Decoding the functional reorganization of the aging brain using machine learning applied to electroencephalography

By

Christian Johannes Gölz

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Acknowledgement

Danke.

Abstract

Aim: Apply data science methods to questions in aging Neuroscience

Methods: Supervised and unsupervised methods in different settings

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Coclusion: ML rocks!

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List of Abbreviations

AI	artificial intelligence
BCI	brain computer interface
CRUNCH	compensation-related utilization of neural circuits hypothesis
CSP	common spatial patterns
DMD	dynamic mode decomposition
EEG	electroencephalography
ERM	empirical risk minimization
ERP	event related potential
FBCSP	filter based common spatial patterns
fMRI	functional magnetic resonance imaging
FN	false negative
FP	false positive
HAROLD	hemispheric asymmetry reduction in older adults
ICA	independent component analysis
LDA	linear discriminant analysis
MLE	maximum likelihood estimation
MRI	magnet resonance imaging
MVC	maximum voluntary contraction
MVPA	multivariate pattern analysis
PASA	posterior–anterior shift in aging
PCA	principal component analysis
STAC	scaffolding theory of cognitive aging
SVD	singular value decomposition
SVM	support vector machine
t-SNE	t-distributed stochastic neighbor embedding
TN	true negative
TP	true positive
UMAP	uniform manifold approximation and projection for dimension reduction

WHO	World Health Organization

Publications and other scientific contributions

Chapter 1

General Introduction

1.1 Motivation

> ”Humans now live longer than at any time in history. But adding more years to life can be a mixed blessing if it is not accompanied by adding more life to years.”
>
> Dr. Tedros Adhanom Ghebreyesus, WHO Director-General, 2020

One of Western society’s most significant societal challenges is the demographic shift towards an older population, which poses enormous demands for society, raising issues for the healthcare system, infrastructure, family policy, and the occupational sector [1]. To avoid overburdening social structures, one of the main goals is to promote healthy, independent aging and improve the quality of life in old age. As part of efforts to promote these goals, the World Health Organization (WHO) launched the *Decade of Healthy Aging (2021-2030)*, which aims to encourage global action to improve the lives of older people, their families, and the communities in which they live with the ultimate goal of *adding life to years* [1].
An essential part of promoting healthy aging and enabling participation in society includes the early identification and treatment of pathological conditions, developing and evaluating targeted interventions for prevention and therapy, or designing assistive technologies for older adults. These efforts require a deep understanding of the dynamics of aging in the context of individual trajectories and general patterns. Since many of the mechanisms leading to cognitive and physical decline are related to changes in the brain, it is of great interest to understand and quantify the aging process at this level.
Not only is aging a highly complex phenomenon, but also the brain is a complex system that is nonlinear, dynamic, and multi-scale in space and time [2]. Machine learning offers valuable data-driven methods to unravel this complexity and gain insights by uncovering complex relationships and identifying predictive markers related to the aging process and associated health status.
In general, progress in science is more and more characterized by the application of methods from artificial intelligence (AI), including machine learning algorithms, which make it possible to systematically analyze large and complex amounts of data [3]. This development has led to proclamations of an ”AI revolution in science” [4] or promoting science has entered a new area characterized by *data-intensive computing*

[5]. Moreover, these methods serve as the foundations for solving various practical problems, as demonstrated by applications in many socially relevant areas, such as public transport, e.g., autonomous or self-driving vehicles [6], the medical sector, e.g., diagnostic imaging [7], or social interaction, e.g., tools for communicative interaction [8], and are thus one of the basic building blocks for assistive technology facilitating the participation of older people with disabilities in society. AI and machine learning as a key technology have become a hope for solving societal challenges.

However, the implementation of machine learning approaches in aging research is still at an early stage compared to the rapid development in the commercial sector, and the most effective applications and integration into the traditional scientific system have yet to be evaluated, despite the potential to better understand the aging brain.

This is the starting point of this work which aims to investigate brain aging using machine learning techniques. The focus is on using these methods to gain a better understanding of the neurophysiological factors that contribute to age-related sensory, motor, and cognitive alterations. To this end, existing hypotheses about the aging brain will be tested and validated while new hypotheses will be generated. The results may inform the development of targeted interventions and assistive technologies to counteract age-related decline.

1.2 Outline

This thesis is separated into five main chapters. This chapter 1 describes the thesis's theoretical framework. A description of aging at the level of the brain focuses on the most relevant concepts for the context of this work and forms the starting point for introducing the added value of applying machine learning in the context of this work. Next, machine learning is introduced to provide the methodological framework. The general terminology and a literature-based overview of the use of machine learning methods in neuroscience and especially in the neuroscientific research on aging will form the basis for the deduction of the research aim and scope of this thesis in the following chapter 2. The following chapter 3 includes a description of the methodological approach of this work. In the subsequent chapter 4, the main results of the published research articles underlying this thesis will be presented. These include:

- Research Article I:
  Goelz, C. *et al.* Classification of visuomotor tasks based on electroencephalographic data depends on age-related differences in brain activity patterns. *Neural Networks* **142,** 363–374 (2021)

- Research Article II:
  Goelz, C. *et al.* Classification of age groups and task conditions provides additional evidence for differences in electrophysiological correlates of inhibitory control across the lifespan. *Brain Informatics* **10,** 11 (2023)

- Research Article III:
  Goelz, C. *et al.* Electrophysiological signatures of dedifferentiation differ between fit and less fit older adults. *Cognitive Neurodynamics* **15,** 1–13 (2021)

- Research Article IV:
  Gaidai, R., Goelz, C., *et al.* Classification characteristics of fine motor experts based on electroencephalographic and force tracking data. *Brain Research* **1792,** 148001 (2022)

The thesis concludes with an overreaching discussion in which the results are evaluated in the light of the current scientific discourse highlighting consequences and future research topics (chapter 5).

1.3 Aging

Biologically aging is "the time-dependent functional decline that affects most living organisms" [13]. It can be observed in the reorganization of multiple interacting physiological systems operating at different spatial and temporal scales [14]. The underlying patterns of reorganization within and between these systems are highly individual, as they are subject to internal (e.g., genetic, cellular, molecular) as well as external (e.g., environmental, and lifestyle) influences [14–16]. At the same time, however, overarching, generalizable patterns can be identified [17]. The most recognizable consequences of aging are alterations in cognitive, sensory, and motor abilities that challenge the daily lives of older adults [18]. However, not all abilities are equally affected by declines, and the alterations are highly individual. While sensory, motor, and cognitive abilities, such as memory and processing speed, are generally declining, abilities in the context of acquired knowledge, such as verbal abilities, tend to be stable or even improve with age [19]. One factor that plays a crucial role in these alterations is reorganization at the level of the brain. A profound understanding is, therefore, of particular interest to research efforts. It is important to note that the reorganization of the brain can be viewed from many perspectives, so in the following, only the aspects and concepts essential for the understanding of this work will be presented.

1.3.1 Age-related Reorganization of the Brain

Reorganization in the brain's structure includes, among others, atrophy of the gray and white matter and enlargement of cerebral ventricles [20]. The efficiency of neuromodulation declines mainly driven by the loss of dopaminergic receptors indicative of a reorganization of neurotransmitter systems [21]. Besides this, the study of the functional properties of the brain and their relationship to behavioral changes is of great interest. In neuroimaging studies, both under-activation and over-activation of brain areas have been reported in older adults compared to younger adults during the performance in various tasks with sensory, cognitive as well as motor demands [22, 23]. Regarding activation dynamics, brain activity in response to a stimulus is often slower or delayed. Moreover, the frequency distribution of oscillatory neural activity changes to a slowing of the primary rhythms and altered temporal dynamics, which is interpreted as changes in neural communication [24].

