Classification of Cardiac Arrhythmias with Intra and Inter-Patient Paradigm using Transfer Learning

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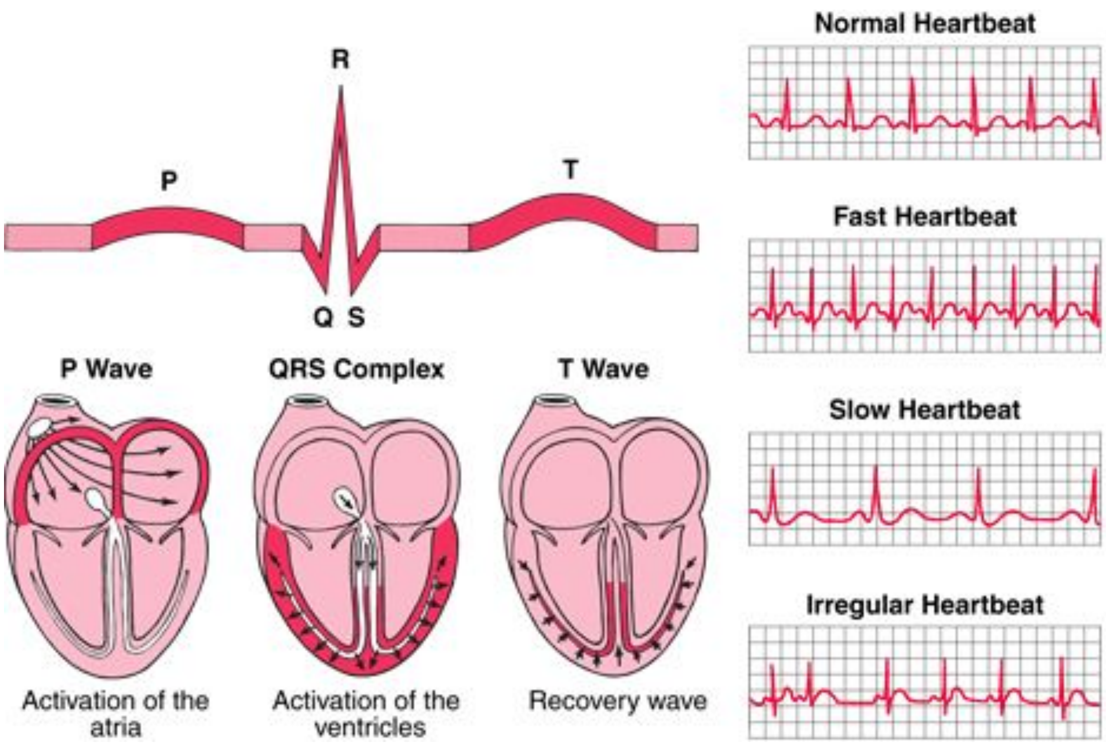


Figure 1: Reading EGC wave signals' and interpretation

What is cardiac arrhythmia?

Cardiac Arrhythmia is related with the cardiac **abnormal** heart beat according to the **bad working of the electrical signals** that coordinate the cardiac pulse.

175 million

- [...] of hospitalizations worldwide for **atrial** fibrillation-like arrhythmia [Sobrac, 2020];
- United States: cardiac arrhythmias account for more than **750,000 hospitalizations** every year;
- The disease with the **highest mortality rate** over the last two decades [Fang, 2019];
- Detection at an advanced stage of the disease, which makes it **potentially fatal** [Ullah et al., 2020], [Newman, 2020].

Objective

This research aims to identify and **classify cardiac arrhythmias** according to the variation of the ECG signal, using a **machine learning method with a neural network**.

The proposed solution will enable the development of systems for the **continuous monitoring of patients**.

Figure 2: Smartband Clock.

Figure 3: Smartband Clock.

