ConvoForest Classification of New and Familiar Faces using EEG

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***Abstract*—Face recognition by familiarity or recollection is a task people perform routinely in their daily lives. In the process of automating human experiences, existing studies have applied traditional machine learning applications and deep learning techniques on enough datasets (samples $>=$ 1000) for human faces classification. However, the application of deep learning on electroencephalography (EEG) for new and familiar faces classification with limited data (samples $<$ 100) has not been studied. We devised a face familiarity judgment EEG experiment and recruited eleven (11) participants for our study. We represented each trial by a visualization technique upon the generated EEG. The average power bands (theta, alpha, lower beta, higher beta, and gamma) from each channel at every 125ms window were computed and combined to form an image. We applied "ConvoForest," a combination of convolution neural network (CNN) and random forest for classification. In comparison with conventional CNN where the dense layer was present, "ConvoForest" performed better with an average subject-dependent classification accuracy of 79.0% and an F_1 score of 0.8**

***Index Terms*—EEG, new face, familiar face, CNN, ConvoForest**

I. Introduction

The electrical activity of the brain is measured via an electroencephalography (EEG) exam. EEG scans are done by putting EEG sensors on the scalp. It has been applied for brain stimulation, brain-computer interface, brain disease detection and more recently to enhance social interactions. Faces are undeniably strong social stimuli because they provide information about identity, gender, age, emotion, and visual speech [1]. However, the connection between a face and the different information it reveals through face processing had sparked a lot of discussion and debate. Our attention in this study is on classifying new or familiar faces based on the EEG of subjects who are made to see a never seen before and a face previously seen.

The human idea of facial recognition is based on the concept of familiarity. For many years, it has been established that the impression of familiar and unknown faces vary in a variety of ways [2] [3]. According to [4] [5] [6], familiar faces are acknowledged faster and more accurately than unknown faces in recognition memory experiments.

In the process of automating human face familiarity judgment, authors in [7] applied pre-trained deep learning convolution neural network (AlexNet) and anti-Hebbian training for generic image familiarity classification. But In [8], they applied only faces for familiarity detection studies where the large-scale face dataset called VGGFace2 was used. They found that memory systems with complex synapses can be used in real-world applications such as familiarity detection. However, the classification of familiar and new faces using a deep learning approach on a limited EEG dataset has not been researched to the best of our knowledge.

In this study, we devised face presentation stimuli, where faces are sequentially presented without repetition to the user. After seeing ten unique faces, they are tested with two faces (one seen and one unseen) shown to them and asked to identify the familiar face. This process went on for ten sets of unique trial blocks. Participants' EEG data were acquired as they experimented. During analysis, each EEG electrode channel was decomposed and identified as distinct waves with different frequencies using Fast Fourier Transform (FFT). The average power value at every 125ms window for five frequency bands (theta (4 – 8 Hz), alpha (8 – 12 Hz), low_beta (12 – 18 Hz), high_beta (18 – 25 Hz), and gamma (18 – 25 Hz)) were collected from each electrode channel. Consequently, each trial became a $14 * 40$ 2D matrix for 1s of data. We represented each trial by a visualization technique to form an image. We applied "ConvoForest," a combination of convolution neural network CNN) and random forest for classification. In comparison with conventional end-to-end CNN where the dense layer was present, "ConvoForest" performed better with an average subject-dependent classification accuracy of 79.0% and an F_1 score of 0.8

This paper is organized as follows. The next section discusses the background and related works. Section III focuses on methods and materials. Section IV presents the results and discussions. The last section concludes our paper.

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II. Related works

In this section, we reviewed the literature on face recognition theories, classification of new, familiar, and remembered faces using encephalography (EEG), event-related potential (ERP), statistics, and machine learning techniques.

