

Integration of Foundation Models and Gaussian Processes for Supporting the Diagnosis and Treatment of Mental Disorders based on EEG Signals

An Stochastic Approach

Julián David Pastrana Cortés

Universidad Tecnológica de Pereira

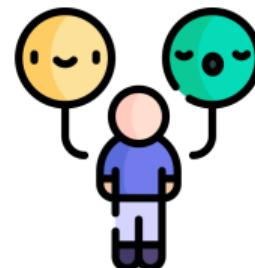
September 12, 2025

Motivation

Mental disorders affect cognition, behavior, and emotions of millions of people worldwide. Around 350 million individuals suffer from a mental disorder [Dehghan-Bonari et al., 2023].



**Oppositional Defiant
Disorder**



Bipolar Disorder



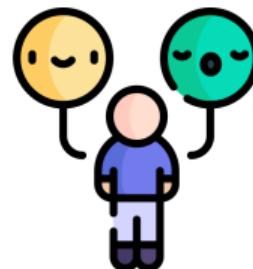
**Attention Deficit
Hyperactivity Disorder**

Motivation

Mental disorders affect cognition, behavior, and emotions of millions of people worldwide. Around 350 million individuals suffer from a mental disorder [Dehghan-Bonari et al., 2023].



**Oppositional Defiant
Disorder**



Bipolar Disorder



**Attention Deficit
Hyperactivity Disorder**

Challenges: lengthy follow-up, subjective interpretations, inefficient criteria, and limited access to clinical care.



Problem Statement and Research Question

Model \ Challenge	Complex Patterns	High Labeled Data Volume	Stochasticity	Data Shift
Model				
Machine Learning [Salari et al., 2023]	✗	✓	✓	✗
Deep Learning [Lohani and Rana, 2023]	✓	✗	✓	✓
Foundation [Sibley, 2021]	✓	✓	✗	✓

Problem Statement and Research Question

Model \ Challenge	Complex Patterns	High Labeled Data Volume	Stochasticity	Data Shift
Model				
Machine Learning [Salari et al., 2023]	✗	✓	✓	✗
Deep Learning [Lohani and Rana, 2023]	✓	✗	✓	✓
Foundation [Sibley, 2021]	✓	✓	✗	✓

Research Question How to develop a stochastic foundational model for inference from biological signals that integrates Gaussian processes to support clinical practice through EEG signal analysis, considering the variability and inconsistencies present in the datasets?

Objectives

General Objective Develop a stochastic learning methodology related to EEG recordings based on a foundational model that integrates labeled and unlabeled databases using self-learning and fine-tuning techniques.

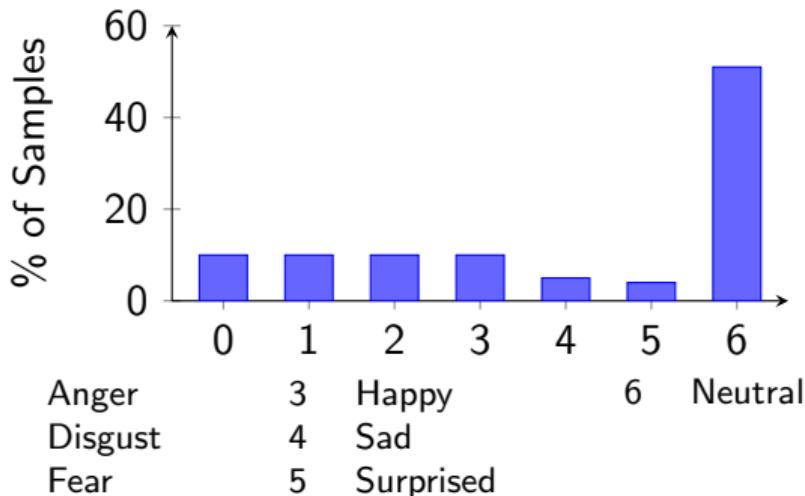
Specific Objectives

- 1 Develop a foundational model for the classification of biological signals related to EEG recordings, leveraging **unlabeled data** during the self-learning phase and labeled data for fine-tuning.
- 2 Implement a **stochastic prediction** tool based on Gaussian processes to model uncertainty in the foundational model's predictions.
- 3 Design a strategy to **manage variability and inconsistency** in EEG recording datasets, enabling the effective integration of databases with diverse standards.