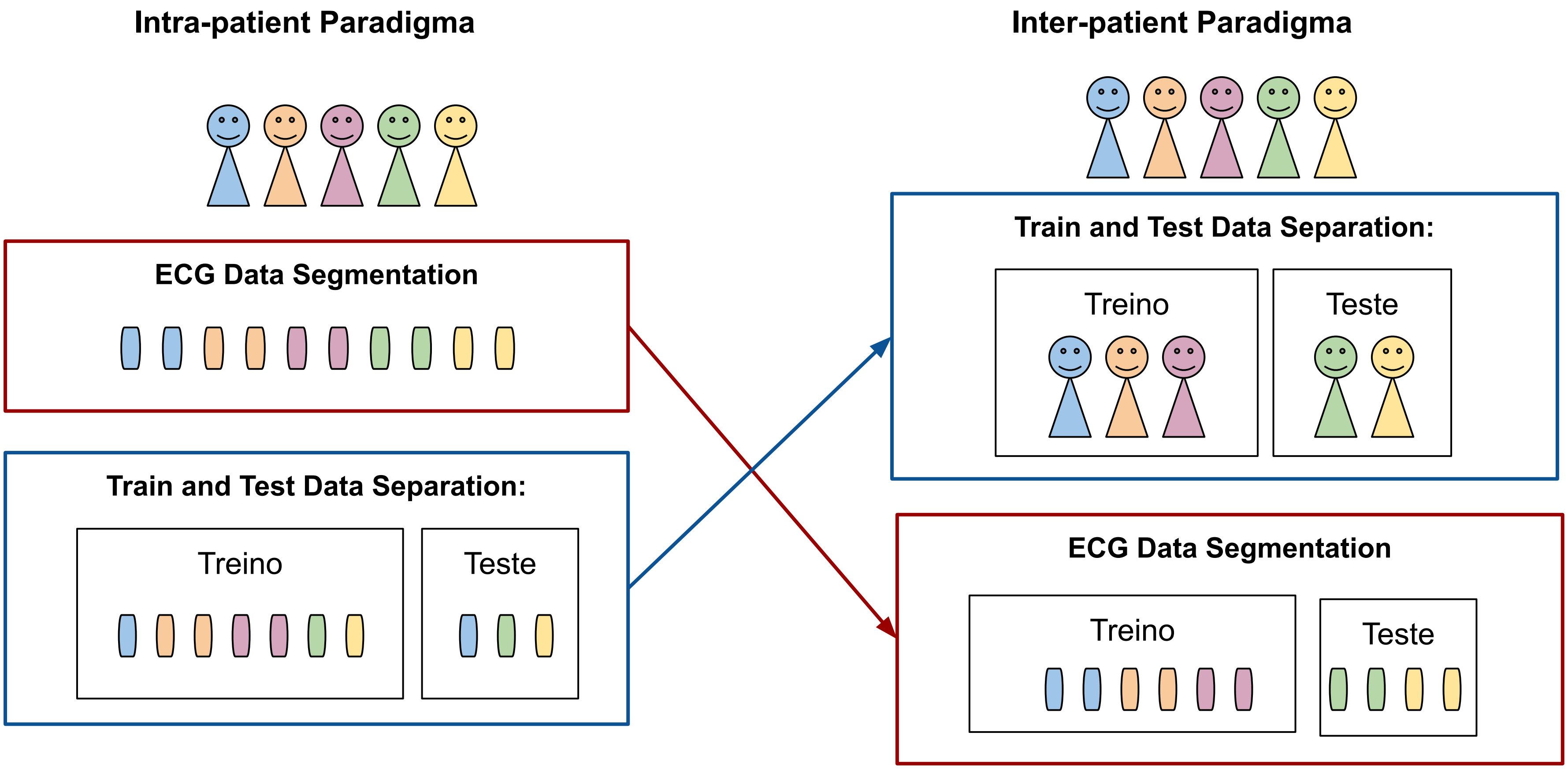


Figure 5: Inter-intra-patient paradigm used.

Related Works

Autor	Data Base	Number of Classes	Method	Application/Notes	Accuracy
Mousavi et al., 2019	MIT	5	CNN	Classificação com redes profundas utilizando intra- inter-paciente e SMOTE	99,92% e 99,53%
Sannio, 2018	MIT	2	DNN	Pré-processamento com técnicas matemáticas	100%
Wu et al., 2018	MIT and DeepQ	5 and 2	CNN	Classificação com redes profundas	93% e 94%
Li et al., 2019	MIT	5	Bi-LSTM	Classificação com redes profundas de Atenção	99,49%
Kachuee et al., 2018	MIT and PTB	5 and 2	CNN	Classificação com técnica de transferência de aprendizagem	93,4% e 95,9%

Table 1: Summary of Related Works (the author, 2022).

