A Novel Capsule Neural Network Based Model For Drowsiness Detection Using Electroencephalography Signals

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DROWSINESS

- State of consciousness with oscillations between sleep and wakefulness, and an irresistible desire to sleep.

- Low in the cognitive and psychomotor performance of the subject.

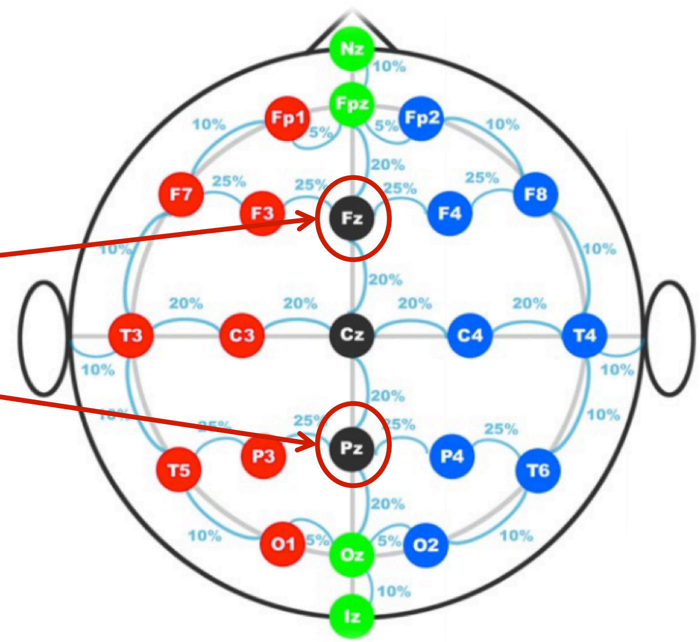
Source: http://www.achs.cl/portal/Comunidad/Paginas/Campana-Fatiga.aspx

ELECTROENCEPHALOGRAPHY

- Record bioelectric activity generated by the cortical neurons.

- International 10/20 system.

- Brain waves:
  - Delta [0.5 – 4 Hz]
  - **Theta [4 – 8Hz]**
  - **Alpha [8 – 13Hz]**
  - Beta [13 – 20Hz]



International 10/20 system.

Source: T. C. Technologies, Cortical Functions, Hong Kong, 2012.

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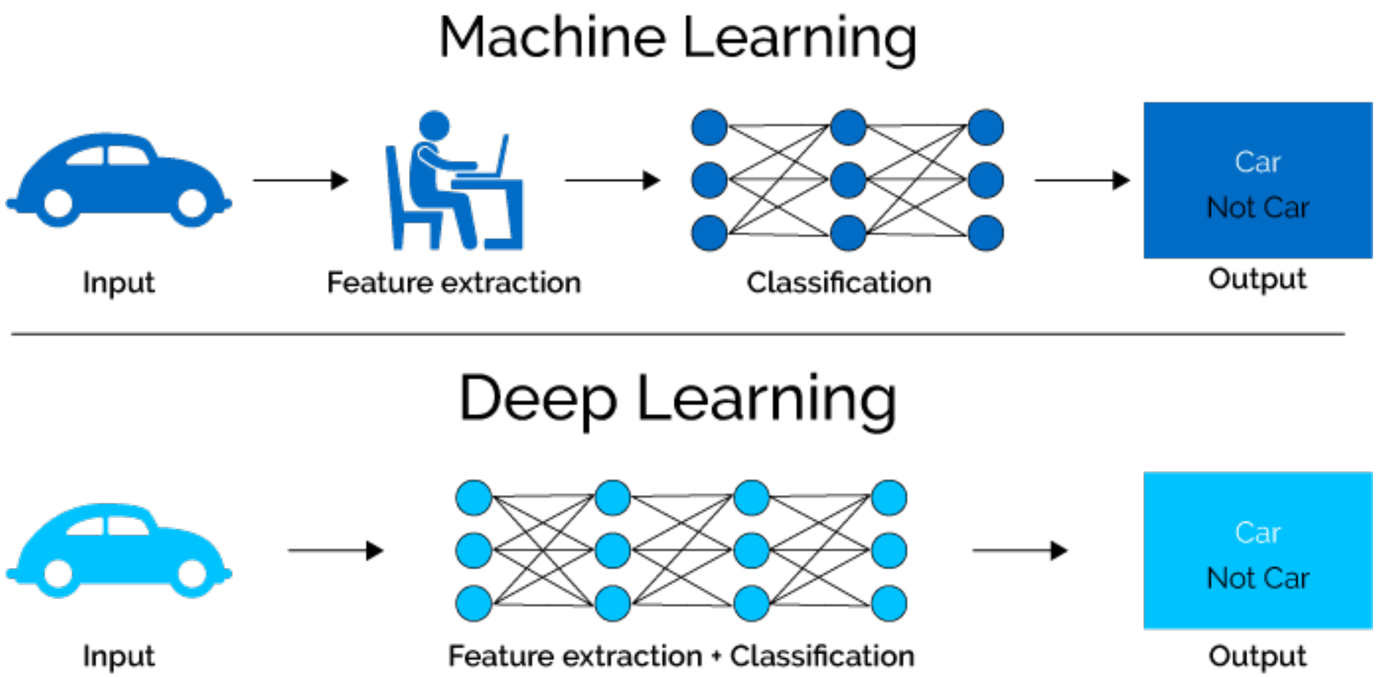
KAROLINSKA SLEEPINESS SCALE (KSS)

- Subjective level of sleepiness perceived by the individual.
- Significant KSS-EEG relationship.