Toadstool 2 Dataset

The dataset consists of video, sensor, and demographic data collected from 10 participants playing a Super Mario Bros.



Signal	Rate (Hz)	Channels
BVP	64	1
ACC	32	3
EDA	4	1
HR	1	1

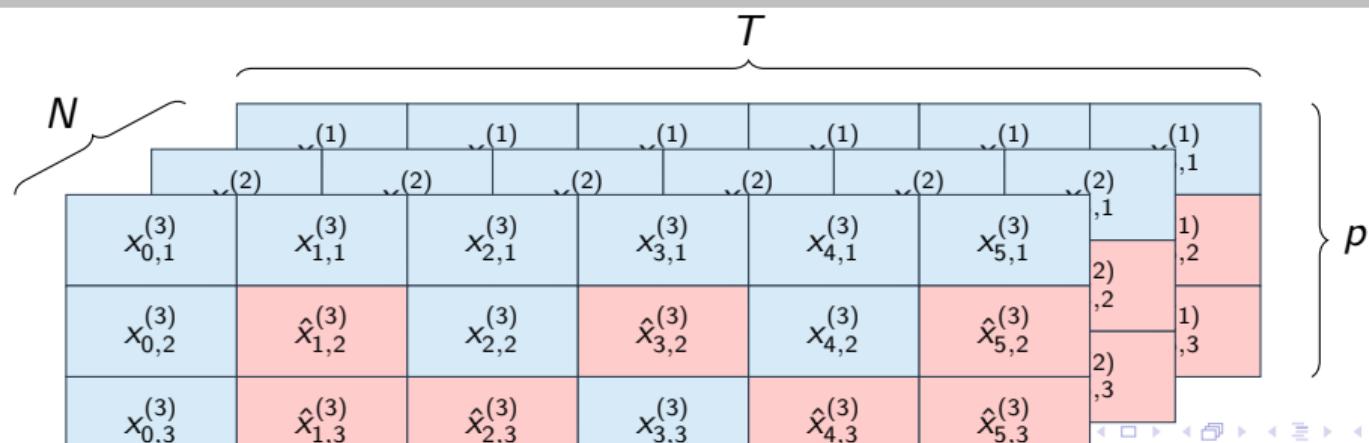
20.970 sensor-only samples (4 s windows)

Problem Setting

Let $\{(\mathbf{X}^{(i)}, y^{(i)})\}_{i=1}^N$ be the training dataset, where $\mathbf{X}^{(i)} \in \mathcal{X}$ and $y^{(i)} \in \{0, 1, \dots, 6\}$. Here \mathcal{X} is the space of vector sequences of length $T = 256$:

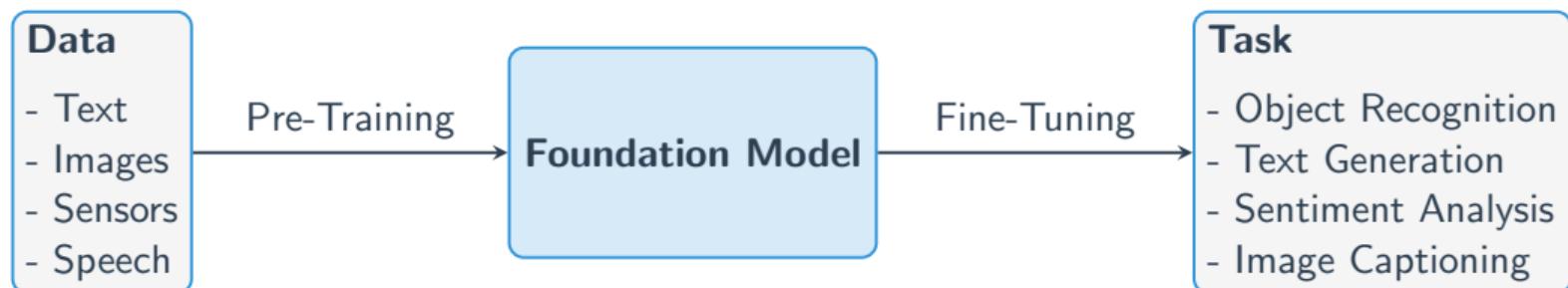
$$\mathbf{X}^{(i)} = [\mathbf{x}_1^{(i)}, \dots, \mathbf{x}_t^{(i)}, \dots, \mathbf{x}_T^{(i)}].$$