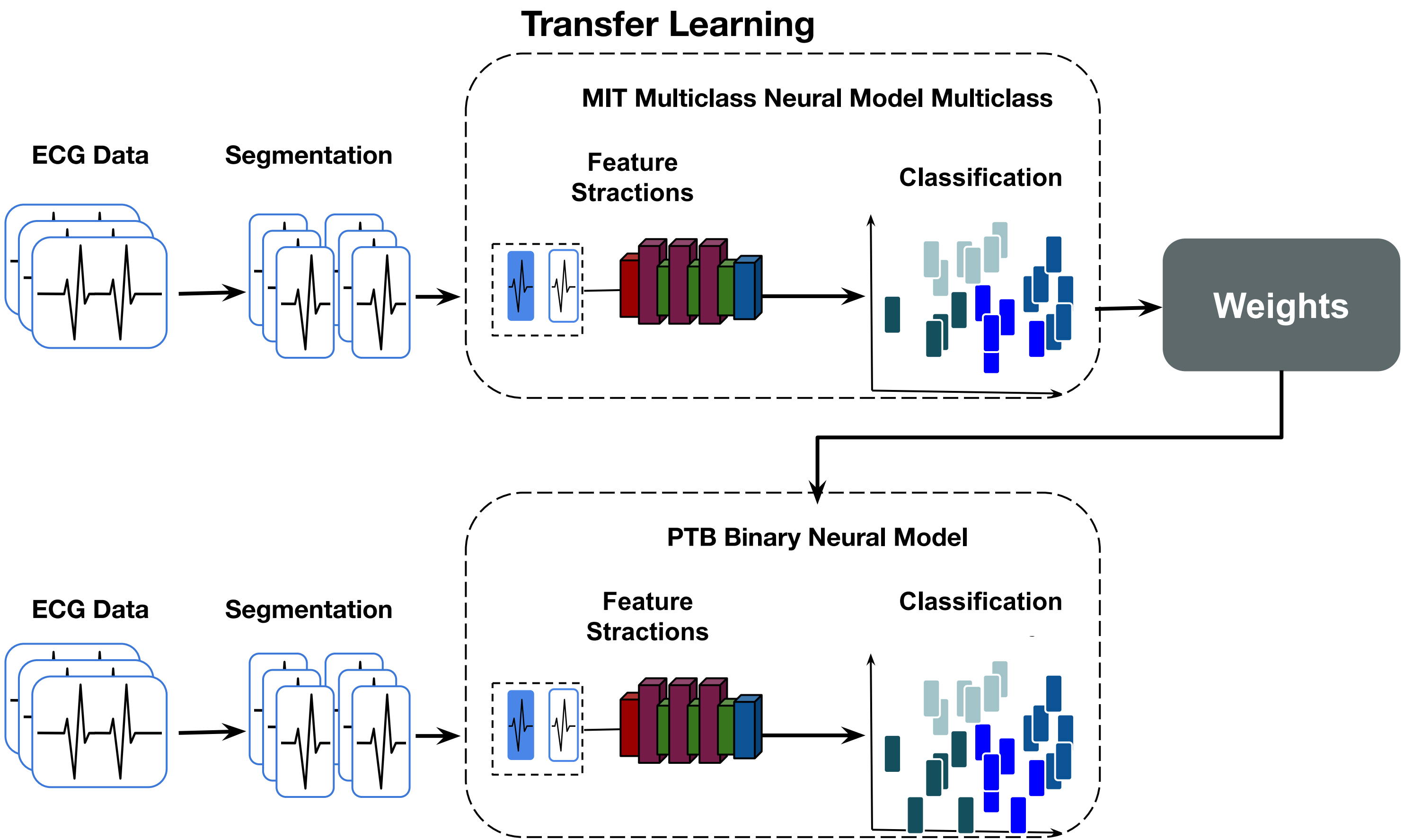


Figure 5: Method to classify cardiac arrhythmia.

