

# DETECTION OF TRAUMATIC BRAIN INJURY USING SINGLE CHANNEL ELECTROENCEPHALOGRAPH IN MICE

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## Traumatic Brain Injury (TBI) Facts

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- > **US Centers for Disease Control and Prevention (CDC) definition:**
  - A disruption in the normal function of the brain that can be caused by a bump, blow, or jolt to the head, or penetrating head injury.
- > **In 2014, 155 people/day die from TBI-related injuries**
- > **Leading causes: falls, struck by/against an object, motor vehicle crashes, intentional self-harm**
- > **Severity: mild (concussions), moderate, severe**
- > **Affects thinking/memory, movement, sensation, emotion**
- > **Major sequelae is persistent sleep-wake dysfunction**

<https://www.cdc.gov/traumaticbraininjury/>

## Mild TBI (mTBI) Mouse Model

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- > **Well-established method to study TBI**
- > **mTBI is introduced by fluid percussion injury (FPI)**
  - High reliability and reproducibility
  - Can be graded in severity
  - Recapitulates human mTBI features
- > **Sleep-wake behavior is studied**
  - quantitative EEG (qEEG) to analyze brain wave patterns
  - Increasing investigation of machine-learning (ML) models for detection of mTBI

## Recent Work on mTBI Detection on Mice EEG

- > [1] examined detection of mTBI from EEG with duration 1 – 4 minutes
- > Used hand-crafted qEEG features:
  - decibel normalized power for different frequency sub-bands
  - ratio of alpha sub-band power to theta subband power
- > ML models: decision tree (DT), k-nearest neighbor (kNN), neural network with 2 hidden layers, random forest (RF), support vector machine (SVM), and convolutional neural network (CNN)
- > Up to 92% accuracy (using CNN)

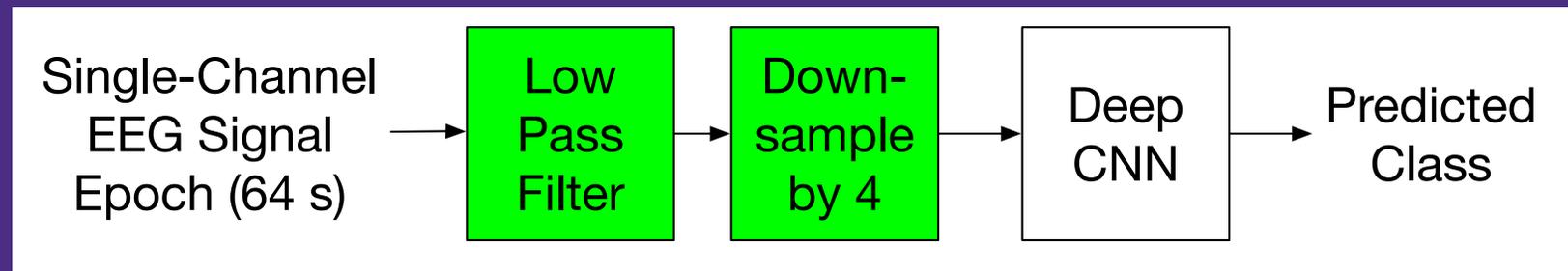
[1] M. Vishwanath *et al.*, "Classification of Electroencephalogram in a Mouse Model of Traumatic Brain Injury Using Machine Learning Approaches," in *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, Montreal, QC, Canada, Jul. 2020, pp. 3335–3338, doi: 10.1109/EMBC44109.2020.9175915.