Table 1: Karolinska Sleepniness Scale.

Rating	Verbal descriptions
1.	Extremely alert
2.	Very alert
3.	Alert
4.	Fairly alert
5.	Neither alert nor sleepy
6.	Some signs of sleepiness
7.	Sleepy, but no effort to keep alert
8.	Sleepy, some effort to keep alert
9.	Very sleepy, great effort to keep alert, fighting sleep

WHY DEEP LEARNING?



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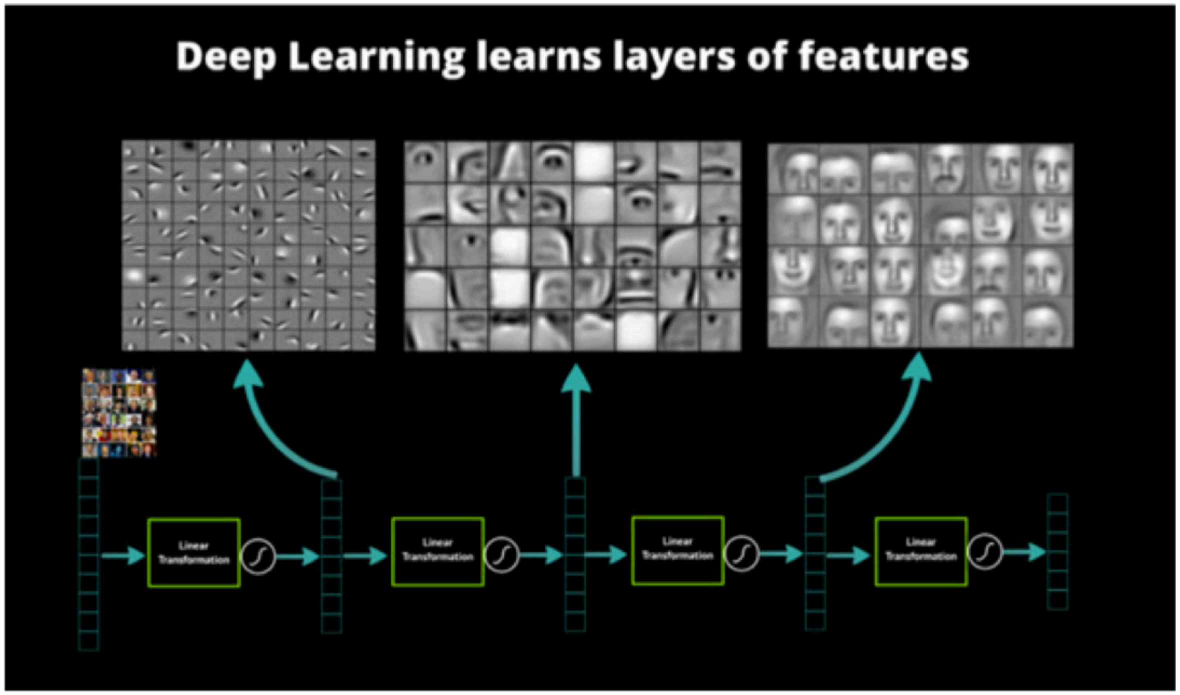
WHY DEEP LEARNING?

