UNIVERSIDAD PERUANA
CAYETANO HEREDIA

RECONOCMIENTO DE PATRONES

# AUTOMATIC CLASSIFICATION OF SLEEP STAGE FROM ECG SIGNAL USING A GATED-RECURRENT UNIT


GRUPO 3
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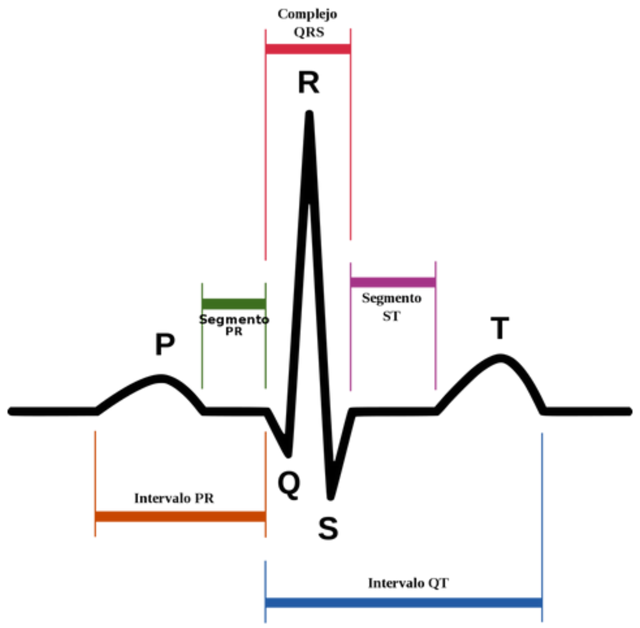
# INTRODUCCION [1]

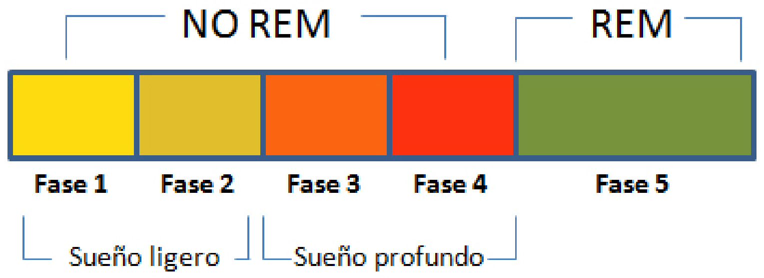
## ELECTROCARDIOGRAMA

La señal ECG registra la actividad eléctrica del corazón, detectando ritmos y anomalías cardíacas a través de electrodos en la piel, crucial para diagnósticos cardíacos.




## ESTADOS DEL SUEÑO

Los estados del sueño incluyen las etapas de sueño ligero, profundo y REM, cada una con características específicas de actividad cerebral y corporal, esenciales para la recuperación.

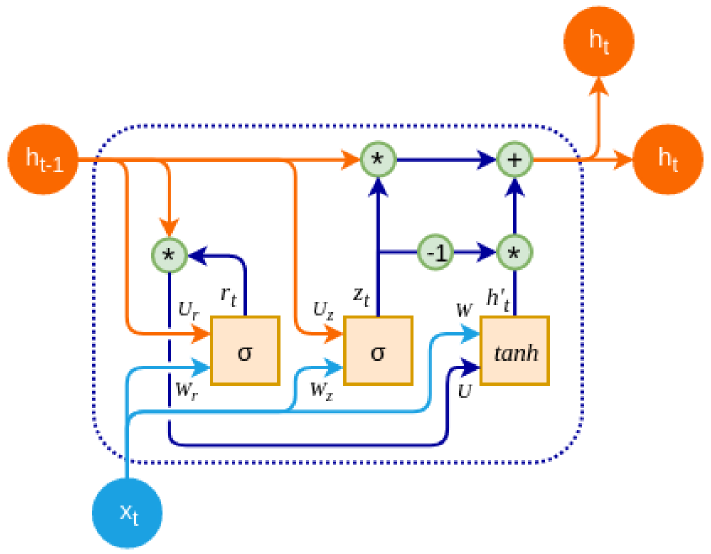



## SEÑALES VITALES INTERMEDIAS

Las señales vitales intermedias monitorean funciones corporales críticas, como la presión arterial y la saturación de oxígeno, entre otras, brindando información sobre el estado fisiológico.