ECG Data- MIT

Rótulo na base MIT-BIH	Anotação	Categoria AAMI
N	Normal Beat	N
L	Left branch block beat	
R	Right branch block beat	
j	Nodal escape beat (junctional)	
E	Ventricular escape beat	
A	Atrial premature beat	S
a	Aberrant atrial premature beat	
J	Nodal (junction) premature beat	
S	Ectopic or supraventricular premature beat	
V	Premature ventricular contraction	V
e	Atrial escape beat	
F	Fusion of ventricular and normal beat	F
/	Beat with rhythm	Q
f	Fusion of normal and rhythmic rhythm	
Q	Unclassified beat	

MIT database:

- MIT-BIH Arrhythmia
- contains 48 half-hour snippets of ambulatory ECG recordings
- Mixed inpatient (about 60%) and outpatient (about 40%) population at Beth Israel Hospital in Boston.
- Database published by the BIH Arrhythmia Laboratory between 1975 and 1979

ECG Data - PTB

Rótulo na base PTB/ Anotação	Categoria
Myocardial infarction	Myocardial infarction
Healthy control	Other Arrhythmias
Cardiomyopathy	Other Arrhythmias
Bundle branch block	Other Arrhythmias
Dysrhythmia	Other Arrhythmias
Hypertrophy	Other Arrhythmias
Valvulopathy	Other Arrhythmias
Myocarditis	Other Arrhythmias
Stable angina	Other Arrhythmias

PTB database:

- PTB Diagnostics by Physionet
- contains 549 records of ambulatory recordings of ECG signals
- 290 individuals aged 17 to 87 years, with 209 men and 81 women
- Base published in 2004
- The base was binarized for classification [Kachuee, 2018]

Segmentation

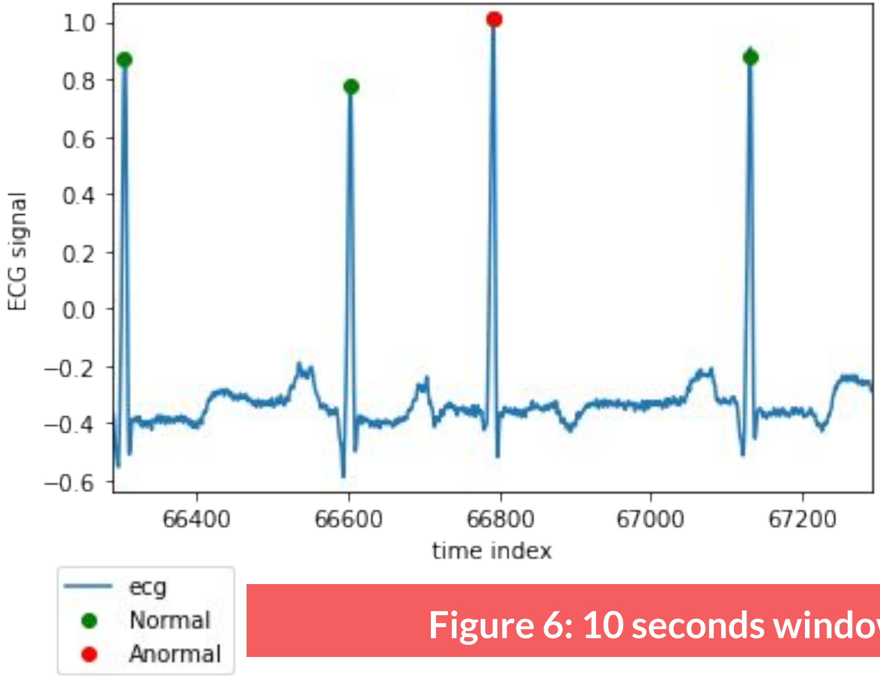
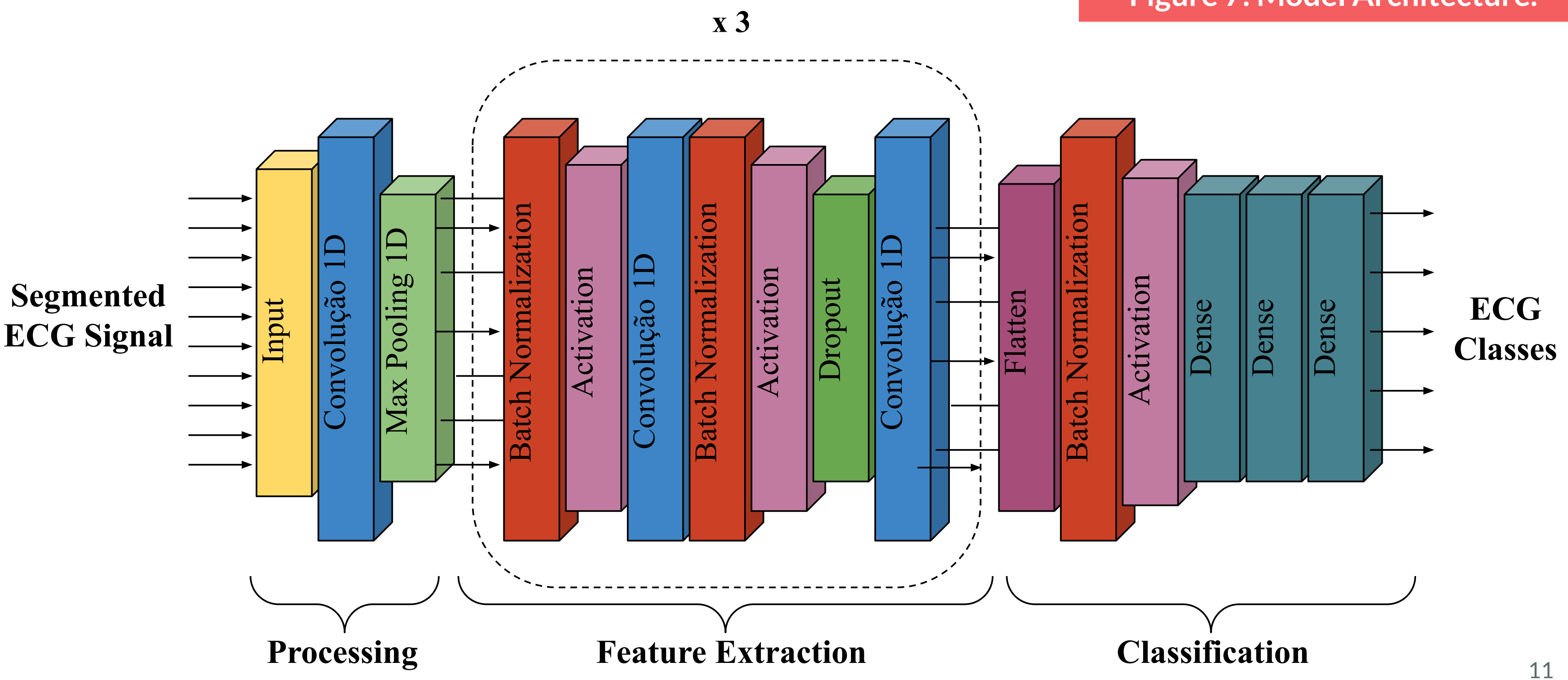