Deep Learning ≈ Representation Learning



Deep Learning Provides Automatic Feature Engineering

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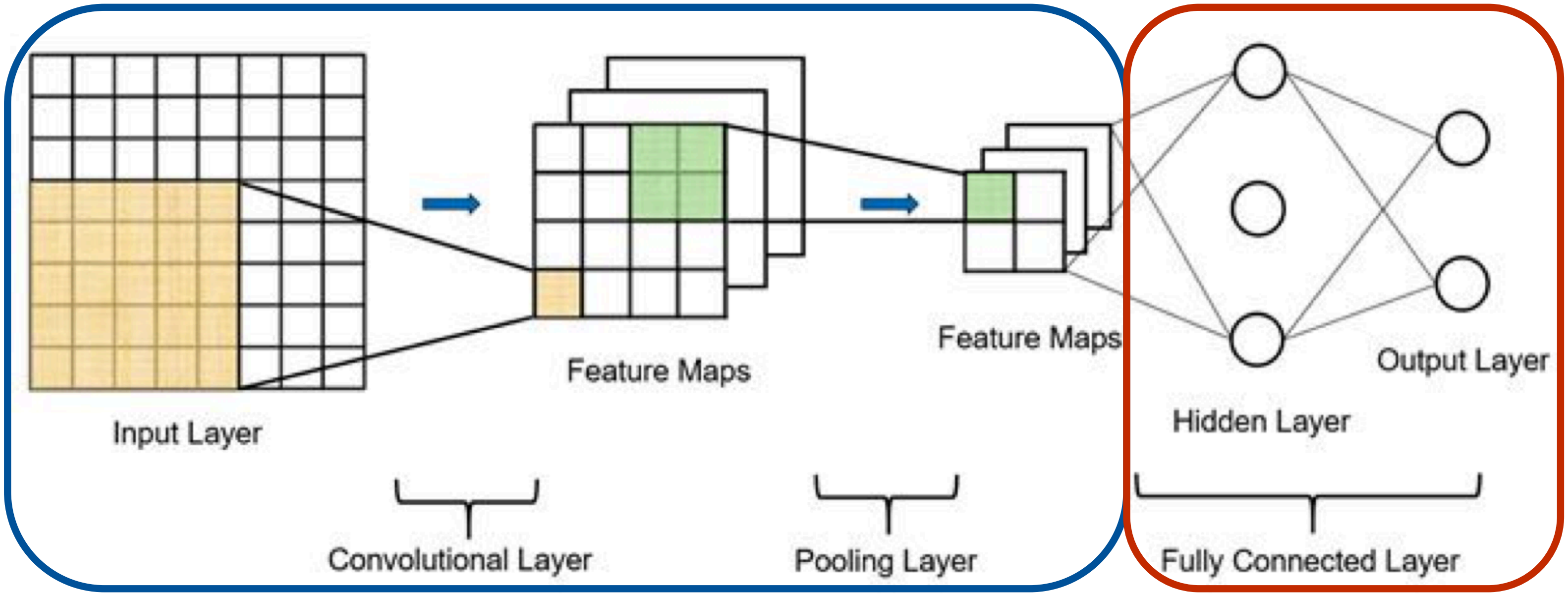
CONVOLUTIONAL NEURAL NETWORKS

Architecture:

- Convolutional layer
- Pooling layer
- Fully connected layer

Advantage/Disadvantage:

✓ Fewer parameters



Automatic Feature Extraction **Diagnosis**

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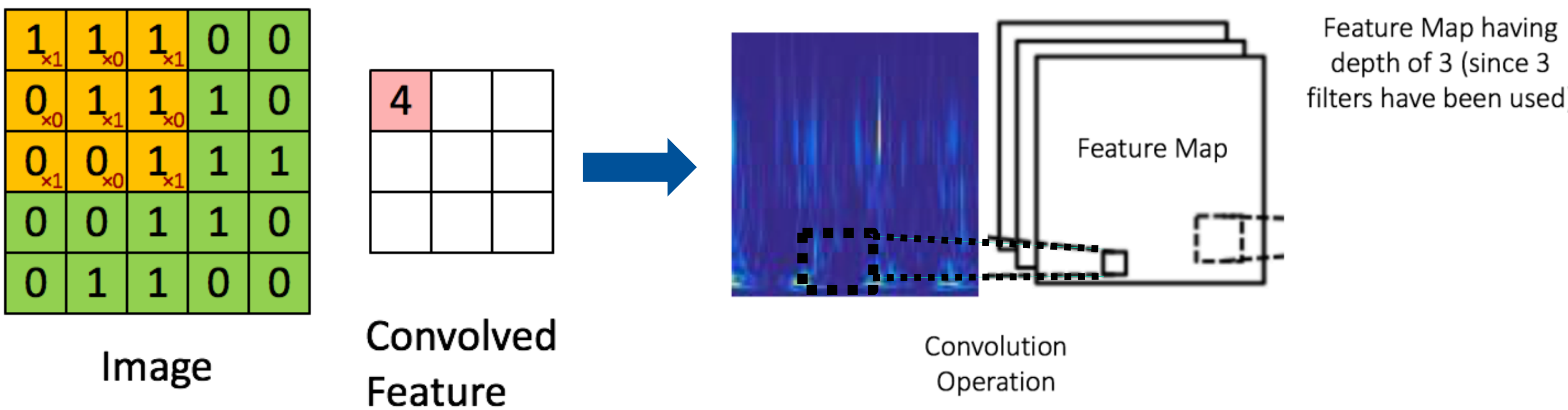
CONVOLUTIONAL LAYERS