$\mathbf{x}_t^{(i)}$ has $p = 6$ elements by channels, denoted $x_{t,j}^{(i)} \in \mathbb{R}$ or be a missing value $\hat{x}_{t,j}^{(i)}$.



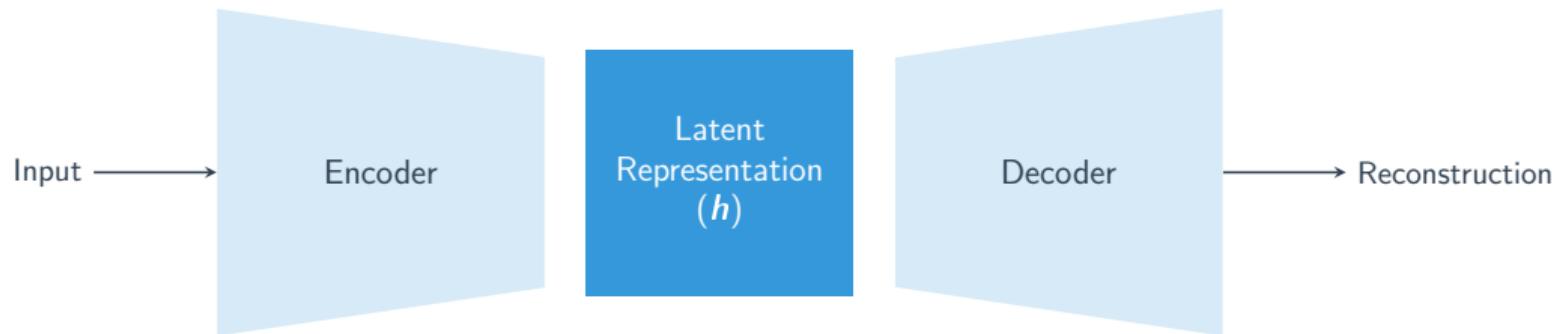
Objective 1: Foundation Model

We aim to train a general model using large amounts of data and tasks that can be fine-tuned easily in different downstream applications.