## GATED RECURRENT UNIT

Los Gated Recurrent Units (GRU) son un tipo de red neuronal recurrente que utiliza puertas para controlar el flujo de información, mejorando el aprendizaje de secuencias largas.



# ESTADO DEL ARTE

Sleep–wake stages classification and sleep efficiency estimation using singlelead electrocardiogram, [2]

ELSEVIER
Expert Systems with Applications
Volume 39, Issue 1, January 2012, Pages 1401-1413

## Sleep–wake stages classification and sleep efficiency estimation using single-lead electrocardiogram

Mourad Adnane [a], Zhongwei Jiang [a], Zhonghong Yan [b]

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Abstract

Detecting sleep–wake stages is of paramount importance in the study of sleep.

ELSEVIER
Computers in Biology and Medicine
Volume 78, 1 November 2016, Pages 138-143

## A method of REM-NREM sleep distinction using ECG signal for unobtrusive personal monitoring

Jaspal Singh [a], R.K. Sharma [b], A.K. Gupta [b]

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Highlights

- A method of identifying REM-NREM sleep based on ECG signal.

# ESTADO DEL ARTE

Sleep stages classification based on heart rate variability and random forest[3]

Biomedical Signal Processing and Control
Volume 8, Issue 6, November 2013, Pages 624-633

## Sleep stages classification based on heart rate variability and random forest

Meng Xiao, Hong Yan, Jinzhong Song, Yuzhou Yang, Xianglin Yang

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https://doi.org/10.1016/j.bspc.2013.06.001

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Highlights

- We classify different sleep stages with 41 HRV features through random forest.

**Original Article**
International Journal of Fuzzy Logic and Intelligent Systems
Vol. 20, No. 3, September 2020, pp. 181-187
http://doi.org/10.5391/IJFIS.2020.20.3.181

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## Automatic Classification of Sleep Stage from an ECG Signal Using a Gated-Recurrent Unit

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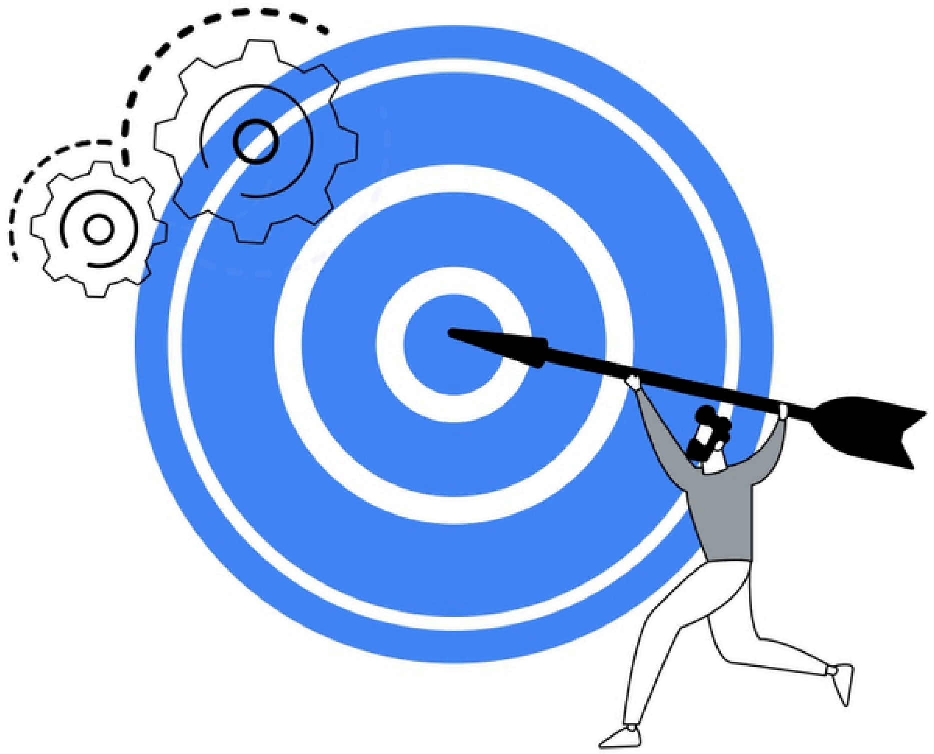
ljfis