## mTBI Detection System in This Work

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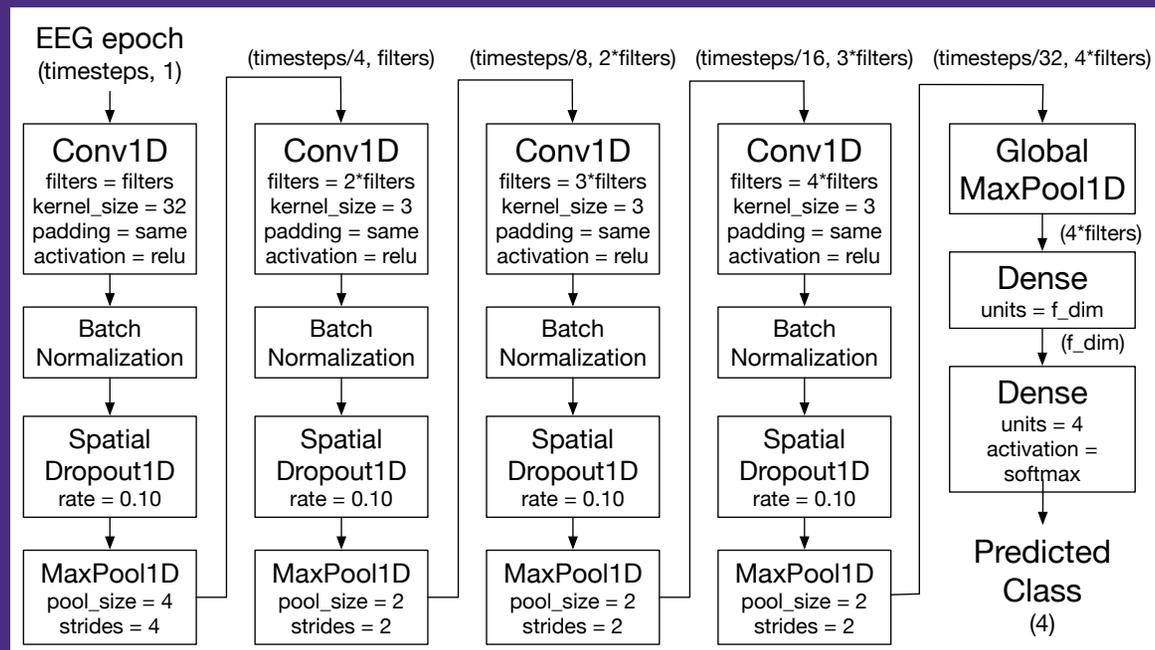
- > **CNN-based deep learning system for processing single-channel mice EEG**
  - learn features from data
  - detect mTBI
  - stage sleep (sleep or wake)
  - deployable on a Raspberry Pi 4
- > **Benefits:**
  - Real-time analysis
  - Inexpensive and portable hardware

## System Architecture



- > **Supervised learning**
- > **EEG epoch duration of 64 s with sampling frequency of 256 Hz**
  - sufficient length for accurate classification and deployment on Raspberry Pi
- > **Predicted class: one out of {Sham (control) Wake, Sham Sleep, mTBI Wake, mTBI Sleep}**

# Deep CNN



Based on neural network in <https://github.com/oscarknagg/voicemap>

## Data Source

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- > **Data acquisition described in [2]**
- > **24-hour EEG records from 11 mice: 6 sham mice and 5 mTBI mice**
  - **mTBI: surgery to implant probes and introduce FPI**
  - **sham: surgery to implant probes**
  - **Stored in European Data Format (EDF) file**
- > **Sampling frequency = 256 Hz -> 22,118,400 timesteps per mouse**
- > **Sleep stages are scored human experts per 4-second epoch**
- > **Break 24-hour recordings into 64-s non-overlapping epochs**

[2] M. M. Lim *et al.*, "Dietary Therapy Mitigates Persistent Wake Deficits Caused by Mild Traumatic Brain Injury," *Sci. Transl. Med.*, vol. 5, no. 215, pp. 215ra173-215ra173, Dec. 2013, doi: 10.1126/scitranslmed.3007092.

# Training Data Arrangement Schemes

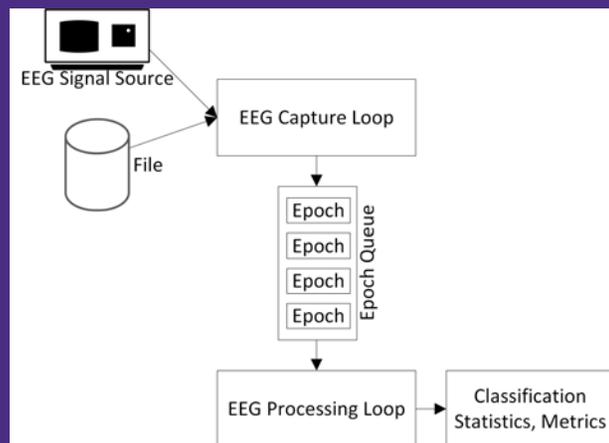
Scheme	Evaluation Goal	Assumptions	Training Set	Testing Set
Random Sampling (RS)	Pattern Learning	<ul style="list-style-type: none"> <li>Mice are identical</li> <li>EEG epochs are independent</li> </ul>	80% of epochs	20% of epochs
Species Aware (SA)	Generality	<ul style="list-style-type: none"> <li>Mice are not identical</li> </ul>	8 mice (4 mTBI and 4 sham)	2 mice (1 mTBI and 1 sham)

