Transfer Learning for EEG Classification with Limited Data

EEG data are often **scarce, noisy, and highly variable** across subjects and tasks, so training deep networks from scratch can easily overfit. Transfer learning (TL) – reusing a model pretrained on one task or dataset for a new EEG task – can mitigate data scarcity. In TL, a "base" model (often pretrained on large data) has its early layers fixed or partially frozen, and later layers are fine-tuned on the target EEG data[1][2]. In practice, this means leveraging knowledge from related EEG tasks (or even image tasks) to improve performance with fewer EEG samples. As Yap *et al.* note, TL "is practical and positively impacts various domains where it is difficult to increase performance due to the lack of training data"[1].

Why EEG needs TL. EEG signals vary widely by person and session, and high-quality EEG datasets are often small. Deep models trained on only a few EEG trials tend to overfit[3]. TL can **boost accuracy and stability when data are limited**. For example, Xie *et al.* (2023) pre-trained a motor-imagery model on one dataset and fine-tuned on another. With limited new data, TL **improved accuracy by up to 27%** over training from scratch[4]. Similarly, Li *et al.* (2025) pretrained a CNN–LSTM on the large DEAP emotion dataset and fine-tuned it for mental-fatigue detection; accuracy soared from ~63% to 92% on the small target data[5][6]. These results show TL can make EEG classifiers **much more accurate and faster to train** under low-data conditions[4][5].

Pretrained EEG Models and Representations

There is **no single "ImageNet" for EEG**, but recent work has started to build large EEG-pretrained models. Wang *et al.* (2024) released **EEGPT**, a 10M-parameter Transformer trained with self-supervised masking on a huge mixed EEG corpus[7][8]. EEGPT uses novel *spatio-temporal alignment* to deal with EEG's low SNR and channel mismatches[7]. Once trained, EEGPT achieved **state-of-the-art accuracy on many downstream EEG tasks** with only linear probes[8], demonstrating the value of a general EEG representation. Likewise, Li & Metsis (2022) proposed **SPP-EEGNet**, a convolutional network with spatial pyramid pooling that can accept variable EEG inputs. They trained it with contrastive self-supervision on large unlabeled EEG data and showed its first layers learn *general EEG features* that significantly improve new-task performance[9][10]. These "foundation" models show that **self-supervised pretraining on unlabeled EEG can provide a powerful base** for later classification.

Besides purely EEG-based pretraining, many studies adapt *image* CNNs for EEG by converting signals to time–frequency images. For instance, Sadiq *et al.* (2022) applied ten different ImageNet-pretrained CNNs (ShuffleNet, ResNet, etc.) to wavelet scalograms of EEG. They achieved up to **99.5% accuracy** on BCI motor/mental imagery tasks[11]. Even without retraining, these pretrained CNNs gave robust performance because they naturally preserve EEG's time–frequency structure[11]. In practice, one can take a standard vision model (e.g. VGG, MobileNet) and fine-tune it on EEG spectrograms, often with great success. Open-source resources like **pretrained EEGNet models** also exist. For example, Guetschel (2021) released a collection of EEGNetv4 networks pretrained on several MI datasets, providing ready-to-use feature extractors for motor-imagery decoding[12].

Examples of Transfer Learning in EEG

Many recent studies illustrate TL benefits in different EEG domains. Key examples include:

- **EEG Authentication:** Yap *et al.* (2023) used TL for user ID via EEG "passcodes". They fed FFT spectrums of EEG into standard pretrained CNNs (VGG, ResNet, etc.) and fine-tuned on a 30-subject authentication task. TL achieved **~99–99.9% ID accuracy** even with two sessions of data[13][14], far better than training from scratch.

- **Motor Imagery (MI):** Xie *et al.* (2023) treated MI datasets as separate tasks in a multi-task model. They pre-trained on one MI dataset and fine-tuned on another. With TL, accuracy rose by **7–27%** depending on data size, and models converged much faster[4][15]. Similarly, subject-adaptive methods (e.g. training on resting-state EEG) have shown better cross-subject MI decoding. Another approach by Sadiq *et al.* (2022) used wavelet-transformed MI signals and pretrained vision CNNs, yielding very high classification rates on BCI Competition data[11].

- **Cognitive/Emotion Recognition:** Li *et al.* (2025) extracted large EEG samples from the DEAP emotion dataset and pretrained a CNN+LSTM. After fine-tuning on a small mental-fatigue dataset, accuracy jumped from 63% to **92%**[5][6]. Lu *et al.* (2023) tackled **cross-subject emotion** using domain-adaptive TL: they pre-trained on mixed-source SEED data then fine-tuned on each subject. This DFF-Net approach exceeded prior cross-subject results, achieving ~93% on SEED[16].

- **Rehabilitation / Motor Intention:** Kueper *et al.* (2024) studied exoskeleton control. They transferred a model trained on *bilateral* arm-movement EEG to a *unilateral* task. Remarkably, this TL model (trained on one task) performed as well on the new task as a model trained from scratch – **without any calibration session** – even using only 4–8 channels[2]. This shows TL can eliminate long calibration when moving between related EEG tasks.

These studies share a theme: **TL dramatically improves EEG classification when data are limited**. Across tasks, pretrained features either speed convergence, raise baseline accuracy, or both[4][5]. Even binary tasks like subject ID or motor imagery become more reliable with TL.

Discussion and Next Steps

In summary, **transfer learning in EEG is an active, promising area**. While there is no single universal EEG base model yet, recent work has produced several strong candidates (e.g. EEGPT[7], SPP-EEG[9], pretrained EEGNets[12]) and simple strategies (using vision CNNs on EEG images) that serve a similar role. Existing studies have demonstrated that such TL approaches can outperform scratch training by a wide margin[4][5].

For your project, these findings suggest multiple avenues. You could start with a known pre-trained EEG network (e.g. EEGPT when available, or one of the EEGNet models from the literature) and fine-tune it on your limited EEG data. Alternatively, apply TL via input transformations (e.g. feeding spectrograms into ImageNet CNNs as in Sadiq *et al.*). Another direction is **cross-domain TL**: for instance, train a large self-supervised model on various EEG datasets (as in SPP-EEG or EEGPT) so that it learns general EEG features, then fine-tune on your target task.

As for using *animal EEG*, to our knowledge this hasn't been explored much. EEG from different species can have different frequency content and electrode setups, so a pretrained human-EEG model may not transfer directly. However, if you have *enough animal EEG data*, you could try the same TL principles (self-supervised pretraining on unlabeled animal EEG, or cross-species adaptation) – the field is open to such exploration.

Conclusion: Transfer learning *for EEG classification* is both feasible and beneficial. Multiple recent works show that applying TL (from large EEG or image models) can dramatically boost accuracy with little target data[1][4]. While a standardized EEG "base model" is still emerging (new models like EEGPT point the way[7]), you can leverage existing pretrained networks and TL techniques in your work. In short, there **is** a foundation of TL in EEG research, and building on it is likely to yield significant gains in any data-limited EEG task.

Sources: Recent EEG transfer learning studies and reviews[1][4][5][9][11][16][7][2] provide the evidence above.

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