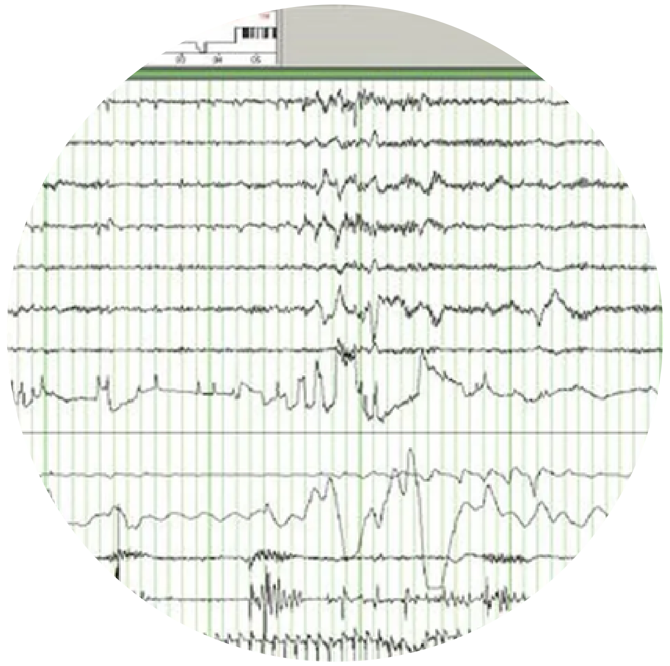
**Abstract**

A healthy sleep structure is clinically very important for overall health. The sleep structure can be represented by the percentage of different sleep stages during the total sleep time. In this study, we proposed a method for automatic classification of sleep stages from an electrocardiogram (ECG) signal using a gated-recurrent unit (GRU). The proposed method performed multiclass classification for three-class sleep stages such as awake, light, and deep sleep. A deep structured GRU was used in the proposed method, which is a common recurrent neural network. The proposed deep learning (SleepGRU) model consists of a 5-layer GRU and is optimized by batch-normalization, dropout, and Adam update rules. The ECG signal was recorded during nocturnal polysomnography from 112 subjects, and was normalized and segmented into units of 30-second duration. To train and evaluate the proposed method, the training set consisted of 80,316 segments from 89 subjects, and the test set used 20,079 segments from 23 subjects. We achieved good performances with an overall accuracy of 80.43% and F1-score of 80.07% for the test set. The proposed method can be an alternative

# OBJETIVO



Crear un metodo de clasificación automatica para los estadios del sueño a partir de una señal ECG usando un Gated-recurrent unit.



