f ed i al i age . e (77% a e age cla ifica i acc ac ; cha ce 50%) a d be ee i al b e ai a d i age (71% cla ifica i acc ac ; cha ce 50%). Lee e al. [16] a able de a e a high a e age cla ifica i acc ac f a d 40% (cha ce 7.69%; 22 a ici a) i a ffli e a al i f 13 i al i age ca eg ie f c d ed f a ie c ica i . Thi i cl ded d i h c c e e e ie (e.g., a b la ce, cl ck, ile) ab ac e ie (e.g., hell , , e).

I e ai clea h ce ai ca eg ie f i age , ch a face a d ce e , e e able be di i g i hed hile he ca eg ie , ch a fl e a d ha e , c ld . Addi i all , beca e he e f i al i age i illi i ea l age , he af e e i ed die ed b a iall diffe e a k c l , a ial a d ec al fea e , a d cla ifica i ech i e hich ade a di ec c a i diffic l . F hi ea , e a e ed ec ea e he e e i e f B b e al. [29] a d K a e al. [24] i g i ila e h d l gie f each ai f i age ca eg ie (fl e ha e a d face ce e). We al a e ed e a d hi k b i g i al i age f face a d ce e ca eg ie i a cl ed-l BCI a lica i .

II. METHODS

A. Participants and Data Collection

D e he a e eg la i f i iga i g he ead f he COVID-19 i i lace a he i e f hi e e i e , l e i di id al a ici a ed i hi il d (ale; igh ha ded; 26 ea f age; e i BCI e e ie ce; e ed di abili ie ; c ec ed- - al i i). EEG da a a c llec ed i g a B ai P d c ac iCa X e T i i h a i ele Li eA a lifie (B ai P d c G bH, Gilchi g, Ge a). Thi head e fea e 32 d elec de cha el i he a da d 10-20 elec de lace e e i h a 500 H a le a e.

B. Experimental Protocol

I hi e e i e , he a ici a a i c ed e f i al b e ai a d i age f fl e , ha e , face, a d ce e i age . The fl e a d ha e i age ed i hi e e i e e e he a e i age f K a e al. [24]. The face a d ce e i age e e elec ed b he e f a da a e f ec g i able face a d ce e ic e . The face i age i cl ded fa ac a d ac e e , li icia , a d a hle e .

J.K. completed this work as a Research Intern at Microsoft Research

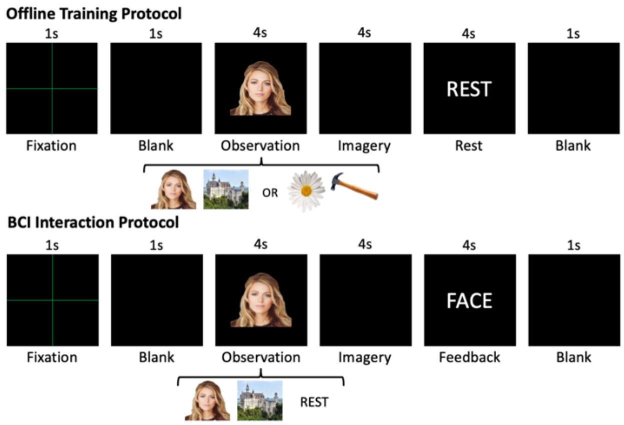

Fig. 1. Experimental task protocol. A. Stimulus presentation and timings during offline training sessions and first 2 runs of the BCI interaction session. B. Stimulus presentation and timings during the final 2 runs of the closed-loop BCI interaction session.

The ce e i age i cl ded fa la d a k ec g i able l cale ch a a beach ai . The f ll e e i e i cl ded e ffli e e i i g fl e a d ha e i li, h ee ffli e e i i g face a d ce e i li, a d e li e BCI i e aci e i .