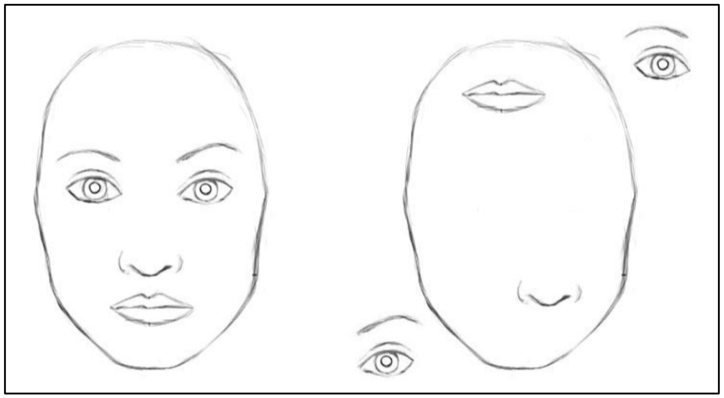


CONVOLUTIONAL LAYERS

- Different values of the kernel matrix will produce different feature maps for the same input image:

WHAT IS WRONG WITH CNN?

- CNN needs a massive dataset
- Translation invariance (viewpoint)
- Pooling layer → loss of information → spatial relation problem



Spatial relation example.

Translation invariance example.

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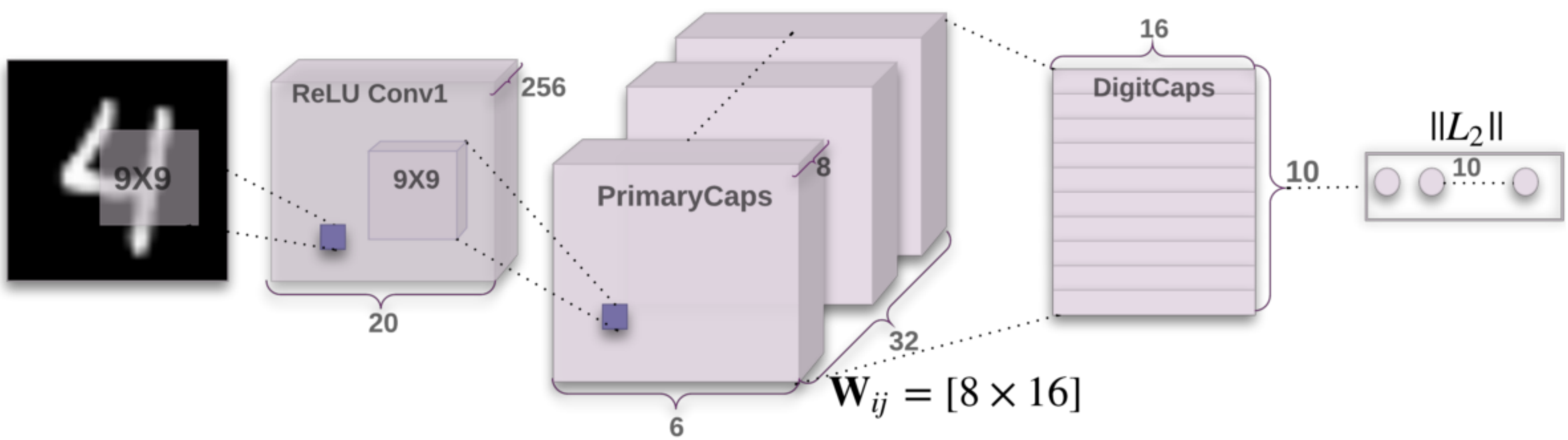
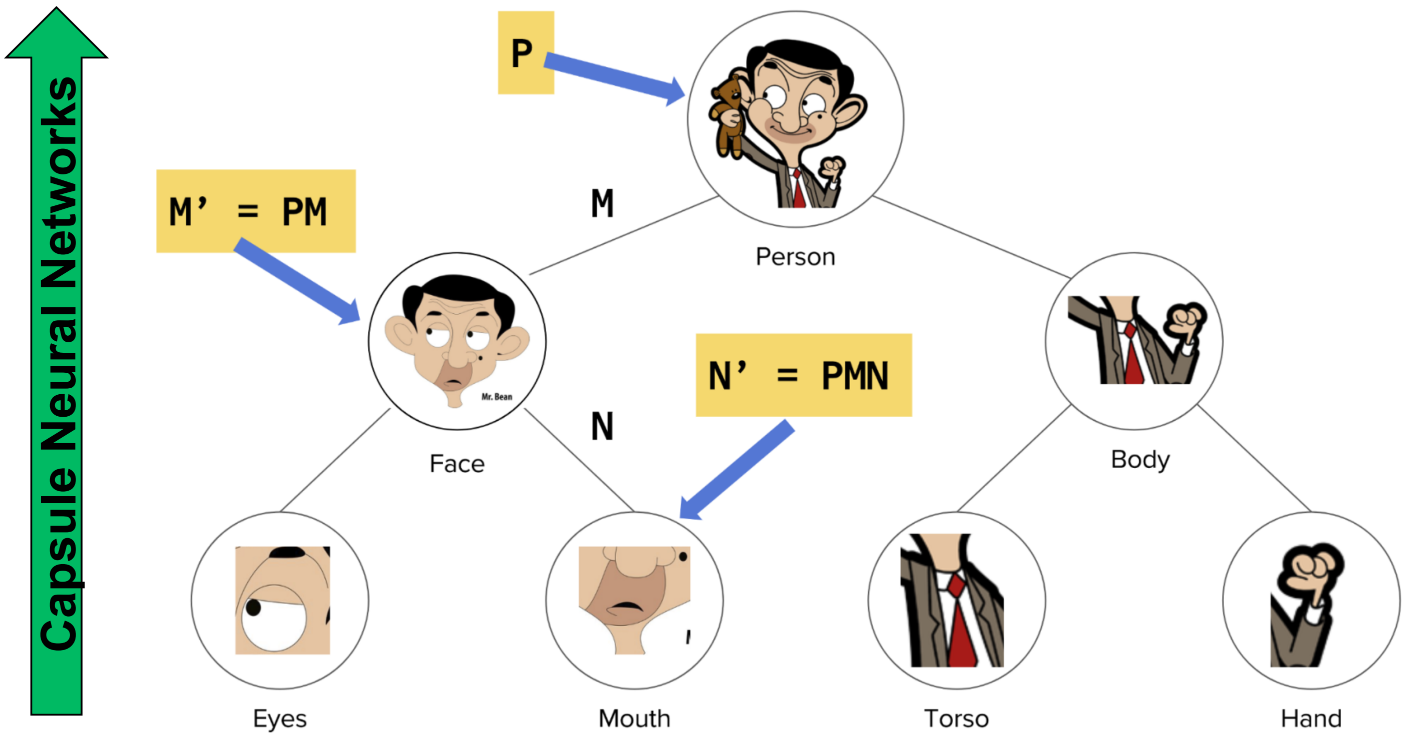
CAPSULE NEURAL NETWORK