A. Theories on face recognition and familiarity judgement

Memory performance varies significantly among individuals [9], it can be observed on both familiarity and recollection abilities of people. Familiar faces are encoded with a comprehensive set of visual, semantic, and emotional cues that facilitate their perception and identification [10]. On the other hand, new faces may pose a more significant challenge to human perception and memory systems. People can recognize familiar faces in bad lighting, low-quality photos, and from a variety of angles [11] [12]. Thus, successfully encoded faces in memories could be successfully decoded or acknowledged if they do not decay before retrieval. According to [13], new experiences in general and a new face, in particular, excite and change old memories, and vice versa; thus, encoding and retrieval are closely connected. Encoding precedes storage without indicating each newly encountered event, and storage precedes retrieval without implying it. Face recognition is a task that humans perform routinely and effortlessly in their daily lives. Since the emergence of artificial intelligence, deep learning models can now perform at human levels on real-world face recognition tests [14].

B. EEG and ERP Studies on Face Classification

EEG signals directly measure neural activities by scalp sensors [15]. In addition, they are used to derive ERPs, which are used to monitor brain voltage changes that occur after (or before) specific visual, auditory, or other sensory inputs, as well as signs signaling motor preparation, motor execution, or covert mental functions [16]. Previous research on face-related ERP responses has revealed that the face stimuli are linked to the Vertex Positive Potential (VPP) [17], the N170 component unique to face represents late stages in the structural face encoding [18]. According to [19], the N250 is associated with the acquisition of a facial representation across many photographs.

The authors in [20], applied CNN to classify single-trial EEG signals when subjects viewed target and non-target face stimuli, and they got 0.936 ± 0.095 for subject-independent analysis and 0.839 ± 0.049 for subject-independent analysis. CNN models were applied on EEG to effectively predict eye states (open or closed) among ten subjects in a resting state [21]. Without using CNN, however, authors in [22], devised an EEG feature extraction method and applied a support vector machine (SVM) for pattern recognition system for person recognition. The concept of separating feature extraction and classification processes has been applied for a long time before the advent of CNN. However, CNN combines deep feature engineering techniques and the classification of any structured data. One of the major factors contributing to the success of deep learning such as CNN is the availability of massive datasets, say, millions of images in datasets like ImageNet [23] [24]. The asymptotic analysis of conventional machine learning and deep learning is described in Figure 1.

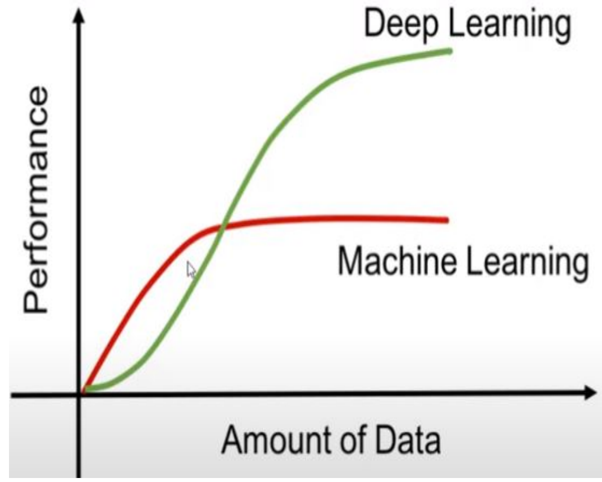

Fig. 1: Deep learning and regular machine learning performance on data

Thus, there are three questions: First, can limited EEG dataset classification still benefit from the CNN technique? Second, how does the combination of a CNN technique and random forest perform on limited data compared to CNN? Three, how do the ERPs and time-frequency analyses reflect the effects of new and familiar faces. In the following sections, we present the ”ConvoForest” technique and time-frequency analyses on new and familiar faces.

III. Materials and Methods

In this section, we present the components and strategies employed in our studies. We describe the: stimuli presentation, data preprocessing, time-frequency analysis, and the classification technique. The code written for these analyses is on a public GitHub repository available at https://github.com/wilie247/SpyderWorks/tree/main/SpyderWorks.

A. Software and Stimuli

The experiment protocol is similar to the one used in [15], but we changed the stimuli presentation duration and inter-block interval. Our changes made it possible to study new faces and be tested on familiarity within a 30s time frame. We used Psychopy [25] to present faces, and the faces were obtained from the Chicago face database [26]. We displayed a group of 10 unique faces sequentially to the user from a block of trials; we showed each face for 2s without any inter-stimulus delay. The faces consist of males and females from all races. The recognition phase starts 2.2s after completing a block of faces from each study phase. At recognition testing, two faces with thesame gender were sequentially positioned on the left and the right of the screen in random order; among these faces, only one appeared at the study block. Participants were tested on all ten faces previously seen whether they knew familiar faces or not. In total, ten blocks of ten faces each were applied during the study, and ten blocks with twenty faces each were applied at testing. Figure 2 describes the presentations during study and testing.