The e e i e al a k f ll ed a i ila ced e a he k f K a e al. [24] a d i e e ed i Fig. 1. Each ial f he ffli e e i a i h he e e ai f a g ee fi a i c i he ce e f he c ee e a black backg d f 1 ec f ll ed b a bla k c ee f 2 ec. Ne , e f he i age f he ca eg ie a ea ed f a e i d f 4 ec. D i g hi i e, he a ici a a i c ed ca ef ll b e e he e e ed i age. The i age he di a ea ed f 4 ec a d he a ici a a i c ed i agi e he ic e ha a e i l di la ed. The d REST a he di la ed f 4 ec f ll ed b a bla k c ee f 2 ec bef e he e ial bega (Fig. 1A). Each ffli e e i a di ided i f f 20 ial he e each i age f he a ge ca eg ie a e e ed e i e i a a d de . Af e each , he a ici a a all ed ake a b ief a e bef e begi i g he e .

I he eal-i e BCI e i g e i , e a e ed e f li e cla ifica i f face a d ce e i al i age . The fi e e ide ical he ffli e e i ide i h addi i al ai i g da a i i iali e he i al i age cla ifie (Fig. 1A). Af e he ec d , he i al i age cla ifie a ai ed i g hi da a al g i h he da a f he e i h ee ai i g e i i g he face a d ce e ca eg ie . I he la , each ial bega i h he fi a i c f 1 ec f ll ed b a bla k c ee f 2 ec. Ne , he a ici a a e e ed i h a i al c e f 4 ec f he a ge i age ca eg e f d i g ha ial. The ca eg ie f hi e i i cl ded he elec ed face ce e i age he d REST. Af e he c e, he a ici a e f ed i al i age f he a ge ca eg e ed f a e i d f 4 ec. Feedback f he edic ed ca eg ba ed hei e al da a a he e e ed f 4 ec i he f f he d FACE, SCENE, REST. Fi all , a bla k c ee a e e ed f 2 ec bef e he a f he e ial (Fig. 1B). The la eal-i e BCI each i cl ded i face ial , i ce e ial , a d i e ial e e ed i a a d de .

C. EEG Preprocessing and Classification

We e ed ffli e cla ifica i d i g b h he i al b e a i a d i age e i d . F he i al b e a i cla ifie f fl e a d ha e , e i cl ded he da a f he O1, O2, a d O elec de di g he i al c e e-efe e ced he a e age f he TP9 a d TP10 elec de e he a id . F cla ifica i f face a d ce e, e ed he da a f elec de O1, O2, O , P3, P4, P , P7, a d P8. We a lied a ba d a fil e f 1-40 H a d a ch fil e a 60 H e e e li e i e. The fi 0.5 f da a f each b e a i ial a e ed eli i a e a a i i effec . The e ai i g 3.5 f da a a e ched i h ee i d f 1.75 i h a 50% e la . The f ll e ec i he 1-40 H a ge a ed a fea e ai a li ea S Vec Machi e (SVM) cla ifie . The cla ifica i e l e e he c - alida ed i g a lea e- e- - a ach.

F he i al i age cla ifie , e i cl ded da a f all 32 elec de e ce TP9 a d TP10 ha e e ed e-efe e ce. P e i li e a e gge ha i f a i c ai ed i he high ga a ba d f e al ac i i a be ele a f i al i age [16]. F hi ea , e a lied a ba d a fil e f 1-125 H i h a ch a 60 H a d 120 H e e e li e i e a di ha ic. The da a f each i age ial a e ched i he a e a a he b e a i cla ifie . The f ll e ec i he 1-100 H a ge a ed a fea e ai a li ea SVM i h a lea e- e- - c - alida i .

D i g he eal- i e BCI e i g e i , he i al i age da a f he fi i i iali a i a e ce ed i he a e a a he i al i age cla ifie ab e. Thi da a, al g i h he h ee e i ai i g e i , a ed ai he li ea SVM f eal- i e e. I he cl ed-l BCI , each i al i age ial a e ce ed a d cla ified i he a e a a bef e; h e e , l he e ch f he iddle f he ial (0.875-2.625) a ed f cla ifica i a d feedback.