By emphasizing neural communication and information flow, rather than viewing the brain as functionally separate, it can be conceptualized as a complex system whose functional units, i.e., neurons, areas, and subsystems, are interconnected structurally and functionally [25, 26]. In this concept, functional connectivity reflects coherent activation patterns within and between these units. Several distinct but interconnected functional networks were identified [27]. The dynamic interplay between and within these networks is characterized by segregation and integration at different levels, indicating the flow of information in the brain [28]. Older adults' information flow tends to be less efficient and is characterized by lower within-network connectivity and higher between-network connectivity associated with a less segregated, less modular, and more integrated brain network organization [23, 26, 29]. However, studies on sensorimotor and visual networks seem very heterogeneous, which could indicate individual reorganization patterns [26].

1.3.1.1 Dedifferentiation

The functional reorganization patterns described in the previous section have been attributed to dedifferentiation [30]. Dedifferentiation refers to the loss of neural specialization or reduced distinctiveness of neural responses resulting in diffuse, nonspecific recruitment of brain resources [31]. Historically, the term originates from behavioral research in which an increased correlation of performance between sensory, cognitive, and sensorimotor domains was reported in older adults [18, 32]. To explain this behavioral dedifferentiation Li and colleagues [18, 21] provided a computational model. According to this model, deficient neurotransmitter modulation observed in older adults may affect the responsiveness of cortical neurons, leading to higher levels of neuronal noise and ultimately to less differentiated, more diffuse neuronal activation patterns in response to different stimuli [18, 21] (see Figure 1.1 for an overview on the computational model). In several computational simulations, the authors demonstrated that the proposed model could explain behavioral co-variation and several other phenomena, such as decreased average behavioral performance or increased behavioral intra- and inter-person variability [18, 33]. In addition, the proposition of a less distinctive, less specific neuronal activation in response to stimuli could be confirmed in neuroimaging studies showing that the neural responses to various visual, cognitive, and motor stimuli are less specific in older compared to young adults [31, 34, 35].

The reorganization of functional networks as described above, i.e., a less segmented and modular, and less specialized organization in older adults, was framed in terms of dedifferentiation [23, 26, 31]. Fornito *et al.* [36] describe dedifferentiation as a fundamental maladaptive mechanism of brain networks that requires compensation. This view is consistent with the argument that dedifferentiation and compensation are complementary mechanisms [22]. However, dedifferentiation could also represent a compensatory response, in that the brain attempts to maintain function in the face of deterioration [37]. By definition, compensation refers to the ability to recruit additional brain resources to compensate for decline and functional loss to maintain cognitive or behavioral functioning [22, 30]. Here, the compensation-related utilization of neural circuits hypothesis (CRUNCH) hypothesizes that compensatory activity changes as a function of task demands. Moreover, compensation often occurs in a specific pattern of under-activation of posterior areas and prefrontal over-activation, known as posterior–anterior shift in aging (PASA) [38]. Another frequently reported pattern is the more bilateral recruitment and loss of hemispheric specialization, known as hemispheric asymmetry reduction in older adults (HAROLD) [39].

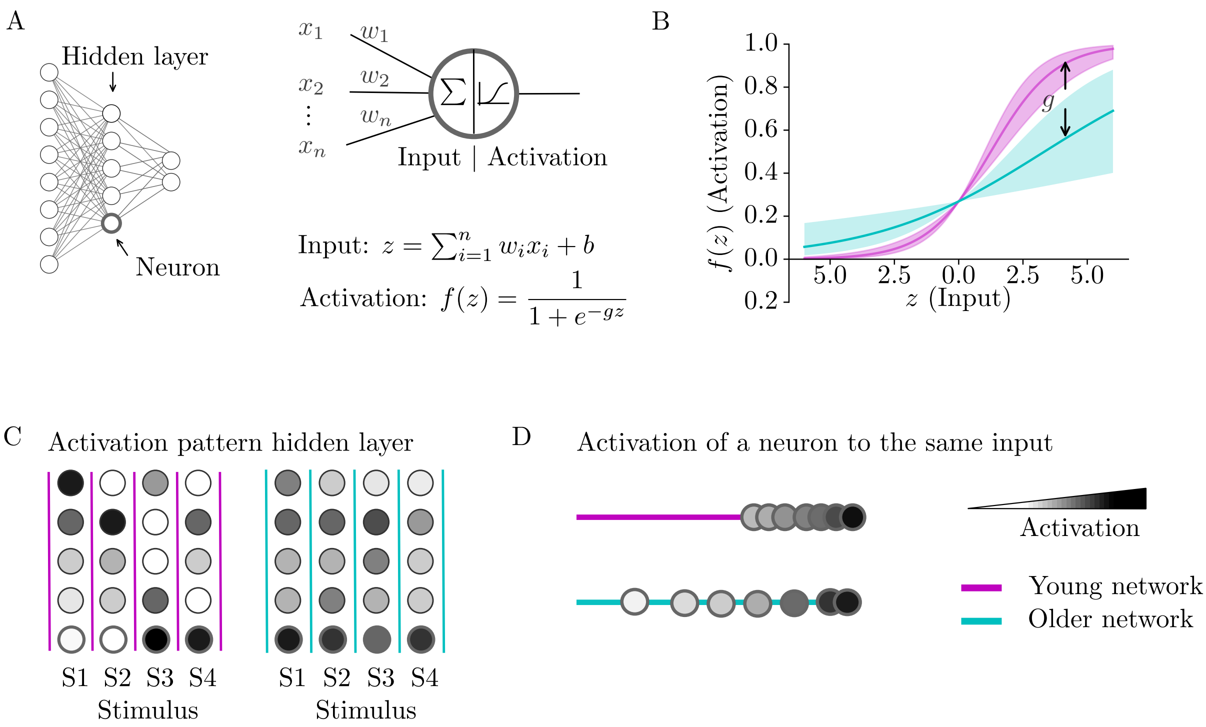

Figure 1.1: The authors used a feedforward backpropagation neural network model with logistic activation function $f(z)$ and simulated altered neuromodulation by varying the gain parameter g in $f(z)$ of each neuron (A). Lower g values represent deficient neuromodulation and responsiveness due to aging, resulting in a dampened neuron activation (B). Simulations showed that the activation pattern of simulated neurons differs less for different stimuli, i.e., the network's hidden layer shows a less distinctive representation of the stimulus (C). The activation of a single neuron is more variable in networks with lower g value, i.e., older networks, for multiple stimulations with the same stimulus (D).

1.3.1.2 Reserve

It is important to note that age-related alterations of the brain and behavior are highly individual and dynamic [15, 31, 40]. In this context, *reserve* was defined as the accumulated capacity of neural resources over the lifespan that can withstand decline or pathology [37, 41]. Although the concept was initially based on observations that the degree of pathological changes in the brain does not necessarily mean clinical manifestation, it has also been applied to explain the individuality of non-pathological aging [37, 41, 42].

Reserve can be both anatomically quantifiable, referred to as brain reserve, and more functional in nature, referred to as cognitive reserve [37]. At the functional level, compensatory activation, as well as more efficient utilization (less activation of neural resources), and increased capacity (increased availability of neural resources) were described as key mechanisms of cognitive reserve [37, 43]. Brain and cognitive reserve influence each other, and Cabeza *et al.* [41] argue against a strict separation of brain reserve and cognitive reserve.

One aspect that explicitly determines the definition of reserve is the lifelong ability of the brain to adapt its structure and function to internal and external requirements. It is known from the animal model that environments rich in cognitive, social, sensory, and motor stimuli contribute to positive plastic changes [44]. As a result, reserve is influenced by an interplay between genetic and environmental factors, including lifestyle factors [41]. Essential elements for increasing reserve have been identified in education, occupation as well as physical activity, with cognitive training, physical fitness, and professional expertise having a considerable impact on the brain's functional organization [45–47].