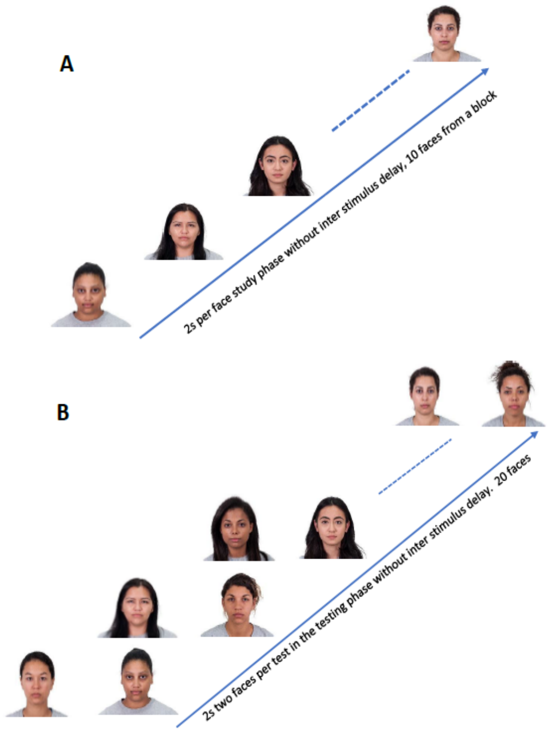

Fig. 2: (A) faces stimuli study protocol, 2s display per face from a block of 10 faces during study phase without inter-stimulus delay. (B) faces stimuli familiarity testing protocol, one face from seen and one unseen face appear for 2s without inter-stimulus delay.

B. Participants and data acquisition

A total of 11 healthy participants (aged 19-40 years) with an average age of 26.36 (± 6.83) participated in this study. All subjects reported normal or corrected vision. Participants gave written consent according to the institutional review board(IRB) approved protocols before participating. The EEG data were recorded using Emotiv EpocX, following the 10–20 international system. This device comprises 14 electrodes positioned at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4 locations and has a sampling rate of 128 Hz.

C. Emotiv EEG Data and preparation

Emotiv pro API generates an EEG quality value for each EEG channel. This value is produced based on channel contact quality, machine learning signal quality, and signal magnitude quality. We ran our analyses on one second of 128 samples data produced after stimuli onset. The EEG quality reported per sampling rate (128) is between 0 and 8 per channel. To guarantee the integrity of the EEG signals used for our analyses. We rejected trials (both corresponding study and familiarity phase) from channels whose EEG quality value was less than 4.

Each EEG electrode channel was decomposed and identified as distinct waves with different frequencies using Fast Fourier Transform (FFT). The average power value at every 125ms window for five frequency bands (theta (4 – 8 Hz), alpha (8 – 12 Hz), low_beta (12 – 18 Hz), high_beta (18 – 25 Hz), and gamma (18 – 25 Hz)) were collected from each electrode channel. Consequently, each trial became a $14 * 40$ 2D matrix for 1s of data. Then we visualized the data using a colormap "jet" [27] from the Python Matplotlib library and saved it as an image file. The "jet" colormap intensities are in the range [0,1], and the color scheme looks like Figure 3. The transformation from EEG to image file was done for all trials. In classification, we split our image files dataset into 70% for training, 15% for validation, and 15% for testing. For preprocessing and analysis, we used a 64-bit windows ten machine, Intel(R) Core(TM) i7 CPU @ 1.80GHz (8 CPUs) $\tilde{2}$.3GHz and 16Gig RAM. It took about 2s for each subject's dataset training and validation and less than 500ms for testing.