D. Evaluation of Performance

The Pa ici a abili c l he BCI a lica i i e al a ed ba ed he be f ial he e he cla ifica i f b ai ac i i a che he c ed i age ca eg f ha ial be d he le el f cha ce. F he i i ial ffli e ai i g e i , a bi a cla ifica i f face . ce e ld ield a ab l e cha ce le el f 50%. H e e , he all a le i e e e i b ai ig al cla ifica i ca lead highe cha ce f fal e i i e . F hi ea , C b i a d Je bi [30] ha e gge ed add e hi i e b adj i g he cha ce le el a a f c i f a le i e, be f cla e , a d he de i ed c fide ce i e al i g a bi ial c la i e di ib i . I hi ca e, each e i f he ffli e ai i g i cl de a al a le i e f 80 b e a i i h 2 cla e idi g a c ec ed cha ce le el f 58.8% a = 0.05 a d 62.5 a = 0.01. Thi ea ha a cla ifie b ai ed a lea 58.8% acc ac be c ide ed ig ifica a = 0.05. The cl ed-l BCI i e ac i c i f a al a le i e f 36 b e a i i h 3 cla e idi g a c ec ed cha ce le el f 47.2%.

III. Results

A. Recreation of Previous Experiments

O fi bjec i e a ec ea e he e ei e f B b e al. [29] a d K a e al. [24] i g i ila e h d l gie f each ai f i age ca eg ie (fl e ha e a d face ce e). F he e i i g he fl e a d ha e i li, e f d a ea cla ifica i acc ac f 63.3% (c ec ed cha ce 62.5 a = 0.01) d i g he i al b e a i e i d. Whe i g he face a d ce e i li, e f d a ea cla ifica i acc ac f 58.7% (c ec ed cha ce 58.8% a = 0.05). The e e l e e i ila h e f di K a e al. [24] h achie ed 61% cla ifica i acc ac d i g i al b e a i .

F he i al i age cla ifie , e f d a ea cla ifica i acc ac f 47.9% f he fl e a d ha e i li a d 64.2% (c ec ed cha ce 62.5 a = 0.01) f he face a d ce e i li (Fig. 2). T be e de a d h i a ible di i g i h be ee he fl e a d ha e i li d i g i al b e a i b i age , e e ea ed hi e ei e i g l i le e fl e a d ha e i age . The e e i age e e f he a e i e a d ha e, b i h ligh l diffe e c l ie a i . I e e i gl , he cla ifica i acc ac d i g he i al b e a i e i d f hi e a k fell bel cha ce le el (46.3%). The cla ifica i acc ac d i g he i al i age e i d e ai ed a d cha ce a 54.6%. F he di c i f he e e l ca be f d i ec i IV.

B. Classification of Visual Imagery Across Multiple Sessions

F e e ei e , e e ea ed he e i i g he face a d ce e i age addi i al i e be e de a d e f a ce a iabili ac e i . U i g he da a f he fi e i d i g he i al i age e i d, e b ai ed a bi a cla ifica i acc ac f 64.2% (c ec ed cha ce 62.5% a = 0.01). H e e , e f d ha hi cla ifica i acc ac a ela i el a iabl ac e i (Fig. 3A). The cla ifica i acc ac f he ec d a d hi d e i e e 61.7 a d 53.8, e ec i el . Thi led a ea cla ifica i f 59.9% e he h ee e i hich a ig ifica a he c ec ed cha ce le el f 58.8% a = 0.05. We al e ed a

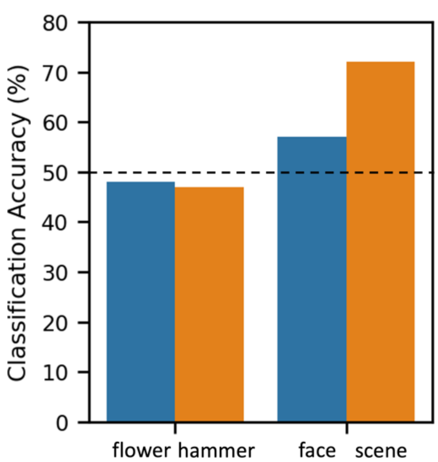

Fig. 2. Classification accuracies for visual imagery of flower vs hammer (47%) and face vs scene (64%) experiments. Dashed line indicates absolute chance level (50%).