Other complementary concepts, such as the maintenance or the scaffolding theory of cognitive aging (STAC) model, highlight these influencing factors additionally. The concept of maintenance emphasizes the ability of the brain to repair. STAC postulates that lifelong positive and negative plasticity defines a framework that enables compensation and shapes the individual trajectory of aging [48].

1.3.2 Studying brain aging by electroencephalography

The complex interplay of the factors mentioned above leading to the dynamics of age-related reorganization of the brain is highly complex. Understanding these dynamics regarding individual trajectories and overarching patterns is a prerequisite to differentiating healthy from pathological changes and developing and verifying treatments and targeted interventions. This requires uncomplicated, easy-to-use, and cost-effective methods and novel analyses to quantify changes in brain organization. Several noninvasive methods are available to study the brain's structure and function. Magnet resonance imaging (MRI) is the most widely used method in science to image the structure or, using functional magnetic resonance imaging (fMRI), the function of the brain, which is the dominant method in the study of the functional reorganization described in the previous section [22]. However, its use in the public health system is mainly limited to cases with a clear indication, making early detection of unfavorable aging trajectories challenging. In addition, limited availability substantially restricts the development of preventive and rehabilitative interventions and therapies and excludes areas and sites with low levels of equipment and expertise. Here, electroencephalography (EEG) could represent a real added value since it is characterized by simple use, mobility, and relative cost-effectiveness. Although it has a lower spatial resolution than MRI based methods, EEG measures neuronal activity directly with a high temporal resolution which allows for the detection of age-related changes in the temporal dynamics of brain activity and networks, which could be of particular interest to understand age-related changes of the brain and their relation to behavior [24].

1.3.2.1 Excursus: A Brief Overview on Electroencephalography

EEG measures time-varying electrical fields on the surface of the head by using several sensors placed in a standardized position [49]. The measured signals reflect synchronously active populations of neurons. Electrical activity can only accumulate and be detected on the surface of the head if spatially similar neurons, aligned perpendicular to the surface, are synchronously activated. Based on the conductive properties of the brain, the signal can travel through the different layers to the surface due to volume capacitive conduction. For this reason, and due to the orientation of neural cell assemblies, the signal in each sensor reflects a summed signal of different neuron patches. The signal expressions are in the range of a few micro-volts and are much lower than other biological and non-biological electrical generators, e.g., muscular activity or line noise, so the EEG signal is often affected by a low signal-to-noise ratio [50].

One of the EEG's most striking signal characteristics is the rhythmic voltage fluctuations that define the signal and are summarized under the term oscillation. Commonly, the EEG signal is analyzed based on the frequency composition of oscillatory activity in loosely defined frequency ranges, i.e., δ (<4 Hz), θ (4-8 Hz), α (8-12 Hz), β (12-30 Hz) and γ (>30 Hz), which have been demonstrated to be related to perceptual, cognitive, motor and emotional processes [50]. Furthermore, the analysis of frequency-dependent synchrony or functional connectivity in terms of statistical dependence of the signals, e.g., by coherence or the phase synchrony of the signal, can provide information about the network characteristics of the brain [51]. Finally, the analysis of event-related activation, so-called event related potentials (ERPs), can provide information on the direct processing of stimuli. The analysis of ERPs involves time-locking the EEG data to the onset of a specific stimulus and averaging the EEG signal across multiple trials to extract a reliable signal related to the processing of the stimulus.

1.3.2.2 Electroencephalographic Signatures of Age-related Reorganization

Age-related changes in EEG characteristics have been extensively studied. Specifically, it has been reported that aging is associated with changes in the frequency composition of the EEG signal, regardless of any specific task involvement. These changes include a decrease in amplitude within the α frequency band, a shift in the α peak frequency towards lower frequencies, an increase in amplitude within the β frequency band, and varying results regarding changes in the amplitude of the θ and δ bands [24, 52, 53]. Moreover, age-related changes have also been reported in terms of reduced EEG synchrony and a more random, less segregated organization of EEG derived network topology [54, 55].

EEG changes in relation to tasks are highly dependent on the task context or domain studied. For example, unilateral motor tasks may display lower frequency specificity and more bilateral spatial expression of α and β frequency power modulations. In contrast, attention tasks may demonstrate enhanced frontal network involvement and power in the θ frequency band [56, 57]. In addition, the neural response to stimuli may exhibit a temporal slowing and altered spatial expression. These alterations can be seen, for example, in a delay of early ERP components as well as a more frontal expression of later ERP components in visual attention tasks [58, 59].

Often these changes are discussed concerning the mechanisms of dedifferentiation and compensation described above. These have been shown to be modulated by lifetime experience such as occupational expertise [45] or physical fitness [40]. However, the relationship between EEG parameters and these mechanisms often needs to be clarified. As such, other EEG findings may point in the opposite direction than described above. Hübner *et al.* [60], for instance, found no age effects in central lateralization in the

β frequency band in a complex fine motor control task, which again highlights the dependency on the task context considered. Age-related changes in decreased ERP latency and lower or increased functional connectivity of the examined networks depending on the task context are also reported [24]. Moreover, the interpretation of dedifferentiation is often based on fMRI findings that report over-activation and loss of segregation of brain networks. However, the relationship between frequency-specific EEG and fMRI findings acting on different spatial and temporal scales and measurement principles might be unclear. Koen & Rugg [31] further points out that over-activation should be interpreted cautiously and does not necessarily imply loss of neural specificity, as predicted in the original model of Li *et al.* [33]. He, therefore, proposes to operationalize dedifferentiation clearly in terms of the selectivity of the neural response between two or more task modulations. While in this operationalization, the evidence regarding dedifferentiation in fMRI studies is quite clear, this has not been explored in EEG studies so far [31].

Altogether the EEG represents an easy-to-use, low-cost method that can provide valuable insights into age-related changes. However, the link to age-related changes reported consistently in the fMRI, such as differentiation, is often challenging and needs to be clarified. EEG signals are temporally and spatially highly dimensional, i.e., large amounts of data points contain intricate patterns of electrical activity. However, the signals often have a low signal-to-noise ratio, making it difficult to detect and visualize age-related brain reorganization and its dynamics. As such, analysis of EEG signals requires advanced signal analysis methods. In this context, methods from the field of machine learning could be of particular interest. By leveraging machine learning techniques, it is possible to extract meaningful patterns from the high-dimensional EEG data and uncover subtle age-related changes that may not be evident through traditional analysis methods.

1.4 Machine learning

Machine learning emerged in the 1950s to enable computers to learn without being explicitly programmed [61]. It is defined by computational methods combining fundamental concepts from computer science, statistics, probability, and optimization that automatically extract patterns and trends, i.e., *learn* from data [62]. The notion of *learning* therein describes the automated inference of general rules based on the observation of examples using algorithms to solve a specific task or problem [63]. In its basic form, these tasks often involve making predictions based on learned relationships or extracting information based on automatically detected patterns and structures from data. Many problems can be formulated by these tasks, and a rise in machine learning started in the 1990s to 2000s with the availability of computing resources, data, and the development of algorithms, which have found their way into everyday life not only since the current advancements in generative AI systems. Examples can be found in numerous areas, such as predicting stock prices, personalized advertising, or autonomous driving [64].

In science, machine learning is increasingly used as a complementary method to classical statistical analyses because of the ability to make predictions and deal with the multidimensional structure and non-linearity in real-world datasets for drawing inference [65]. Especially in areas where high-dimensional data is prevalent, such as in neuroscience, machine learning methods offer insight by extracting complex patterns purely data-driven [3]. In terms of EEG, machine learning can help identify subtle patterns and nonlinear relationships from the complex multidimensional structure of EEG data, allowing for more accurate and efficient analysis of brain recordings. A wide variety of methods are available for this purpose, which can be roughly characterized based on various properties.