- Capsules are group of neurons represented as a vector, where each neuron represents a feature from object
- Capsules are organized in layers with different levels of hierarchy
- Through *Dynamic Routing* each capsule in a layer makes a prediction about the output of the capsules in the next layer



Source: S. Sabour, N. Frosst, and G. E. Hinton, “Dynamic Routing Between Capsules”, 2018

CAPSULE NEURAL NETWORK



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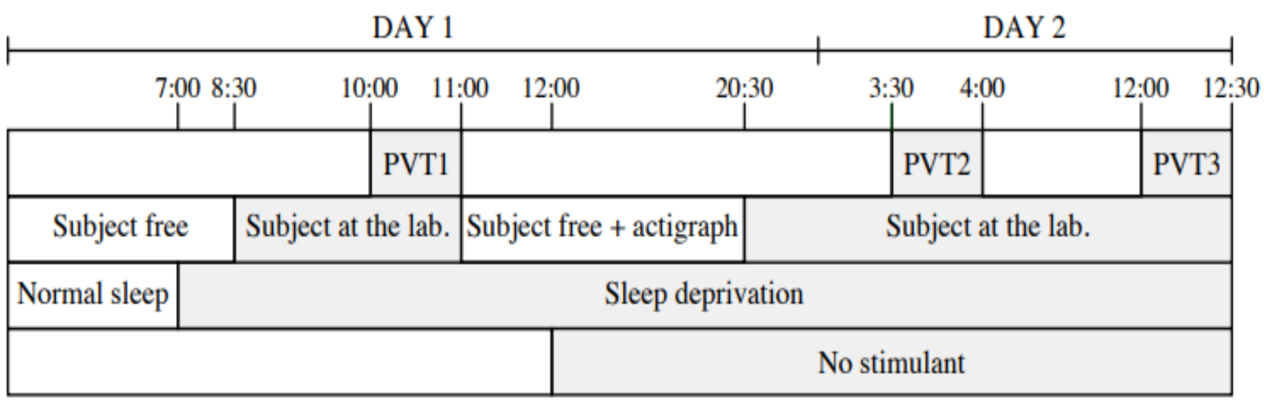
CNN *vs* CapsNet

- Differences between CNN and CapsNet:

Capsule vs. Traditional Neuron			
Input from low-level capsule/neuron		vector($\mathbf{u}_i$)	scalar(x_i)
Operation	Affine Transform	$\hat{\mathbf{u}}_{j\|i} = \mathbf{W}_{ij}\mathbf{u}_i$	$-$
	Weighting	$\mathbf{s}_j = \sum_i c_{ij}\hat{\mathbf{u}}_{j\|i}$	$a_j = \sum_i w_i x_i + b$
	Sum		
	Nonlinear Activation	$\mathbf{v}_j = \frac{\|\mathbf{s}_j\|^2}{1+\|\mathbf{s}_j\|^2}\frac{\mathbf{s}_j}{\|\mathbf{s}_j\|}$	$h_j = f(a_j)$
Output		vector($\mathbf{v}_j$)	scalar(h_j)

EXPERIMENT

- 14 young, healthy subjects (11 females, 3 males)
- Three successive 10 minutes psychomotor vigilance tests (PVT's)
- Sleep deprivation induced by prolonged wakefulness



Pictorial summary of data collection schedule.