Fig. 3: Jet Color map intensity spectrum. Red highly intense and blue least intense

D. ConvoForest for Classification

We coined the word "ConvoForest" because the algorithm combines a convolution neural network for feature extraction and random forest for classification. First, we removed the dense layer of the convolution neural network and then replaced it with a random forest. The dense layers consist of 128 neurons and another prediction layer with two neurons. Before removing the fully connected layer, the network structure is described in Figure 5, where we applied the filter size $3x3$ in all convolution layers. We believe the "ConvoForest" approach will effectively classify a limited dataset where a fully connected (dense) layer classification may not efficiently generalize its performance on a new dataset. The reason is that; first, the random forest is an ensemble technique that categorizes trials based on a randomly selected subset of the total features; second, it does not overfit as the number of trees grows. Figure 4 illustrates our approach, and the mathematical representation of the convolution was computed using (1).

$$conv(I,K)_{x,y} = \sum_{i=1}^{nH} \sum_{j=1}^{nW} \sum_{k=1}^{nC} K_{i,j,k} I_{x+i-1,y+j-1,k}, \qquad (1)$$

After the fully connected layer removal, we flattened the extracted features. Then, we applied random forest [28] [29]

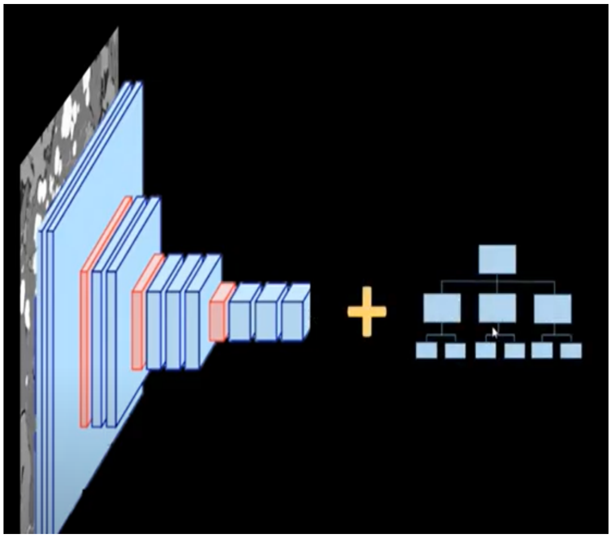

Fig. 4: CNN + Random Forest

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 128, 128, 32)	896
batch_normalization (BatchNo	(None, 128, 128, 32)	128
conv2d_1 (Conv2D)	(None, 128, 128, 32)	9248
batch_normalization_1 (Batch	(None, 128, 128, 32)	128
max_pooling2d (MaxPooling2D)	(None, 64, 64, 32)	0
conv2d_2 (Conv2D)	(None, 64, 64, 64)	18496
batch_normalization_2 (Batch	(None, 64, 64, 64)	256
conv2d_3 (Conv2D)	(None, 64, 64, 64)	36928
batch_normalization_3 (Batch	(None, 64, 64, 64)	256
max_pooling2d_1 (MaxPooling2	(None, 32, 32, 64)	0
conv2d_4 (Conv2D)	(None, 32, 32, 64)	36928
batch_normalization_4 (Batch	(None, 32, 32, 64)	256
max_pooling2d_2 (MaxPooling2	(None, 16, 16, 64)	0

Total params: 103,520
Trainable params: 103,008
Non-trainable params: 512

Fig. 5: CNN structure and parameter before dense layer removal

for classification because it is robust to outliers and noise, and the algorithm does not overfit the data.

IV. Results and Discussion

This section discusses the time-frequency analysis at electrode site O_1 and classification results.

A. Time-frequency analysis

The change in the frequency domain of a non-stationary EEG signal as time increases is described by time-frequency decomposition. Figure 6 represents the EEG frequency and time relationship at the O_1 electrode site when users were shown a new face stimulus. We observed that between 300ms and 400ms, there were significant activities at the delta(1-4Hz), theta(4-8Hz), and low beta(8-13Hz) frequency bands. However, in Figure 7, at the same O_1 electrode site, more activities were observed at the delta, theta, alpha, and beta frequency bands at a very early stage between 50ms and 300ms after stimulus onset. This is consistent with the literature [4] [5] [6] where it was reported that familiar faces are acknowledged faster and more accurately than unknown faces in recognition memory experiments.