1.4.1 Forms of Machine Learning

The three main forms of machine learning are supervised, unsupervised, and reinforcement learning. These forms are defined by the type of feedback a machine learning algorithm has access to during learning [66].

Supervised machine learning aims to learn a generalizable relationship between data and associated information, so-called labels or targets. The learned model can then be used to predict the label of new data not used during the learning process. If the labels are categorical, the prediction task is called classification; for continuous labels, the term is regression. Unsupervised machine learning aims to find hidden structures in data without considering associated labels. This could be grouping similar data points, i.e., clustering, or uncovering a meaningful low dimensional representation of high dimensional data, i.e., dimensionality reduction. This type of learning is also referred to as *knowledge discovery*[67]. Reinforcement learning describes the task of learning optimal actions to solve a particular problem by maximizing the reward linked to that action. See Figure 1.2 for an overview.

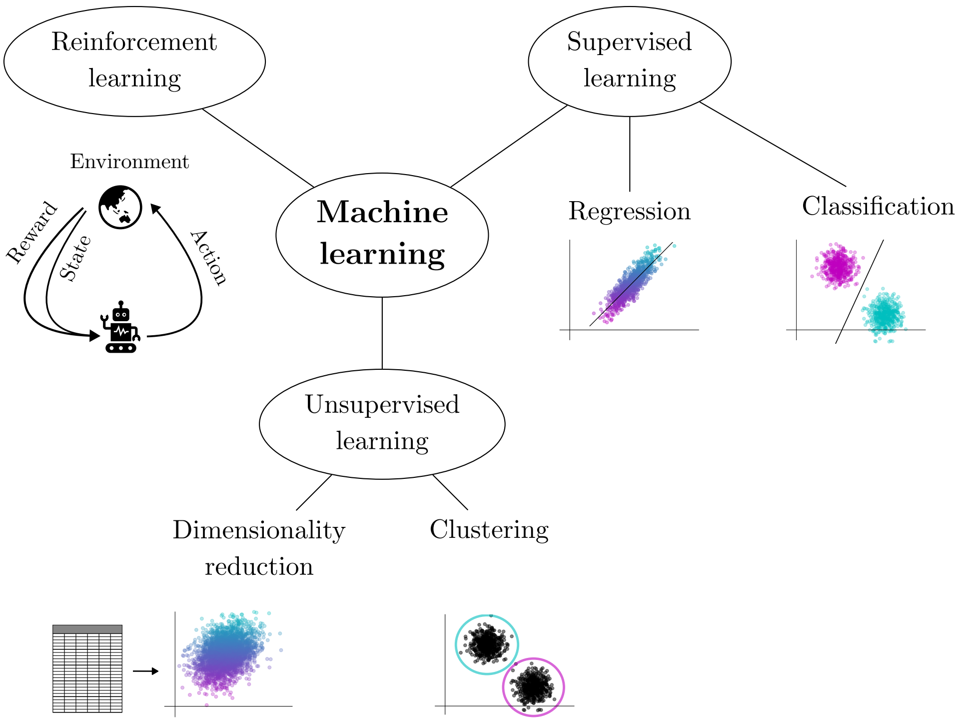

Figure 1.2: The three main forms of machine learning.

In practice, however, a clear separation is often impossible. As such, dimensionality reduction can also be supervised, i.e., labels are provided to learn a new representation of the data [68]. Besides, in semi-supervised learning, the goal is the same as in supervised learning. However, the data set used to learn the relationship contains labeled and unlabeled examples. The hope is to build a stronger representation by providing more information in the form of data [69].

In addition, traditional machine learning is often contrasted with deep learning methods involving the use of artificial neural networks, which are composed of many layers of interconnected nodes often used in an end-to-end fashion in which the input data is used without any form of (pre-)processing. Usually, they require a vast amount of data and computational power. In the context of this thesis, the tasks considered involve the processing of EEG from experiments with mid to small sample sizes to learn meaningful patterns and relationships in data. In the following state of the art approaches in the application to EEG data are presented.

Excursus: How Does a Machine Learn?

"A computer program is said to learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E" [70]. In other words, learning in the context of machine learning typically involves solving a specific task by using algorithms that improve their performance by using example data. There are numerous algorithms designed to solve the problems outlined above. Some basic building blocks can be defined, which can be used to describe computational learning formally. In the following description, the view of statistical learning theory is considered, and notation is adapted from Shalev-Shwartz & Ben-David [66], von Luxburg & Schölkopf [63].

Learning is always based on data, i.e., measurable information about some phenomenon, consisting of attributes of the phenomenon, so-called features, and an associated label in supervised learning. It is mathematically defined as an open bounded set $\mathcal{Z} \subset \mathbb{R}^n$ of dimension n. Typically there is only a set of examples or training data $S = \{z_i, ..., z_m\} \subset \mathcal{Z}^m$ available, where $i = 1, \ldots, m$, and each z_i is sampled independently from $\mathcal{Z}$ according to an underlying probability distribution $\mathcal{D}$. Thus the only assumption is that the example data are independent and identically distributed. No assumption on D is made.

In supervised learning, $\mathcal{Z}$ comprises the space of input data $\mathcal{X}$ and the space of labels or output $\mathcal{Y}$. The example data S consists of labeled input-output pairs $z_i = x_i, y_i \in (\mathcal{X} \times \mathcal{Y})^m$, where x_i is an input data vector and y_i is its corresponding output label. The pairs are sampled by some unknown joint probability distribution $\mathcal{D}$ on the space $\mathcal{X} \times \mathcal{Y}$.

The space $\mathcal{Z}$ in unsupervised learning comprises the input data space $\mathcal{X}$ only and the example set S consists of unlabelled examples $z_i = x_i \in \mathcal{X}^m$, sampled according to some unknown probability distribution $\mathcal{D}$ on the space $\mathcal{X}$.

Learning ultimately can be thought of as approximating an underlying ground truth function f, also called model, that represents the relationship between input and output in supervised learning, i.e.,

$$f : \mathcal{X} \to \mathcal{Y}, \tag{1.1}$$

or the mapping to a space of hidden patterns or structure $\mathcal{W} \subset \mathbb{R}^p$, where p can be equal or smaller than n, i.e.,

$$f : \mathcal{X} \to \mathcal{W}. \tag{1.2}$$

A learning task can be conceptualized as searching through the space of all possible solution functions. As this is not feasible, a finite class of functions, so-called hypotheses, is typically selected a priory. Thus, learning can be thought of as selecting a hypothesis h from a space of potential solutions $\mathcal{H}$ with $\mathcal{H} = \{h : \mathcal{X} \to \mathcal{Y}\}$ in supervised learning and $\mathcal{H} = \{h : \mathcal{X} \to \mathcal{W}\}$ in unsupervised learning.

A learner or learning algorithm is the means of selecting the best element from $\mathcal{H}$. The cost of a false prediction or an inaccurate representation of the data is quantified using a loss function, $\ell : \mathcal{H} \times \mathcal{Z} \to \mathbb{R}_+$. In other words, it measures how well a specific hypothesis is doing.