Source: Q. Massoz, T. Langohr, . C. Francois y J. G. Verly, "The ULg Multimodality Drowsiness Database (called DROZY) and Examples of Use", 2016.

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DATABASE

KSS Scores

Stimulus times and corresponding reaction times

Kinect v2 sensor images

Kinect v2 sensor videos

Face landmarks (obtained manually)

Face landmarks (obtained automatically)

Polysomnography signals (5 EEG channels)

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METHODOLOGY

Selection of EEG channels
(*Fz* y *Pz*)

METHODOLOGY

Selection of EEG channels (*Fz y Pz)* → Generation of labels using KSS

Karolinska Sleepiness Scale.

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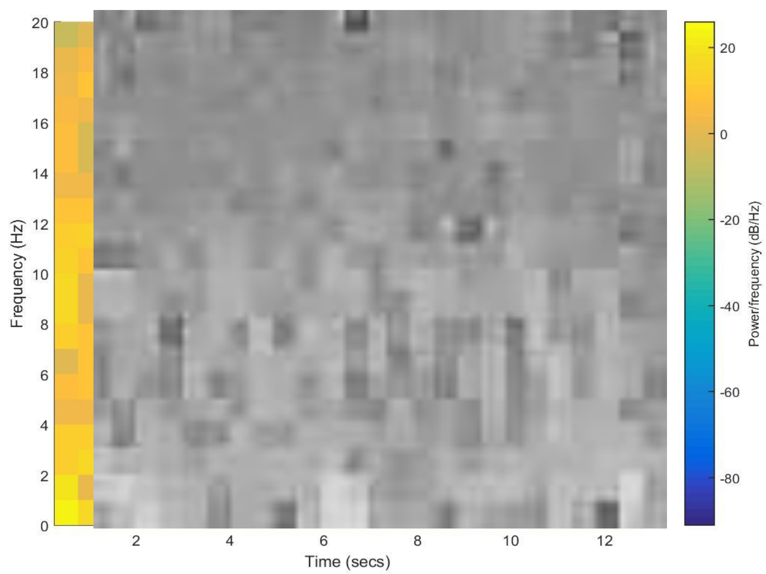
METHODOLOGY

Selection of EEG channels (*Fz* y *Pz*) → Generation of labels using KSS → Data segmentation into sequences of thirteen seconds

METHODOLOGY

Selection of EEG channels *(Fz y Pz)* → Generation of labels using KSS → Data segmentation into sequences of thirteen seconds → Generation of spectrograms



- Window: 512 samples
- 50% overlap
- Frequencies 0-20 Hz
- 32x32 pixels

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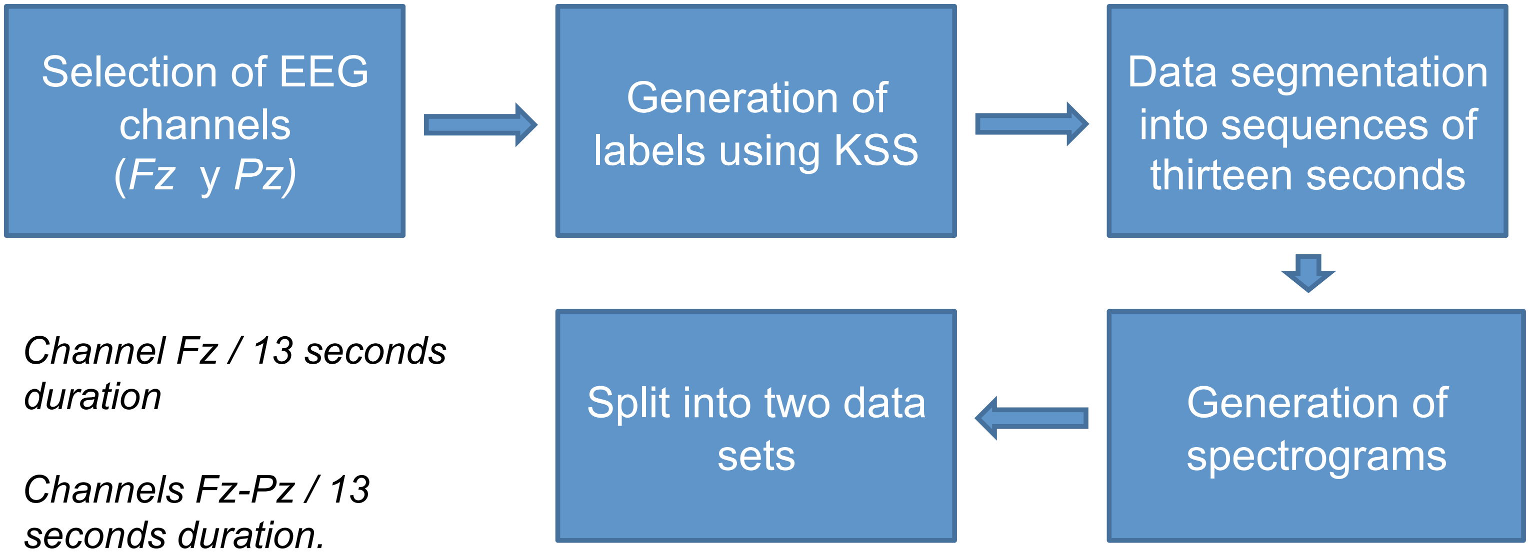
METHODOLOGY