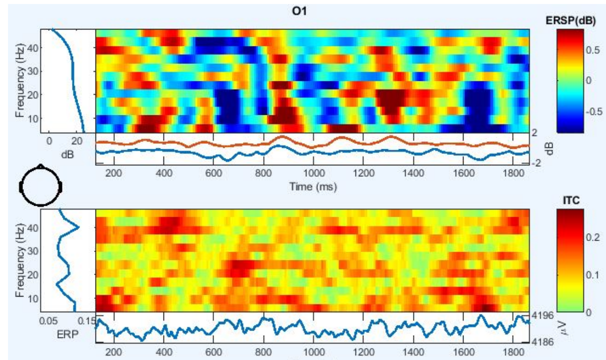

Fig. 6: Study phase participant seeing a face for the first time

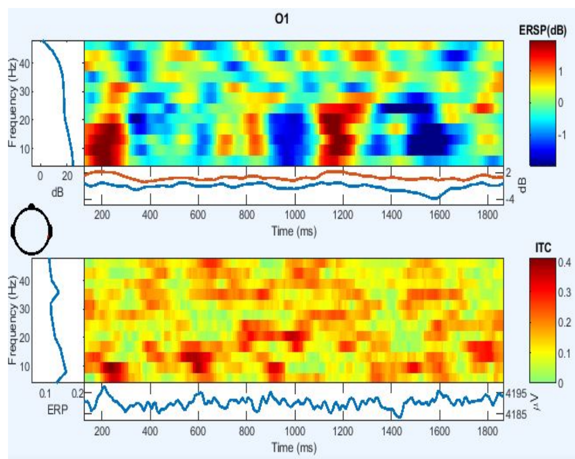

Fig. 7: Familiarity testing participant seeing a face for the second time

With respect to the plot in Figure 8, The scale-free (1/f) component from each frequency bands is plotted. Brain activities dynamics often follow the 1/f characteristics. Some studies call it pink noise. It is the phenomenon where the power spectral density is inversely proportional to the frequencies, i.e., low frequencies have high power, and high frequencies produce low power. Increasing evidence in recent years suggests that the 1/f brain activity contributes actively to brain functioning. Therefore, concerning theta, experts believe that the theta waves are essential for processing information and making memories; there are actually two categories of the theta, the higher range of theta brainwaves are commonly found when we are engaging in complex, inwardly-focused problem solving – like doing math problems in our head. And the low theta waves are present when we daydream or fantasize and are commonly associated with creativity and intuition [30]. But our studies did not differentiate between the high and low theta; instead, we combined all together; thus, the observed 1/f values could be the activities of higher theta indicating inwardly-focused problem-solving tasks like memorization or recall. Studies have shown Alpha power could indicate a person is focused on a specific thought and not paying attention to unwanted distractions [30]; it is also associated with a state of relaxation and represent the brain shifting into an idling gear, waiting to respond when needed. On the other hand, the Beta power is present when we are in a state of mental or intellectual activity and outward focus, like thinking, problem-solving, processing information, or feeling anxious [30]. And Gamma is considered essential for information and sensory-binding and is present during cognitive thought when the brain is processing and linking data from all parts of the brain [30]. However, the presence of all these frequency bands in our studies is an indication of the presented face cognitive process that involves the participant's peaceful expectation, memory process, familiarity, thinking, and problem-solving activities. The histogram plots do not necessarily indicate which of these bands is bigger over time or which is more frequent over time because the (1/f) is a scale-free metric. While theta and alpha showed differences and a slight difference in the gamma band, the beta (both low and high) showed no difference. This suggests that at the occipital electrode 0_1, theta, alpha, and gamma bands may be suitable candidate frequencies bands for investigating familiar faces at the occipital electrode 0_1.