The expected risk is a measure of the average loss of a hypothesis, $h \in \mathcal{H}$ with respect to the probability distribution $\mathcal{D}$ over $\mathcal{Z}$ and can be defined as

$$L_D(h) := \mathbb{E}_{z \sim D}[\ell(h, z)] \tag{1.3}$$

A learner should select a hypothesis with the lowest possible expected risk. However, the underlying probability distribution is unknown. Using S, the expected risk can be estimated using the empirical risk over the training data. This is defined by:

$$L_S(h) := \frac{1}{m} \sum_{i=1}^{m} \ell(h, z_i). \tag{1.4}$$

Following this, learning can be formalized as solving an optimization problem of the form:

$$\hat{h} = \arg\min_{h \in \mathcal{H}} L_S(h), \tag{1.5}$$

which can be solved computationally. In parameterized models, this often involves the automated selection of those parameters $\theta \in \Theta$ of a chosen class of models that minimize $L_S(h_\theta)$. This optimization problem can then be solved by methods such as gradient descent or, e.g., analytically, using least squares estimation. The solution $\hat{h}$ is the learned model that can be used to solve the task at hand, e.g., predicting the label of new input data or uncovering patterns or structures in data. This is known as empirical risk minimization (ERM).

Upon ERM, more complex learning paradigms can be used to address common problems such as overfitting, in which the learned hypothesis too closely relies on the training data and therefore has low generalization performance, e.g., regularized risk minimization, which introduces regularization to ERM or structural risk minimization that penalizes complex models and encourages simplicity.

Although most machine learning can be conceptualized within the framework of ERM, there are models that, instead of minimizing risk, assume that the underlying distribution over the data has a specific parametric form, and the goal is to estimate these parameters by using maximum likelihood estimation (MLE) which seeks to find the model parameters that maximize the likelihood of the observed data under the assumed parametric distribution, i.e.,

$$\hat{\theta}_{\text{MLE}} = \arg\max_{\theta \in \Theta} \prod_{i=1}^{m} p_\theta(z_i), \tag{1.6}$$

where $p_\theta(z)$ is the joint probability function of the assumed parametric distribution and $\hat{\theta}_{\text{MLE}}$ is the estimated value of the parameter vector θ.

1.4.1.1 State of the Art Approaches to Electroencephalographic Data

A variety of established supervised and unsupervised algorithms are used to analyze the analysis of EEG data, and the selection is usually based on the goal of the analysis. Unsupervised learning aims to highlight specific information in the data, so the selection is made based on the information one aims to highlight [66]. This is to highlight group structure in EEG data when using clustering or to highlight EEG inherent characteristics in dimensionality reduction. In contrast, the selection of a suitable supervised learning algorithm is more guided by its performance, i.e., its ability to derive generalizable rules that allow predictions from the available data. Typically this involves an iterative approach that divides the available data into training and testing sets, trains and validates various models within the training portion (cross-validation), and finally tests the best-performing model on the testing portion to estimate its ability to generalize [62].

Thereby, recent work highlights deep neural networks that can be used for unsupervised and supervised machine learning applications to EEG [71]. However, their advantage comes into play with large data resources, which are often expensive to acquire in the case of EEG [72]. Traditional learning approaches can be more efficient with good performance and promise better interpretability, especially for comparatively smaller data sets and limited computational resources [73].

Due to the low signal-to-noise ratio and high complexity of EEG data, the inputs in these approaches are often represented by well-known EEG characteristics or features that are believed to be related to the problem being learned. Typical features include time, frequency, time-frequency, connectivity, and theoretical information parameters extracted for each sensor (see [73] for common choices). However, this approach may lead to less flexible and generalizable models with low spatial resolution and vulnerability to low signal-to-noise ratios [74].

To address this, some approaches compute the sources of the EEG signals in the brain using biophysical models as a preprocessing step prior to feature extraction [75, 76]. Other approaches use supervised and unsupervised decomposition techniques belonging to the field of dimensionality reduction as a preprocessing step for further prediction tasks or provide information themselves in the sense of knowledge discovery. These methods aim at *unmixing* the highly correlated sensor time series by assumptions about the underlying signal components. For example, independent component analysis (ICA) assumes statistical independence. In contrast, principal component analysis (PCA) assumes that the extracted components are maximally uncorrelated to each other, capturing the largest amount of variance in the data [50]. Dynamic mode decomposition (DMD) is a method that explicitly considers the temporal structure of the signals, which requires the extracted signal patterns (modes) to be temporally coherent, thus accounting for the network character of the brain [77]. Additionally, supervised methods such as common spatial patterns (CSP) [78] or xDAWN [79] extract signal components that correlate with the labels to be predicted.

While supervised and unsupervised ways of examining the complex EEG signals in terms of components and patterns to generate knowledge, non-linear methods such as t-distributed stochastic neighbor embedding (t-SNE) and uniform manifold approximation and projection for dimension reduction (UMAP) take into account the non-linear relationships between the data points and provide a lower-dimensional representation of the data that is often easier to interpret and visualize [68]. These methods can be beneficial for exploring the relationships between different EEG features or identifying subgroups within a dataset.

It is important to note that these methods can be applied not only to the EEG signals itself but also to previously extracted EEG parameters or in combination in terms of knowledge discovery. Thus, supervised and unsupervised dimension reduction provides data-driven insights into the complex underlying information but also serves as preprocessing for further tasks such as prediction.

1.4.2 Applications in the Context of Aging Research

Traditionally, the previously presented machine learning approaches have been the core building block for developing intelligent systems that can automate tasks or enhance and assist humans in performing their tasks. Such systems are critical in terms of assistive technology, for example, to support older adults with disabilities to live their daily lives, but are also relevant in the medical field. In the latter, the hope is to develop intelligent medical systems to inform clinical theory and support clinical decision-making, i.e., assist in diagnosis and risk management by predicting health status or forecasting treatment responses [80]. In this context, supervised learning is often used to identify markers from EEG by identifying signal features that are predictive of a particular disease or health condition, which is highly important in promoting a healthy aging trajectory [81, 82]. An application is to estimate biological age based on regression models trained based on neural data, e.g., EEG data, recorded in extensive population studies [83]. Using data from an individual person, a regression model can predict that person's age. If the brain appears older than it would chronologically, this can be an early indication of an unfavorable state of health [84].

Another highly relevant application in the context of aging is the development of devices to assist, augment or enhance humans' capabilities, such as brain computer interfaces (BCIs). In BCIs, neural activity is decoded, using classification to generate control commands for various external devices such as computers or prosthetic limbs [85, 86]. Decoding refers to learning a classification or regression model that predicts behavioral outcomes or cognitive states based on neural data.

Beyond the application in BCIs, decoding techniques are widely used in neuroscientific research to gain insights into the neural mechanisms underlying perception, cognition, and behavior. This type of analysis is often referred to as multivariate pattern analysis (MVPA) because its goal is to detect multivariate patterns, e.g., a set of voxels in fMRI or an electrical pattern at a given time point in EEG, associated with an experimental condition [87]. While the use has a long history in the field of fMRI analysis, it has only become more widespread in the field of EEG in recent years. Therefore, decoding approaches to understanding age-related reorganization are mostly limited to fMRI studies. A common approach is to measure dedifferentiation at the individual level, i.e., the loss of neural specificity. Since dedifferentiation, by definition, results in more similar brain activation patterns for different tasks or stimuli, a poorer performance of classifiers trained to discriminate between them based on neural recordings is indicative of a less distinctive neural representation [31, 88].

Furthermore, classifying group membership or group-level regression can provide information about interesting relationships and their generalizability. Particularly for EEG markers representing functional network characteristics can reveal insightful findings about the relationship to age-related changes [89].

In addition to the use of supervised learning algorithms, unsupervised learning and dimensionality reduction algorithms, in particular, have been used to reflect the temporal structure of signals with respect to the dynamics of brain networks with aging [45, 72]. Vieluf *et al.* [45] analyzed electrophysiological correlates of age- and expertise-related differences in fine motor force control and inferred group-specific characteristics of sensorimotor network activity.