# DATASET

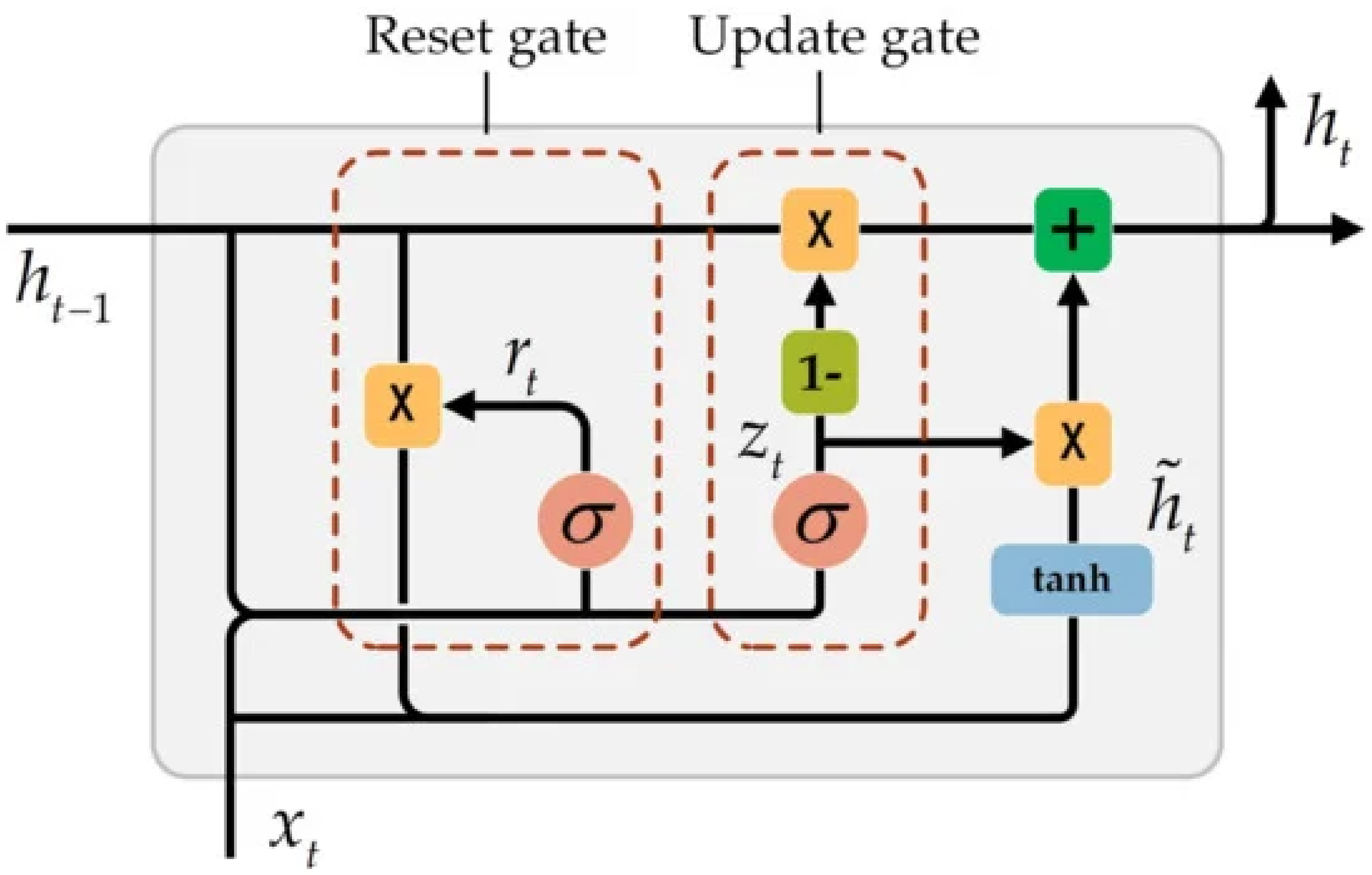
## OBTENCIÓN DE SEÑALES ECG

- 112 partcipantes,52 de controly 60 con Apnea
- Frecuencia de sampleo de 200 Hz.
- Segmentados en 30 segundos
- Estadios del sueño etiquetados segun American Association of Sleep Medicine.
- Se utilizo un transductor de una derivacion y se resampleo a 100 Hz con 3000 muestras por episodio para colectar la señal.
- El set de entrenamiento consiste de 80 316 episodios de 89 sujetos y el test de 20 070 episodios de 23 sujetos.

| | Training set | Test set | Total |
|---|---|---|---|
| Sex | 89 | 23 | 112 |
| Male | 55 | 16 | 71 |
| Female | 34 | 7 | 41 |
| Age (yr) | 53.1±10.5 | 55.1±10.4 | 53.5±10.5 |
| BMI (kg/m$^2$) | 24.2±3.0 | 24.2±3.0 | 24.2±3.0 |
| AHI (/hr) | 10.6±9.5 | 10.0±8.5 | 10.4±9.3 |
| TST (hr) | 6.2±1.0 | 6.2±0.7 | 6.2±0.9 |
| SE (%) | 84.8±13.1 | 86.0±8.7 | 85.1±12.3 |