- *Channel Fz / 13 seconds duration*
- *Channels Fz-Pz / 13 seconds duration.*

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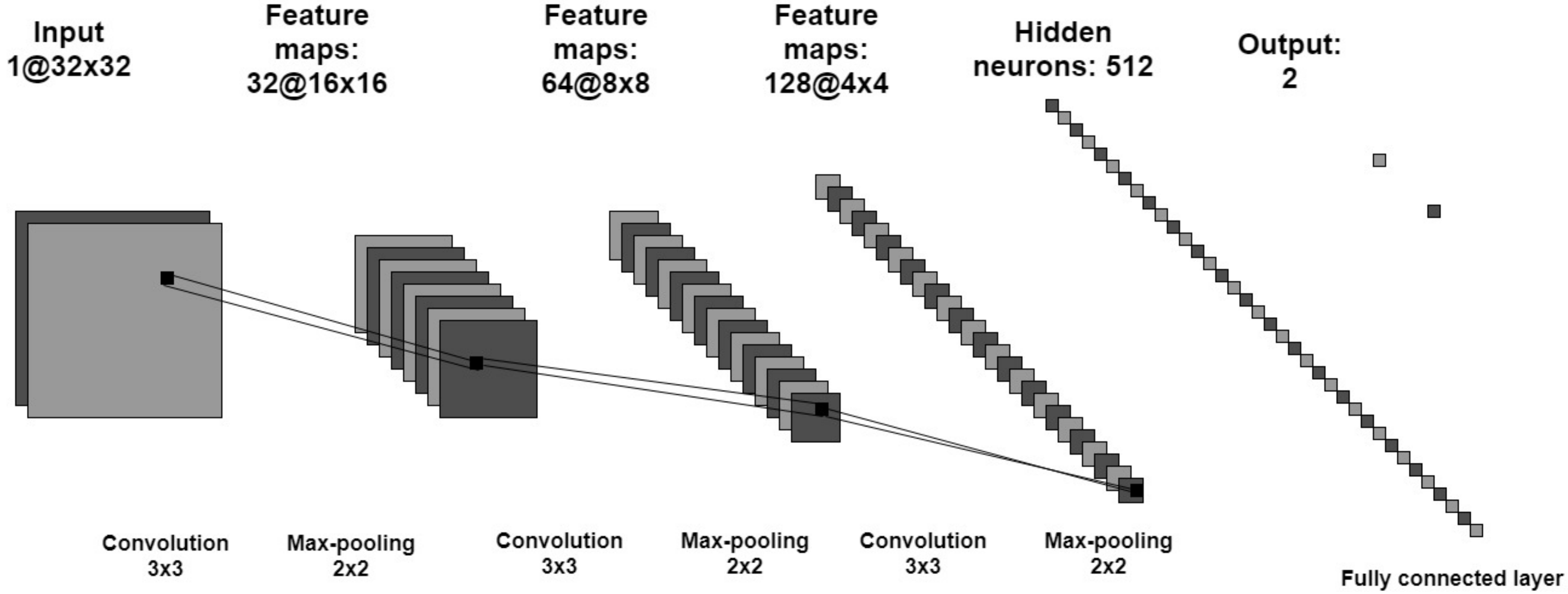
METHODOLOGY

1. Selection of EEG channels (*Fz y Pz)*
2. Generation of labels using KSS
3. Data segmentation into sequences of thirteen seconds
4. Generation of spectrograms
5. Split into two data sets
6. Models development (CNN and CapsNet)