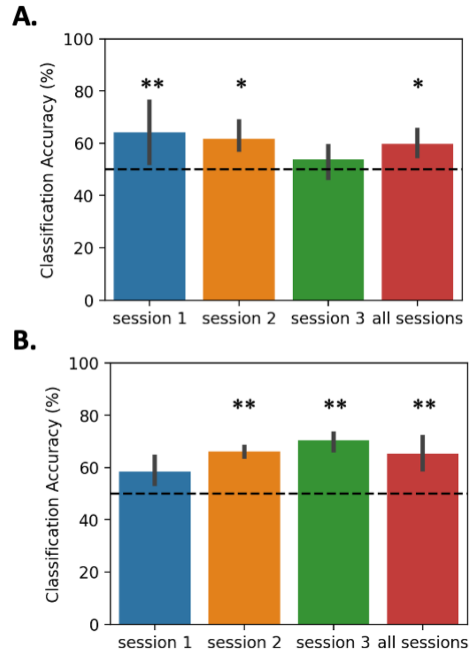

Fig. 3. Offline classification of visual imagery. A. Binary classification accuracy of face vs. scene imagery for session 1 (64.2%, blue), session 2 (61.7%, orange), session 3 (53.8%, green), and between-session accuracy (59.7%, red). B. Binary classification accuracy of visual imagery vs. rest for session 1 (58.3%, blue), session 2 (66.0%, orange), session 2 (70.4%, green), and between-session accuracy (65.2%, red). Dashed lines indicate absolute chance level (50%); * indicates significance for corrected chance level of 58.8% at p = 0.05; ** indicates significance for corrected chance level of 62.5% at p = 0.01. Error bars indicate 95% confidence interval.

be ee - e i cla ifie i hich he cla ifie a ai ed e i a d e ed a lef - e i . Thi e l ed i a ea cla ifica i acc ac f 59.7% hich a ig ifica a he c ec ed cha ce le el.

We al e ed bi a cla ifica i f i al i age . e i g a e. T acc li h hi , he i al i age ial f face a d ce e e e c bi ed de a i gle label. O cla ifie achie ed 58.3% cla ifica i acc ac d i g he fi e i , 66.0% d i g he ec d e i , a d 70.4% d i g he hi d e i . Thi ielded a ea cla ifica i acc ac f 64.9% e he h ee e i hich a ig ifica a he c ec ed cha ce le el f 62.5% a = 0.01. A be ee - e i cla ifie ai ed hi da a ielded 65.2% cla ifica i acc ac hich a al ig ifica a he c ec ed cha ce le el f 62.5% a = 0.01 (Fig. 3B).

C. Real-Time Classification of Visual Imagery

O fi al e ei e a e al a e f a ce d i g eal- i e BCI i e ac i . The cla ifie a ai ed he da a f he h ee ffli e e i i g face a d ce e i age l he da a f he fi f he i e ac i e i . The bjec i e a di c i i a e be ee i al i age f a face, i al i age f a ce e, e i g a e. We e e able achie e a ig ifica l ab e cha ce cla ifica i acc ac f 47.2% (c ec ed cha ce 47.2% a = 0.05) d i g he eal- i e BCI (Fig. 4).