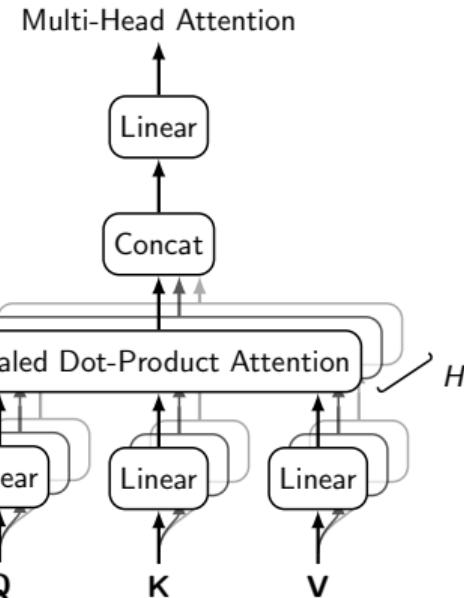
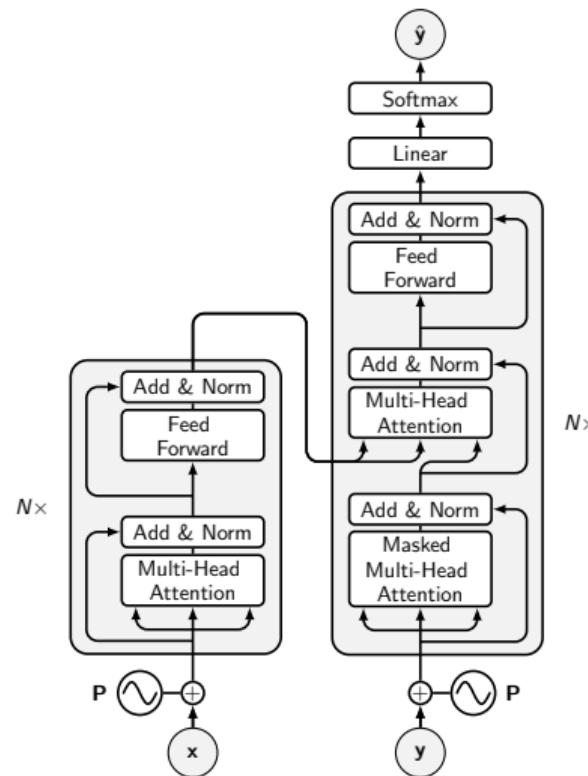


Architecture

We can leverage large amounts of unlabeled data to learn hidden-state representations without committing to any specific downstream task.