PROPOSED CNN MODEL



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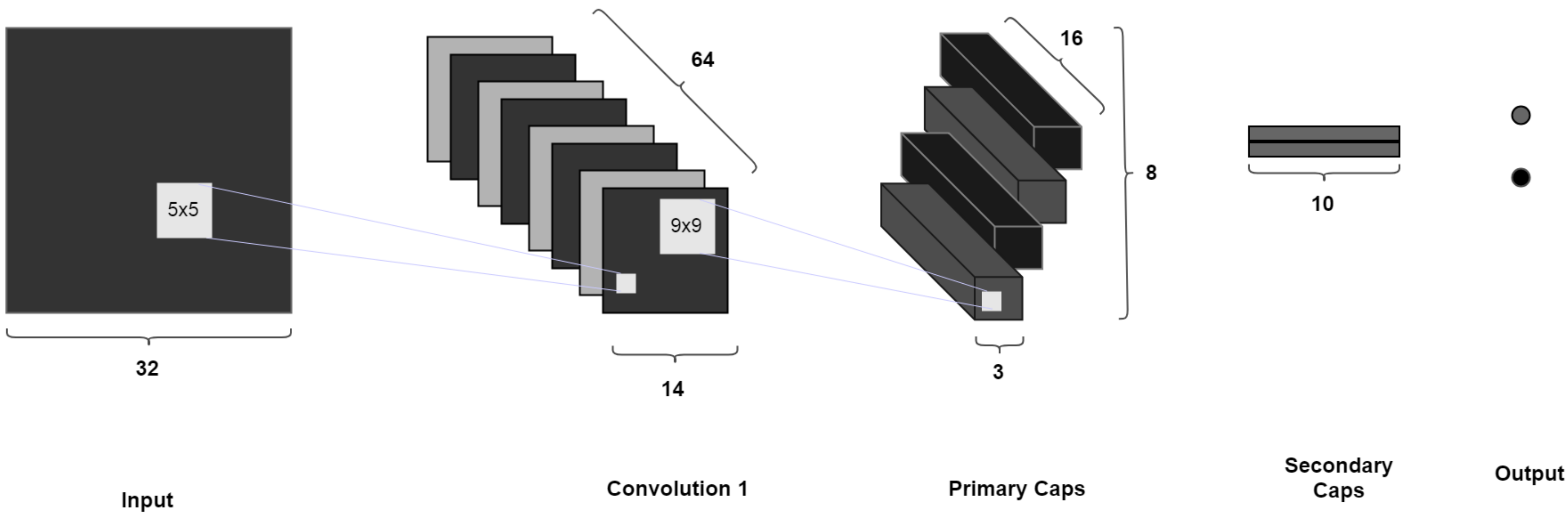
PROPOSED CAPSNET MODEL



METHODOLOGY

1. Selection of EEG channels (*Fz y Pz)*
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6. Models development (CNN and CapsNet)
7. Models validation and comparison with Neural Network (NN), Support Vector Machines (SVM) and Random Forest (RF)

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RESULTS

Performance metrics for CNN and CapsNet.

Dataset	Model	Accuracy	F1 Score	Sensitivity
Fz	CNN	79,46% ± 4,60%	79,55% ± 4,36%	80,80% ± 3,95%
	CapsNet	84,45% ± 0,62%	83,76% ± 0,65%	85,81% ± 0,97%
Fz-Pz	CNN	75,86% ± 2,39%	76,93% ± 3,24%	79,47% ± 5,54%
	CapsNet	86,74% ± 1,57%	85,97% ± 1,53%	87,57% ± 4,67%

Dataset	Model	Specificity	Precision
Fz	CNN	78,07% ± 5,41%	78,30% ± 4,96%
	CapsNet	83,26% ± 0,91%	81,81% ± 0,81%
Fz-Pz	CNN	71,98 % ± 2,82%	74,67 % ± 2,68%
	CapsNet	86,53% ± 4,29%	85,20% ± 3,52%

RESULTS

Performance metrics for SVM, RF and NN.

Dataset	Model	Accuracy	F1 Score	Sensitivity
Fz	SVM	67,28% ± 3,06%	66,13% ± 3,65%	63,85% ± 4,13%
	RF	73,58% ± 3,39%	72,00% ± 3,66%	68,12% ± 6,42%
	NN	69,56% ± 2,46%	68,11% ± 4,11%	65,62% ± 7,73%
Fz-Pz	SVM	71,30% ± 3,67%	72,59% ± 1,83%	72,16% ± 3,46%
	RF	72,50% ± 4,90%	71,00% ± 5,63%	68,28% ± 7,58%
	NN	67,28% ± 3,06%	66,13% ± 3,65%	63,85% ± 4,13%

Dataset	Model	Specificity	Precision
Fz	SVM	70,84% ± 6,00%	69,94% ± 6,07%
	RF	79,71% ± 8,81%	77,48% ± 8,62%
	NN	72,97% ± 7,10%	71,29% ± 2,10%
Fz-Pz	SVM	69,58% ± 9,88%	73,25% ± 3,86%
	RF	76,68% ± 2,82%	74,11% ± 3,49%
	NN	80,69% ± 7,31%	74,99% ± 7,26%

CONCLUSIONS

- Theta waves variations are more significant than that of the alpha waves
- *Fz* channel represents the best option to detect drowsiness
- CapsNet delivers better average results and smaller standard deviations
- Automatic feature extraction via convolutional layers
- CapsNet model handles smaller datasets better
- CapsNet handles transient signals and positional invariance
- Deep CapsNet model seems to be a promising approach for dealing with bioelectrical signals for drowsiness detection