In summary, machine learning is very diverse and ranges from engineering applications to scientific knowledge discovery. Especially in the latter case, it offers the advantage of automated extraction of patterns from highly complex data that can contribute to studying age-related changes. While decoding approaches are particularly interesting for measuring age-related changes in the organization of neural systems, such as the level of differentiation, group analysis could provide new insights into datasets. Especially classification methods that predict a particular experimental condition or a group membership are particularly suitable. The combination with unsupervised learning algorithms, such as dimensionality reduction methods, could be particularly beneficial and used to visualize high-dimensional data.

Chapter 2

Aims and scope

The main goal of this dissertation is to study age-related brain reorganization, considering both global patterns and individual trajectories, by applying established methods from supervised and unsupervised machine learning to EEG signals. The focus is investigating age-related phenomena such as dedifferentiation, extending existing studies, and testing the replicability of hypotheses such as reserve. Four empirical studies use datasets with subjects from different life stages and lifestyles, including work experience and physical fitness. These datasets include experiments covering sensory, motor, and cognitive domains. The following published research articles will be presented.

Research Article I focused on whether classification techniques applied to EEG data can effectively reflect the dedifferentiated properties of brain networks in older people, using the motor system as an example. This work builds on a previous publication that found differences between younger and older adults in EEG markers of sensorimotor processing, and the idea was to extend these results using classification [45]. We, therefore, compared the classification performance, i.e., the discriminability of different visuomotor tasks, between younger and older adults.

Continuing this approach, **Research Article II** aimed to investigate whether the cortical representation of inhibitory control differs across age groups. Again, previously published findings, in which different mechanisms of selective attention in older adults and children were detected, should be extended [90]. For this purpose, the performance of the classification of different stimulus types of a flanker task was compared between different age groups. Furthermore, it was investigated whether the age group membership can be predicted based on the EEG data.

Research Article III aimed to examine the potential influence of cardiorespiratory fitness, a lifestyle factor, on patterns of dedifferentiation extracted through dimensionality reduction. This investigation was motivated by the reserve hypothesis, which postulates that cardiorespiratory fitness could impact age-related brain reorganization and the observed patterns of dedifferentiation.

In addition to cardiorespiratory fitness, another significant lifestyle factor is professional expertise. Therefore, the subsequent **Research Article IV** aimed to characterize middle-aged experts using supervised and unsupervised machine learning techniques.

The application of machine learning methods, both on individual and group levels, will allow to draw conclusions about predictors of reorganization of the brain and will help to identify the individual status as well overreaching trajectories. The information gained from these tools could be used to determine and evaluate intervention programs, on-the-job-trainings, and support diagnosis, and may have applications in the development of assistive technological systems.

Chapter 3

General methodology

3.1 Datasets

The datasets were selected from experiments in published projects in which different study paradigms were used to investigate age-related differences between age groups and groups with different lifestyle backgrounds. The following is a brief description of the datasets. Table 3.1 gives an overview of which datasets were used in the respective Research Article I to IV.

3.1.1 Dataset I

Dataset I was collected as part of the Bremen Hand Study@Jacobs, which investigated the influence of age and expertise on hand dexterity over the working life [91]. This dataset was analyzed in Research Article I and IV.

3.1.1.1 Participants

The dataset contains recordings from 59 participants, Based on their age and occupation, participants were labeled as young novice, middle-aged novice, middle-aged expert, late middle-aged novice, ore late middle-aged expert. Novices were defined as occupational profiles whose daily routine does not require fine motor control of the hands, such as service personnel, insurance agents, office workers, and students. Experts, on the other hand, referred to persons with more than 10 years of professional experience in a job with pronounced fine motor requirements for hand control such as opticians, goldsmiths, dentists, dental technicians, or hearing aid technicians [92]. In Research Article I only the young novices (N=13, age: 18 to 25 years) and late middle-aged (N=13, age: 55 to 65 years) were considered. In Research Article IV all middle-aged and late middle-aged experts (N=22, age: 34 to 65 years) as well as all middle-aged and late middle-aged novices (N=21, age: 35 to 64) were included in the analyses.

3.1.1.2 Experimental Procedures

The experiment conducted was a force-tracking experiment conducted blockwise (see Figure 3.1 and Research Article I and II for experimental details). The task was to apply the correct force to a force

transducer using the right or left hand to track a target force level as precisely as possible. A total of 160 trials were conducted. The first 40 trials involved a steady force level and the following 40 trials a sine force level. The sequence was then repeated with the left hand.
Grip force and EEG were recorded. Before the experiments resting EEGs with eyes open and eyes closed were recorded for 30 s each while participants sat comfortably on a chair.

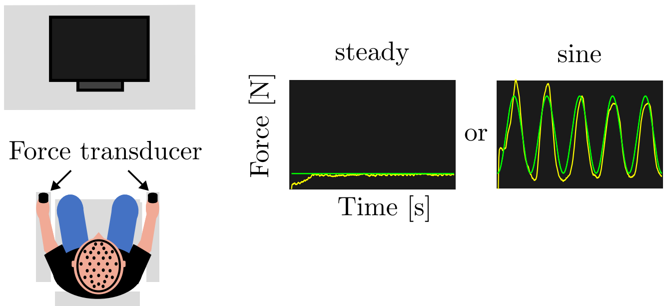

Figure 3.1: Schematic presentation of the force-tracking task conducted in dataset I. The task was to apply the correct force to a force transducer using the right or left hand to track a target force level (green line) as precisely as possible. Participants received feedback, i.e., they saw their applied force (yellow line).

3.1.2 Dataset II

Dataset II contains recordings from three experimental studies, each focusing on a different age group and referred to below as Study 1, Study 2, and Study 3.
Study 1 is the Bremen-Hand-Study@Jacobs presented above. Study 2 is the Re-LOAD project, which investigated the relationship between motor learning and cognitive function in older adults [60, 93]. Study 3 is the CEBRIS project, in which the influence of physical training on the cognitive functions of children was investigated [94]. The dataset is described detailed in [90] and was analyzed in Research Article II

3.1.2.1 Participants

The full dataset contains recordings from a total of 222 participants including 92 participants recorded in Study 1, 81 participants recorded in Study 2, and 49 participants recorded in Study 3. Participants are separated into the following age categories [90]: children (N=46, age: 8 to 10 years), young adults (N=39, age: 20 to 29 years), early middle-aged adults (N=21, age: 36 to 48 years), late middle-aged adults (N=25, age: 55 to 64), old adults <75 (N=40, age: 66 to 75 years), very old adults >75 (N=38, age: 76 to 83 years)[1].

[1] In the sample used here 13 participants were excluded due to bad data quality.

3.1.2.2 Experimental Procedures

All participants performed a modified version of the Flanker task previously reported in [59, 95, 96], and summarized in [90] (see Figure 3.2 and Research Article II). The task was to press as quickly as possible the correct key corresponding to a central target stimulus surrounded by distracting flanker stimuli. In Study 1 and Study 3, participants performed 300 trials (approx. 100 trials per stimulus), whereas, in Study 2, they performed 150 trials (approx. 50 trials per stimulus) in randomized order. Other than this the same experimental procedures were applied in all studies including the EEG measurements system.

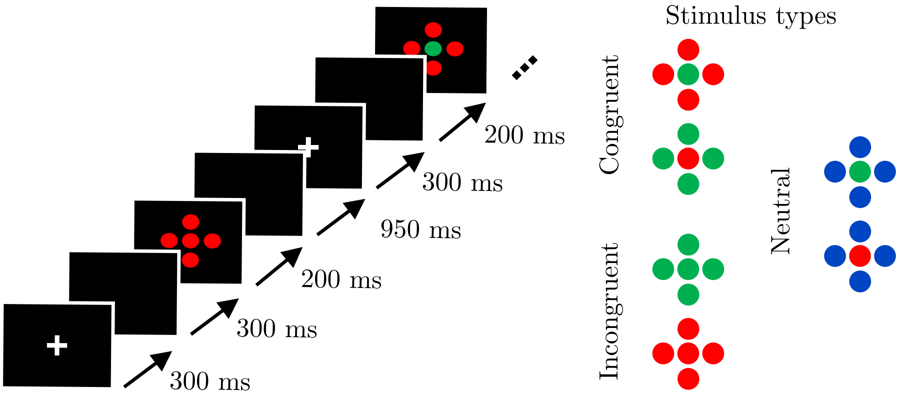

Figure 3.2: Schematic presentation of the flanker task conducted in dataset II.