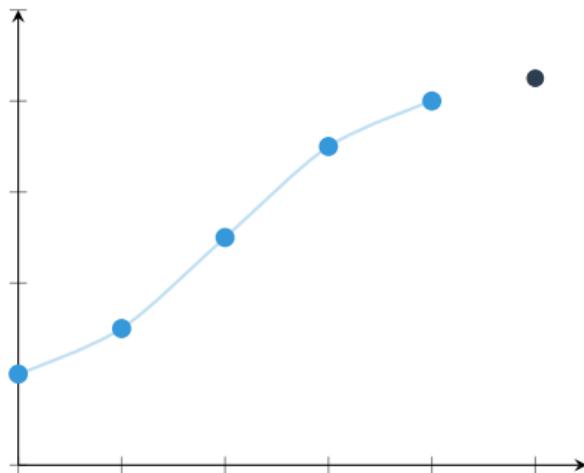


Transformer and Attention Mechanism

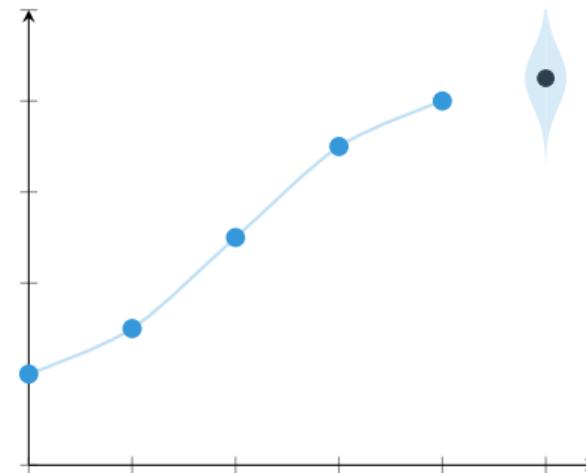


Objetive 2: Gaussian Process

Point Estimation

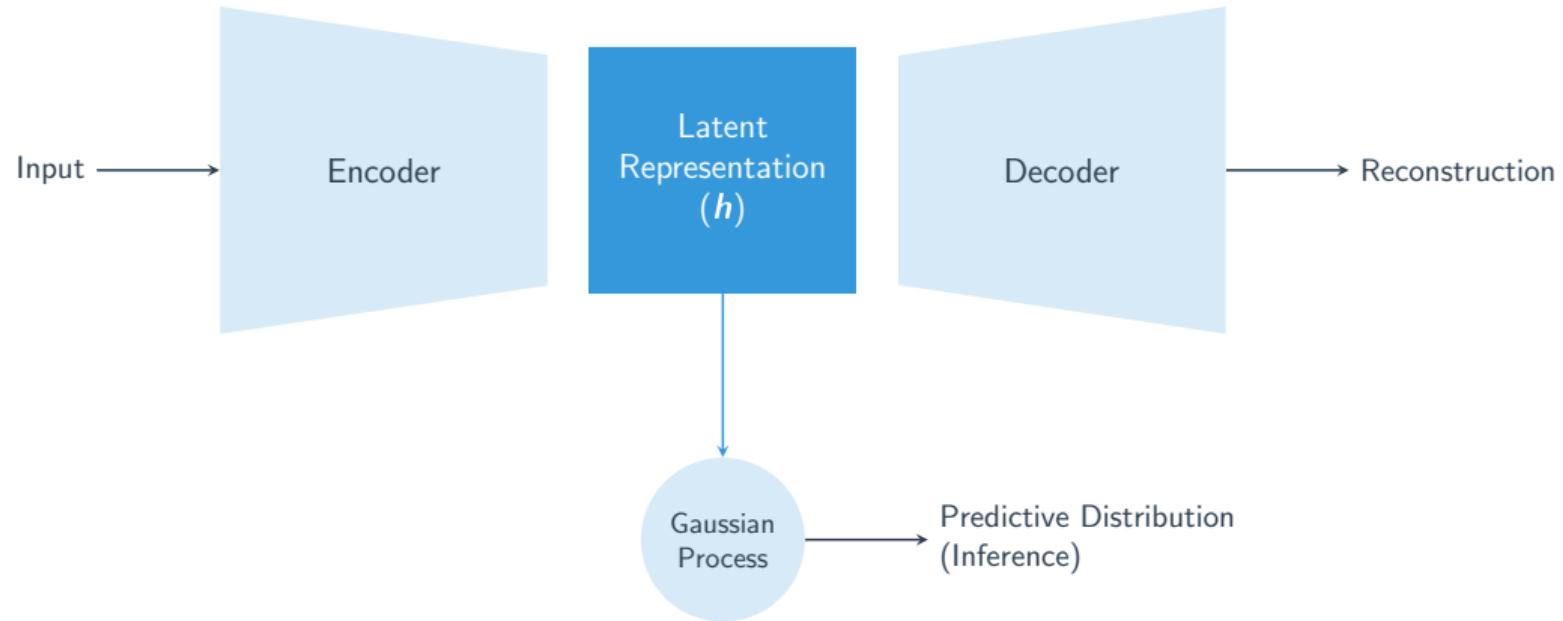


Distribution Estimation

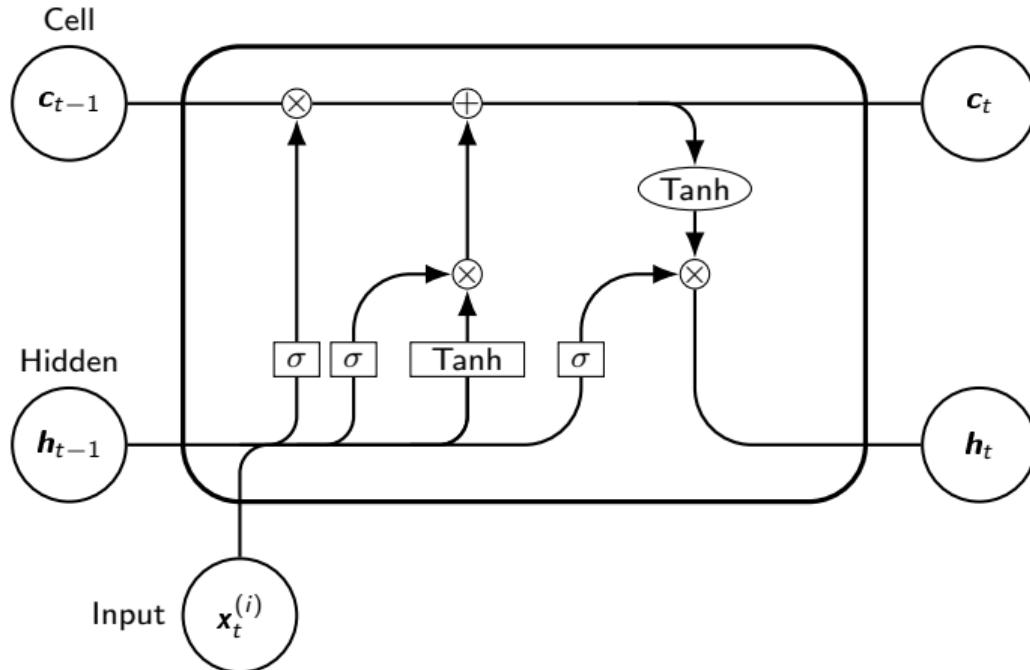


Sometimes, a single point prediction is not enough. How confident is the model in its prediction?

Architecture



Objective 3: Long Short-Term Memory (LSTM) Architecture