## System Evaluation

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- > **accuracy** =  $\frac{TP+TN}{TP+TN+FP+FN}$
- > **precision** =  $\frac{TP}{TP+FP}$
- > **recall** =  $\frac{TP}{TP+FN}$
- > **F1** =  $2 \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$

# System Deployment



```

#####
Iteration: 942
Current Prediction: {0: 10}
Overall Count: {0: 4458, 1: 4745, 2: 139, 3: 78}
Completed in 0.9131
Average completion time: 0.8995

Labels distribution
#####
|-----| 4458 Sham W
|-----| 4745 Sham NR & R
|-----| 139 TBI W
|-----| 78 TBI NR & R
  
```

- > Trained model in Hierarchical Data Format version 5 (HDF5) file is loaded to Raspberry Pi
- > Processing time per 64-s epoch << Epoch capture time

# Performance Metrics

<b>filters</b>	<b>32</b>	<b>32</b>	<b>32</b>	<b>64</b>	<b>64</b>	<b>64</b>	<b>128</b>	<b>128</b>	<b>128</b>
<b>f_dim</b>	<b>4</b>	<b>8</b>	<b>16</b>	<b>4</b>	<b>8</b>	<b>16</b>	<b>4</b>	<b>8</b>	<b>16</b>
<b>Random Sampling (RS) Data Arrangement</b>									
<b>Accuracy</b>	<b>0.821</b>	<b>0.808</b>	<b>0.811</b>	<b>0.821</b>	<b>0.826</b>	<b>0.825</b>	<b>0.815</b>	<b>0.823</b>	<b>0.821</b>
<b>Average F1</b>	<b>0.801</b>	<b>0.790</b>	<b>0.794</b>	<b>0.804</b>	<b>0.810</b>	<b>0.810</b>	<b>0.799</b>	<b>0.810</b>	<b>0.806</b>
<b>Species Aware (SA) Data Arrangement</b>									
<b>Accuracy</b>	<b>0.534</b>	<b>0.504</b>	<b>0.525</b>	<b>0.537</b>	<b>0.476</b>	<b>0.542</b>	<b>0.557</b>	<b>0.492</b>	<b>0.571</b>
<b>Average F1</b>	<b>0.411</b>	<b>0.371</b>	<b>0.395</b>	<b>0.424</b>	<b>0.376</b>	<b>0.413</b>	<b>0.425</b>	<b>0.361</b>	<b>0.380</b>

# Comparison with Previous Work

Item	Ref. [2]			This Work					
Arrangement	SA	SA	SA	SA	SA	SA	RS	RS	RS
Total mice	9	9	9	10	10	10	11	11	11
Train epochs	Sleep	Wake	All	All	All	All	All	All	All
Test epochs	Sleep	Wake	All	Sleep	Wake	All	Sleep	Wake	All
Network	CNN			CNN					
First layer	Feature extraction (extracting sub-band average powers)			Conv1D					
Accuracy (Sham/mTBI)	0.780	0.854	0.920	0.568	0.684	0.634	0.830	0.902	0.869

[2] M. Vishwanath *et al.*, "Classification of Electroencephalogram in a Mouse Model of Traumatic Brain Injury Using Machine Learning Approaches," in *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, Montreal, QC, Canada, Jul. 2020, pp. 3335–3338, doi: 10.1109/EMBC44109.2020.9175915.

## Conclusions

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- > **We demonstrated a deep CNN system to detect mTBI and classify sleep/wake stage from single-channel mice EEG epochs**
- > **System was deployed on a Raspberry Pi 4 showing same prediction metrics as a general computer**
- > **Deep CNN showed ability to learn necessary features, but generality of learnt features was not good (likely due to low number of mice in the dataset)**
- > **The system has potential to provide low-cost, real-time detection of mTBI and scoring of sleep/wake stage**

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**Thank You**