Tabla 1. Informacion de los participantes

# MODELO SLEEPGRU




**Estructura de la unidad de red neuronal: Unidad recurrente cerrada (GRU) [5]**

El modelo SleepGRU consta de 5 capas GRU.
Mecanismo de compuerta de GRU:

$$z_t = g(W_z \cdot [h_{t-1}, x_t]), \qquad (1)$$

$$r_t = g(W_r \cdot [h_{t-1}, x_t]), \qquad (2)$$

$$\tilde{h}_t = \tanh(W \cdot [r_t \cdot h_{t-1}, x_t]), \qquad (3)$$

$$h_t = (1 - z_t) \cdot h_{t-1} + z_t \cdot \tilde{h}_t, \qquad (4)$$

Donde:
z_t: compuerta de actualización
r_t: la compuerta de reseteo
h's: los vectores de activación de celda
σ: función de activación sigmoide
τ: función tangente hiperbólica
x_t: entrada a la celda actual

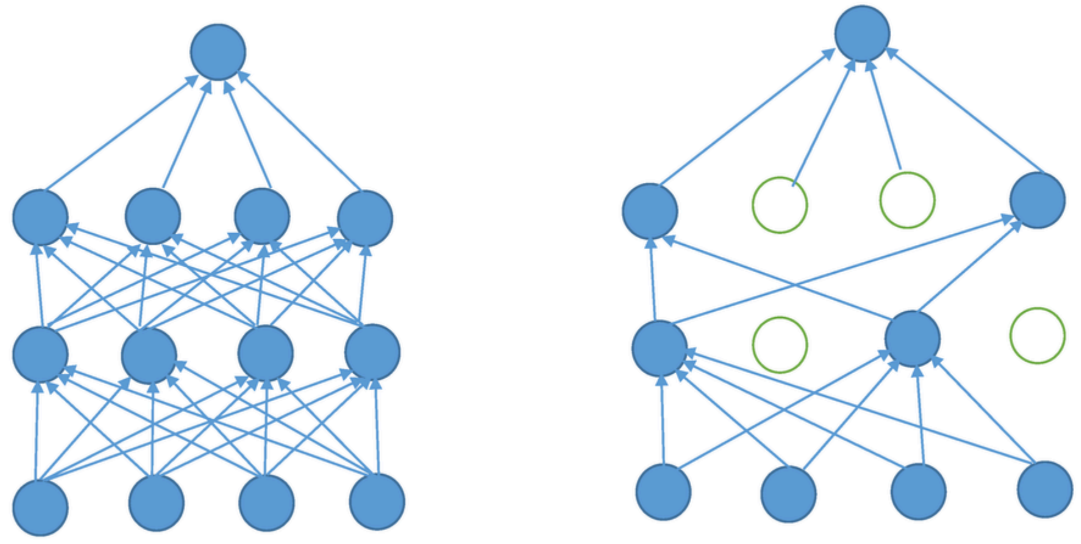
# OPTIMIZACIÓN DEL MODELO SLEEPGRU

$$x_b = \alpha \cdot \left( \frac{x_i - \mu}{\sqrt{\sigma^2 + \varepsilon}} \right) + \beta,$$

**Batch normalization**

$$f(x) = \max(0, wx + b),$$

**Rectified linear unit (ReLU)**



**Dropout**

# ESTRUCTURA DE MODELO SLEEPGRU

| No | Layers | Units | Dropout | Feature maps | Params |
|---|---|---|---|---|---|
| 1 | bNorm | - | - | 3000×1 | 4 |
| 2 | GRU1 | 24 | 0.5 | 3000×24 | 1,920 |
| 3 | GRU2 | 20 | 0.5 | 3000×20 | 2,760 |
| 4 | GRU3 | 16 | 0.4 | 3000×16 | 1,824 |
| 5 | GRU4 | 8 | 0.3 | 3000×8 | 642 |
| 6 | GRU5 | 4 | 0.2 | 3000×4 | 168 |
| 7 | MLP0 | 3 | - | 15×3 | 45 |