$$\begin{aligned} i_t &= \sigma(W_{ii}x_t^{(i)} + W_{hi}h_{t-1} + b_i), \\ f_t &= \sigma(W_{if}x_t^{(i)} + W_{hf}h_{t-1} + b_f), \\ g_t &= \tanh(W_{ig}x_t^{(i)} + W_{hg}h_{t-1} + b_g), \\ o_t &= \sigma(W_{io}x_t^{(i)} + W_{ho}h_{t-1} + b_o), \\ C_t &= f_t \odot C_{t-1} + i_t \odot g_t, \\ h_t &= o_t \odot \tanh(C_t). \end{aligned}$$

○ is the Hadamard product, and σ the sigmoid function.

Missing-Value Imputation

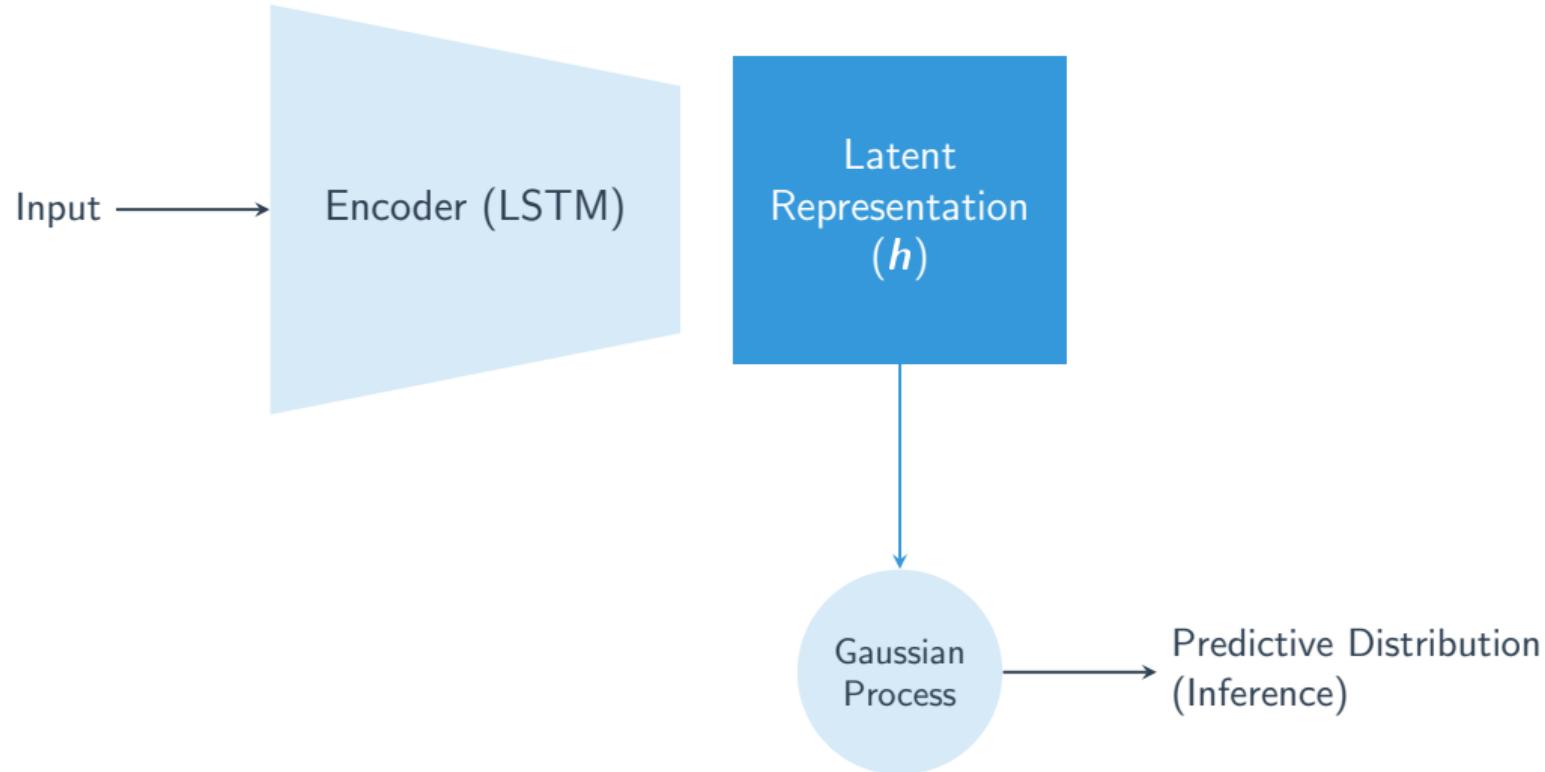
At each time step t , missing channel entries in $\mathbf{x}_t^{(i)}$ can be imputed sequentially from the hidden state via an affine map:

$$\hat{x}_{t,j}^{(i)} = \mathbf{w}_j^T \mathbf{h}_t + b_j, \quad j = 1, \dots, p.$$

$$\begin{aligned}\{\mathbf{W}_{ii}, \mathbf{W}_{if}, \mathbf{W}_{ig}, \mathbf{W}_{io}\} &\in \mathbb{R}^{H \times p}, \\ \{\mathbf{W}_{hi}, \mathbf{W}_{hf}, \mathbf{W}_{hg}, \mathbf{W}_{ho}\} &\in \mathbb{R}^{H \times H}, \\ \{\mathbf{b}_i, \mathbf{b}_f, \mathbf{b}_g, \mathbf{b}_o\} &\in \mathbb{R}^H, \\ \mathbf{w}_j &\in \mathbb{R}^H, \\ b_j &\in \mathbb{R}, \\ \mathbf{h}_t, \mathbf{C}_t &\in \mathbb{R}^H.\end{aligned}$$

Here H denotes the dimensionality of the hidden state.

Architecture



-  Dehghan-Bonari, M., Alipour-Vaezi, M., Nasiri, M. M., and Aghsami, A. (2023). A diagnostic analytics model for managing post-disaster symptoms of depression and anxiety among students using a novel data-driven optimization approach.
Healthcare Analytics, 4.
-  Lohani, D. C. and Rana, B. (2023). Adhd diagnosis using structural brain mri and personal characteristic data with machine learning framework.
Psychiatry Research: Neuroimaging, 334:111689.
-  Salari, N., Ghasemi, H., Abdoli, N., Rahmani, A., Shiri, M. H., Hashemian, A. H., Akbari, H., and Mohammadi, M. (2023). The global prevalence of adhd in children and adolescents: a systematic review and meta-analysis.
Italian Journal of Pediatrics, 49(1):48.
-  Sibley, M. H. (2021). Empirically-informed guidelines for first-time adult adhd diagnosis.

Journal of Clinical and Experimental Neuropsychology, 43(4):340–351.
PMID: 33949916.