3.1.3 Dataset III

Dataset III was collected during an intervention study at Paderborn University. The dataset is described in detail in Research Article III.

3.1.3.1 Participants

The dataset contains recordings from 41 elderly participants. Based on their performance on a 6 min walking test participants' cardiorespiratory fitness was assessed in preceding appointments and two groups were formed, a less fit (N=16, age: 63 to 77 years) and a fit group (N=15, age: 60 to 66 years).

3.1.3.2 Experimental Procedures

Participants performed sensory, motor, and cognitive tasks each lasting 90 s during which EEG was recorded (see Figure 3.3) Prior to the tasks, EEG was recorded for four minutes in a rest condition in a supine position with eyes closed.

Motor task The motor task corresponded to a force tracking experiment as described in subsubsection 3.1.1.2. Here, the target was a line that moved from the right to the left on the screen for 90 s and changed level every 3 s in randomized order between heights that represented 10%, 20% and 30% of participants' individual maximum voluntary contraction (MVC).

Cognitive task The cognitive task was an auditory n-back task. In essence, participants were asked to listen to a sequence of letters presented via two speakers behind them and press the foot switch with the right foot if a letter appeared again two letters later (2-back).

Sensory task The index fingertips of the participant's left hand were stimulated with the pins of a braille device presenting two pin configurations in random order.

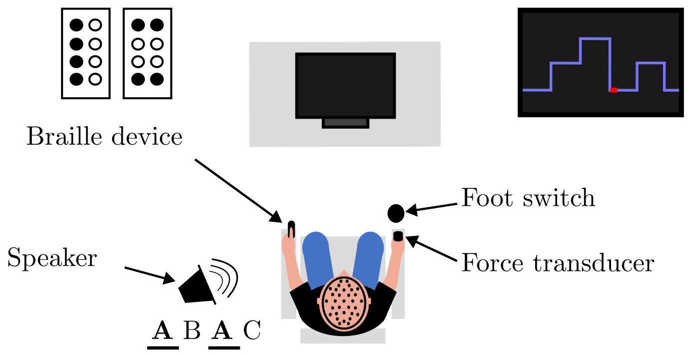

Figure 3.3: Schematic presentation of the motor, sensory and cognitive tasks conducted in dataset III.

Table 3.1: Overview of datasets and participants in each research article.

	Dataset	**Paradigm**	**Participants**	
Research Article I	Dataset I	Force Control	Late middle-aged adults	N=13, age: 55 to 65 years
			Young Adults	N=13, age: 18 to 25 years
Research Article II	Dataset II	Flanker	Children	N=46, age: 8 to 10 years
			Young adults	N=39, age: 20 to 29 years
			Early middle-aged adults	N=21, age: 36 to 48 years
			Late middle-aged adults	N=25, age: 55 to 64
			Old adults <75	N=40, age: 66 to 75 years
			Old adults >75	N=38, age: 76 to 83 years
Research Article III	Dataset III	Nback	Low fit	N=16, age: 63 to 77 years
		Tactile Oddball	Fit	N=15, age: 60 to 66 years
		Force Control		
Research Article IV	Dataset I	Force Control	Experts	N=22, age: 34 to 65 years
			Novices	N=21, age: 35 to 64

3.2 Machine learning procedures

Following state of the art approaches (see subsection 1.4.2) we used a combination of dimensionality reduction methods and classification. Dimensionality reduction was used to extract a suitable representation of the EEG data for the following classification, i.e. for feature extraction, and also to detect and visualize patterns in the data sets. Classification procedures were used both at the individual level as well as at the group level. The former means that one model per subject was trained, which represents the cortical representation of an experimental condition, e.g., a task, and finally allows conclusions, e.g., about the dedifferentiation of cortical processes at the individual level. The latter means that a model was trained for the whole group to detect general overlapping patterns in the group structure. The selection of a suitable method was based on the dataset, i.e. data structure and experimental conditions, and the aim of the analysis. This approach is visualized in Figure 3.4 and Table **??** summarizes the used methods for each research article. In the following, the methods will be briefly described. The exact pipelines are described in the appended research articles I to IV.

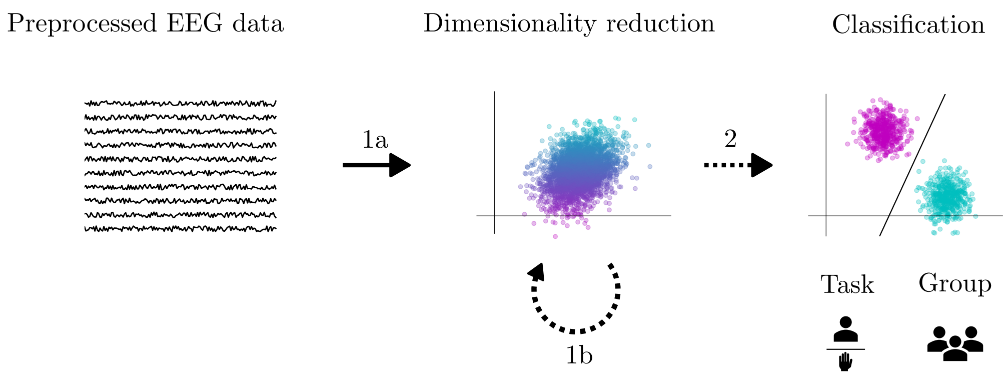

Figure 3.4: Machine learning approach used in this thesis. Dimensionality reduction was used to produce a suitable representation of the EEG data (1). Optionally a second level dimensionality reduction was applied to extract patterns and for visualization (1b). Finally Classification was used to classify either the task at individual level or the group membership (2) using either the results of 1a or 1b.

Table 3.2: Dimensionality reduction and classification methods utilized in each research article

	Dimensionality Reduction		**Classification**	
	1st level	2nd level	Task	Group
Research Article I	DMD	CSP	LDA	SVM
Research Article II	xDAWN	-	SVM	SVM
Research Article III	DMD	CSP, UMAP	LDA	SVM
Research Article IV	DMD	PCA	-	-

DMD: dynamic mode decomposition, CSP: common spatial patterns, LDA: linear discriminant analysis, SVM: support vector machine, PCA: principal component analysis

3.2.1 Dimensionality reduction

3.2.1.1 Dynamic mode decomposition

To extract a relevant representation of the continuous EEG activity, we chose DMD because it is able to decompose the signals into spatial activation patterns that are dynamically coherent, reflecting the network nature of the underlying brain activity [77]. DMD was developed in the field of fluid mechanics and was applied to various fields to model time-varying dynamical systems including neuroscience proving to extract physiological valid signal patterns [77, 97–99]. The activation patterns (modes) extracted from DMD analysis can reveal key features such as the spatial distribution of coherent dynamics in relation to oscillation frequencies and mechanisms of growth or decay. This provides a deeper understanding of the functional reorganization of the brain and can serve as a starting point for further analysis [77].
For the computation of DMD, the *exact DMD* algorithm introduced by Tu *et al.* [100] and described in [77] as applied to electrophysiological data. The analysis was based on the preprocessed and windowed EEG data and DMD modes associated with the frequency ranges θ (4 to $<$ 7 Hz), α (7 to $<$ 12 Hz), β_1 (12 to $<$ 16 Hz), and β_1 (16 to $<$ 30 Hz) were considered. We calculated the DMD mode magnitude (absolute value) to obtain the influence of each electrode in a DMD mode representing spatially coherent activation [77].