Tabla 2. Estructura detallada del modo SleepGRU construido

# IMPLEMENTACIÓN DEL MODELO SLEEPGRU

Preprocesamiento de datos PSG

MATLAB

Construcción del modelo

Keras

Estación de trabajo

intel CORE i9

NVIDIA GEFORCE RTX

# EVALUACIÓN DEL MODELO

| | Predicted Positive | Predicted Negative | |
|---|---|---|---|
| Actual Positive | TP<br>*True Positive* | FN<br>*False Negative* | Sensitivity<br>$\frac{TP}{(TP+FN)}$ |
| Actual Negative | FP<br>*False Positive* | TN<br>*True Negative* | Specificity<br>$\frac{TN}{(TN+FP)}$ |
| | Precision<br>$\frac{TP}{(TP+FP)}$ | Negative Predictive Value<br>$\frac{TN}{(TN+FN)}$ | Accuracy<br>$\frac{TP+TN}{(TP+TN+FP+FN)}$ |

$$\text{F1 Score} = \frac{2}{\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

# RESULTADOS

Table 3. The performance of the SleepGRU model

| Datasets | Classes | Precision | Recall | F1 | Accuracy (%) |
|---|---|---|---|---|---|
| Training set | Wake | 0.86 | 0.68 | 0.76 | 84.01 |
| | REM | 0.88 | 0.67 | 0.77 | |
| | NREM | 0.86 | 0.90 | 0.89 | |
| Test set | Wake | 0.58 | 0.42 | 0.51 | 80.43 |
| | REM | 0.77 | 0.81 | 0.73 | |
| | NREM | 0.86 | 0.84 | 0.83 | |

# DISCUSIÓN

Table 4. Comparison with previous studies

| Author | Signal | Classes | Accuracy (%) |
|---|---|---|---|
| SVM [9] | HRV | 2 | 79.9 |
| Randon Forest [10] | HRV | 3 | 72.5 |
| SVM [11] | RR interval | 2 | 72.8 |
| Random Forest [12] | ECG | 3 | 78.0 |
| DNN [19] | ECG | 3 | 77.8 |
| CNN [20] | ECG | 3 | 73.0 |
| RNN [21] | HR, Activity | 3 | 66.6 |
| GRU | ECG | 3 | 80.4 |

# CONCLUSIONES

- El modelo SleepGRU clasifica automáticamente las etapas del sueño (despierto, REM y NREM).
- Usa una señal de ECG de una sola derivación.
- Logra una precisión del 80.43%.
- No requiere extracción de características.
- Se recomienda validar el modelo con conjuntos de datos más grandes y diversos en futuras investigaciones.

# REFERENCIAS

[1] U. Erdenebayar, Y. Kim, J.-U. Park, S. Lee, y K.-J. Lee, “Automatic Classification of Sleep Stage from an ECG Signal Using a Gated-Recurrent Unit”, Int. J. Fuzzy Log. Intell. Syst., vol. 20, n.o 3, pp. 181-187, sep. 2020, doi: 10.5391/IJFIS.2020.20.3.181.

[2] M. Adnane, Z. Jiang, and Z. Yan, “Sleep–wake stages classification and sleep efficiency estimation using singlelead electrocardiogram,” Expert Systems with Applications, vol. 39, no. 1, pp. 1401-1413, 2012. https://doi.org/10.1016/ j.eswa.2011.08.022

[3] M. Xiao, H. Yan, J. Song, Y. Yang, and X. Yang, “Sleep stages classification based on heart rate variability and random forest,” Biomedical Signal Processing and Control, vol. 8, no. 6, pp. 624-633, 2013. https://doi.org/10.1016/j. bspc.2013.06.001

[4] J. Singh, R. K. Sharma, and A. K. Gupta, “A method of REM-NREM sleep distinction using ECG signal for unobtrusive personal monitoring,” Computers in Biology and Medicine, vol. 78, pp. 138-143, 2016. https://doi.org/ 10.1016/j.compbiomed.2016.09.018

[5] P. Li et al., “Bidirectional Gated Recurrent Unit Neural Network for Chinese Address Element Segmentation”, ISPRS Int. J. Geo-Inf., vol. 9, n.o 11, Art. n.o 11, nov. 2020, doi: 10.3390/ijgi9110635.

# GRACIAS