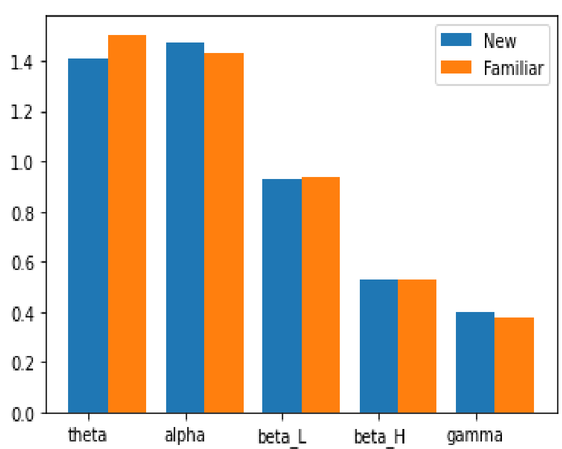

Fig. 8: New faces vs. familiar faces from the 0_1 electrode.

Table I show the classification results of whether a face is new or familiar. We compared the conventional CNN and the "ConvoForest" on the validation and test sets. CNN result was 49.0% average accuracy on the validation set with an F_1 score of 0.44. CNN produced 52.0% average accuracy on the test set with an F_1 score of 0.45. This suggests that CNN may not be effective at generalizing when trained on limited (< 100) datasets. However, the "ConvoForest" produced 74.0% average accuracy on the validation set with an F_1 score of 0.75. And on the test set, it had 79.0% average accuracy with an F_1 score of 0.8. We are suggesting the "ConvoForest" performed better than our crafted CNN because the same convolution layers were applied to both procedures but "ConvoForest" performed better. We believe the better performance of "ConvoForest" is because only a subset of the features from the flattened CNN features is applied and the robust behavior of random forest against overfitting. We believe other ensemble classifiers where a subset of the features are used to find the decision boundary may also be effective when combined with CNN for limited dataset image classification. Random forest generates multiple trees; for each tree, the number of features applied to each tree equals the square root of the total features from the convolution layer. Thus, only a subset of the full features is used for each tree, and during testing, they(all trees) form an ensemble classifier. Moreover, we displayed the F_1 score because sometimes our datasets are imbalanced, and the F1 score is a better metric for evaluating the model.

TABLE I: CNN and "ConvoForest" Classification of new and familiar faces

Subject-dependent Classification								
-	CNN				ConvoForest			
-	Val.		Test		Val.		Test	
Subject	Acc.	F_1	Acc.	F_1	Acc.	F_1	Acc.	F_1
S03	0.5	0.0	0.5	0.0	0.75	0.77	0.87	0.88
S05	0.17	0.17	0.5	0.36	0.58	0.71	0.79	0.82
S06	0.5	0.67	0.5	0.67	0.71	0.67	0.78	0.78
S07	0.79	0.8	0.56	0.53	0.79	0.8	0.75	0.75
S09	0.42	0.46	0.64	0.67	0.58	0.44	0.79	0.80
S11	0.5	0.67	0.5	0.67	0.5	0.46	0.75	0.75
S12	0.5	0.0	0.5	0.0	0.5	0.63	0.75	0.78
S13	0.5	0.67	0.5	0.67	0.93	0.93	0.75	0.71
S15	0.5	0.0	0.5	0.0	1.0	1.0	0.75	0.78
S16	0.5	0.67	0.5	0.67	0.93	0.93	0.94	0.93
S17	0.5	0.67	0.5	0.67	0.83	0.86	0.79	0.77
AVG	**0.49**	**0.44**	**0.52**	**0.45**	**0.74**	**0.75**	**0.79**	**0.8**

V. Conclusion

In this paper, we presented the "ConvoForest" classification technique on a limited dataset of EEG from face familiarity judgments (seen and unseen faces) in an episodic short-term recognition memory test. Deep learning has proven effective for image classification when enough training datasets are present. However, when there is a limited dataset for training, CNN fully connected layer may overfit the data and fail to generalize effectively. Therefore, we removed the dense layer from CNN and replaced it with a random forest classifier. So that the feature extraction ability of CNN can be preserved while we use a subset of the extracted feature for classification through a random forest. Compared with conventional CNN, where the dense layer was present, "ConvoForest" performed better with an average subject-dependent classification accuracy of 79.0% and an F_1 score of 0.80. The effectiveness of random forest is a prospect for applying other applicable traditional classifiers together with CNN in the future. We hope to conduct more experiments and analyses with face-name associations to investigate familiarity and recollection memory in the future.

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