3.2.1.2 Principal component analysis

PCA aims at extracting the statistically most descriptive components from highly dimensional data [101]. For this we used the singular value decomposition (SVD) algorithm and reduced the dimension of all time windows to their main features. We calculated a SVD over all frequency specific modes over all time windows per participant and extracted the singular vectors and singular values. The singular vectors represent the principal components and capture the most significant data patterns while the singular values capture the proportion of variance accounted for by this pattern. Higher singular values indicate that the associated dominant mode captures more variation among all DMD modes during task completion and can be considered representative of the stability or prominence of this pattern.

3.2.1.3 Uniform manifold matrix approximation and projection

While PCA was used to explain patterns of variation within a participant, we relied on UMAP to capture the structure both on a local level, i.e. within a participant, as well on a global level, i.e. between participants. UMAP constructs a low-dimensional representation by modeling the data as a topological manifold, considering both the distances between data points and the local density, and is particularly effective in visualizing and exploring complex data patterns and meaningful relationships in the data [68]. For this we first calculated the arithmetic mean over the DMD modes of all windows per frequency band, trial, and participant and then applied UMAP to obtain a lower-dimensional representation that captures underlying patterns and meaningful relationships in the data, facilitating visualization and exploration of DMD patterns.

3.2.1.4 Common spatial patterns

To extract the information from the DMD modes that would allow the best possible differentiation between the tasks we leveraged supervised dimensionality reduction (see subsubsection 1.4.1.1). This approach is based on filter based common spatial patterns (FBCSP) a widely used algorithm for the classification of continuous tasks that extracts a weighting for each EEG channel that maximizes the class discriminative energy for selected frequency bands [102]. By multiplying these weights with the channel values, meaningful features are generated. The weightings were calculated based on DMD magnitudes in each frequency band (see Research Article I [9] for details on the implementation).

3.2.1.5 xDAWN

To process the event-related EEG data we relied on the xDAWN algorithm [79]. Similar to CSP by applying the xDAWN algorithm it is possible to obtain a set of weights that emphasize the relevant EEG activity while suppressing noise and artifacts, leading to improved signal quality for further analysis or classification tasks. In this way, it is possible to induce activation patterns, i.e. neural responses to external stimuli at the level of individual trials. In contrast to the previous methods, we did not use DMD first but applied xDAWN to the preprocessed trials as originally described to ensure comparability to previous ERP analyses [90].

3.2.2 Classification

Classification was performed on a trial-by-trial basis, i.e. models were learned that can predict for each participant to which task a given trial belongs or cross-participant to which group the performing subject belongs. Typically, different classification algorithms and their parameters are selected, trained on one portion of the data, the so-called training data, and then tested for their performance on data not used for training, the so-called testing data [103]. The training data can further be divided into a training and validation portion in order to compare different model types or user defined settings of learning algorithms, so-called hyperparameters. Finally, the best model configuration is tested for its predictive performance on the test data and reported. However, this three time division may drastically reduce the data size usable for training and my result in flawed generalization evaluation due to the randomness of the split [104]. Therefore several procedures can be applied. In simple k-fold cross-validation, for example, the training data is divided k-times. Thus each time a different subset of the data is used for validation while the rest is used for training. Usually, this is repeated for a range of models and subsequent hyperparameters and the model and hyperparameter performing best on average are selected for final testing. We used a more advanced method denoted nested cross-validation, which adds a second cross-validation loop for the final model evaluation (see Figure 3.5 for a visual representation of the procedures).

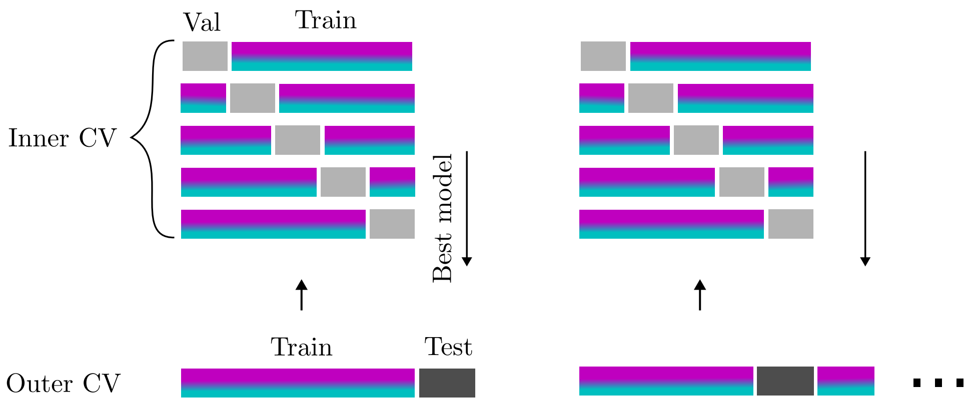

Figure 3.5: Nested cross-validation procedure. CV: cross-validation, Val: Validation

For all datasets, 10 splits were used in the inner and outer cross-validation loops, keeping 80% of the dataset for training and 20% for testing. In the inner loop, hyperparameters were tuned according to a grid search procedure in which a given parameter space is provided to comprehensively select the best fitting parameters [104]. Consequently, one model was tested for each of the 10 outer splits. The final metrics are the average over the outer splits and represent the performance of the classification algorithm. For classifiers, these can be derived using a so-called confusion matrix (Table 3.3), which summarizes all correct and false predicted instances of the test set [105].

Table 3.3: Confusion Matrix

		Predicted Class	
		Positive	Negative
Actual Class	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

If an actual value is positive and is classified as positive, it is a true positive (TP) result. If the positive instance is classified as negative, it is a false negative (FN) result. If an instance is actually negative and classified as negative, it is called true negative (TN). Consequently, if an instance is negative and classified as positive, it is a false positive (FP) [105]. This forms the basis for various metrics reported in the research articles. Table 3.4 summarizes the metrics and their meaning.

Table 3.4: Summary of Metrics

Metric	Formula	Description
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	Measures the overall correctness of the model's predictions.
Precision	$\frac{TP}{TP+FP}$	Measures the proportion of true positive predictions among all positive predictions.
Recall (Sensitivity)	$\frac{TP}{TP+FN}$	Measures the proportion of true positive predictions among all actual positive samples.
Specificity	$\frac{TN}{TN+FP}$	Measures the proportion of true negative predictions among all actual negative samples.
F1 Score	$\frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$	Harmonic mean of precision and recall, providing a balanced measure between the two.
AUC	-	Area under the receiver operating characteristic curve which measures the performance of a binary classification model across various threshold settings.

TP: true positive, TN: true negative, FP: false positive, FN: false negative, AUC: area under the receiver operating characteristic curve

In this study, we experimented with multiple algorithms based on recent literature to find the most suitable models for the respective tasks [106]. In doing so, we finally used support vector machine (SVM) and linear discriminant analysis (LDA), which both have a wide history of application to neuroscience data and are well suited to our specific problems. SVMs is one of the most commonly used algorithms for neuroscience data [104]. The algorithm generates optimal decision boundaries, called hyperplanes, and can thus handle both linearly separable and non-linearly separable data by using kernel functions to map the input space into a higher-dimensional feature space [106]. LDA is specifically used in the context of BCI and has proven to be successful in task decoding [78]. This algorithm aims to find a linear combination of features that maximizes the separation between different classes, making it particularly effective in situations where the classes are well-separated [106].

Chapter 4

Results

4.1 Paper 1

4.2 Paper 2

4.3 Paper 3

4.4 Paper 4

Chapter 5

General discussion

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Research article II

Research article III

Research article IV