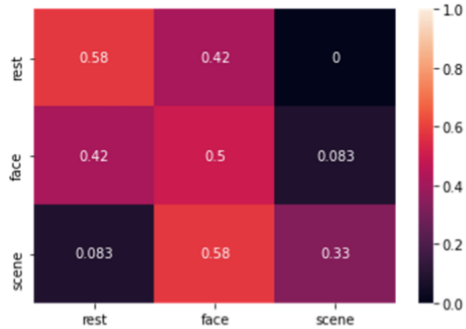

Fig. 4. Confusion matrix of classifier predictions during the closed-loop BCI interaction runs. Overall classification accuracy was 47.2% (corrected chance 47.2% at p = 0.05).

IV. Discussion

The e l f ffli e a al e d i g he i al b e a i a d i ali age e i d e e i ila acc ac f d i e i k [24], [29]. We f d ig ifica l ab e cha ce cla ifica i acc ac d i g he ffli e a d cl ed-l BCI i e ac i f i ali age i g he c ec ed cha ce al e calc la ed i acc da ce i h C b i a d Je bi [30]. I e e i gl , e al f d ha i ali age cla ifie e ai ed effec i e he ai ed lel da a ec ded d i g diffe e e i . Thi all ed ha e a la ge l f da a i h hich ai he cla ifie f eal- i e BCI e.

I i i e e i g h i ali age f ce ai ca eg ie f i age c ld be eliabl di i g i hed (face a d ce e) hile he c ld (fl e a d ha e). Thi a be d e a highe e e e ai al i ila i be ee he b ai ac i i f fl e a d ha e hich ake cla ifica i diffic l [31]. P e i e ea ch i g f c i al ag e ic e a ce i agi g [32], i gle cell ec di g [33], ag e e ce hal g a h [34], a d EEG [35] ha e i e iga ed he e e e ai al i ila i f b ai ac i i d i g i al b e a i h a face , h a b die , a i al face , a i al b die , a al bjec , a d a ade bjec . The e die ha e h ha ce ai ca eg ie (e.g., h a a d a i al face) a e highl di i g i hable, hile he ca eg ie (e.g., a al a d a ade bjec) h highe i ila i i hei e e e ai al c e. Thi a e lai h e had diffic l i cla if i g be ee i ali age f he fl e (a al bjec) a d ha e (a ade bjec) i age .

A f h e e e able cla if be ee he e ca eg ie d i g i al b e ai , i igh be d e he a e f he i l e e ai . The fl e i l ed b K a e al. [24] a a la ge, b igh i age he ea he ha e a a da ke , alle i age di la ed agai a black backg d. Thi a ha e all ed he cla ifie ide if be ee he diffe e i e i ie f he i age , a he ha hei c ce al e e e ai . Thi idea i ei f ced b e e i e i g li le e fl e a d ha e i age f diffe e c l . Thi e e ed he i fl e ce f c l a d ie a i f he i li, a d e e e able eliabl cla if be ee he ca eg ie .

V. Conclusion

Thi d e ed a a i i ial il e i e iga e he efficac f i g i ali age a a BCI c l a adig a d a c d c ed de he a e eg la i f i iga i g he ead f he COVID-19 i . F hi ea , he e l f hi d a e li i ed b he i cl i f l a i gle bjec . Addi i all , hi d a li i ed b he ali a d a f da a ha c ld be ca ed i g a d -elec de EEG ca . D elec de ca a e e ce ible i e a d e e a ifac , a d ca bec e c f able af e l ged e [36]. F he k i h a la ge bjec l, e -elec de EEG ca , a d l ge ai i g i e i ece a f ll e if he fea ibili f i g i ali age a a BCI c l a eg . Addi i al k i al eeded i e iga e he e e e a i al i ila i be ee i ali age f a i bjec ca eg ie ea ed b EEG. Ne e hele , he e l f hi il d i dica e ha i ali age ca be ed a a effec i e c l a adig f BCI. O e l ielded ig ifica l ab e cha ce cla ifica i acc ac i di i g i hi g be ee i ali age f a face a d a ce e i age i a ffli e a al i . The a ici a i hi d a al able achie e ig ifica l ab e cha ce e f a ce i a eal- i e i ali age BCI a lica i i h h ee cla e .

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