Figure 6: 10 seconds window.

- Inter-patient paradigm used in the separation of the base
- 90% for training base and 10% for testing base [Li, 2019] [SOBRAC, 2020]
- 10 second windowing [Kachuee, 2018]

Feature Extraction Model and Classification

Figure 7: Model Architecture.



Results- MIT Dataset

Table 2: Results of the MIT Intra-Patient Paradigm.

Method	Class	Acc(%)	se(%)	sp(%)	+p(%)
Current	N	**91,53**	**98**	**73**	**92**
	S		**39**	**99**	**88**
	V		**71**	**99**	**88**
	F		**60**	**100**	**50**
	Q		**86**	**99**	**96**
Baseline	N	90,87	91	89	98
	S		73	99	67
	V		75	95	28
	F		60	99	15
	Q		92	97	80

Table 3: Results of the MIT Inter-Patient Paradigm.

Method	Class	Acc(%)	se(%)	sp(%)	+p(%)
Current	N	**86,21**	**92**	**45**	**94**
	S		**11**	**97**	**09**
	V		**49**	**96**	**39**
	F		**0**	**100**	**0**
	Q		**46**	**97**	**40**
Baseline	N	86,12	87	8	98
	S		0	97	0
	V		0	93	0
	F		**0**	99	**0**
	Q		8	95	2

Results - PTB Dataset

Table 4: Results of the PTB Intra-Patient Paradigm.

Method	Class	Acc(%)	se(%)	sp(%)	+p(%)
Current	Myocardial infarction	97,10	78	66	93
	Others'		66	78	33
Baseline	Myocardial infarction	**99,95**	**100**	**100**	**100**
	Others'		**100**	**100**	**100**

Table 5: Results of the PTB Inter-patient Paradigm.

Method	Class	Acc(%)	se(%)	sp(%)	+p(%)
Current	Myocardial infarction	**81,81**	**86**	**60**	**91**
	Others'		**60**	**86**	**48**
Baseline	Myocardial infarction	76,40	83	59	84
	Others'		59	83	59

Future Works

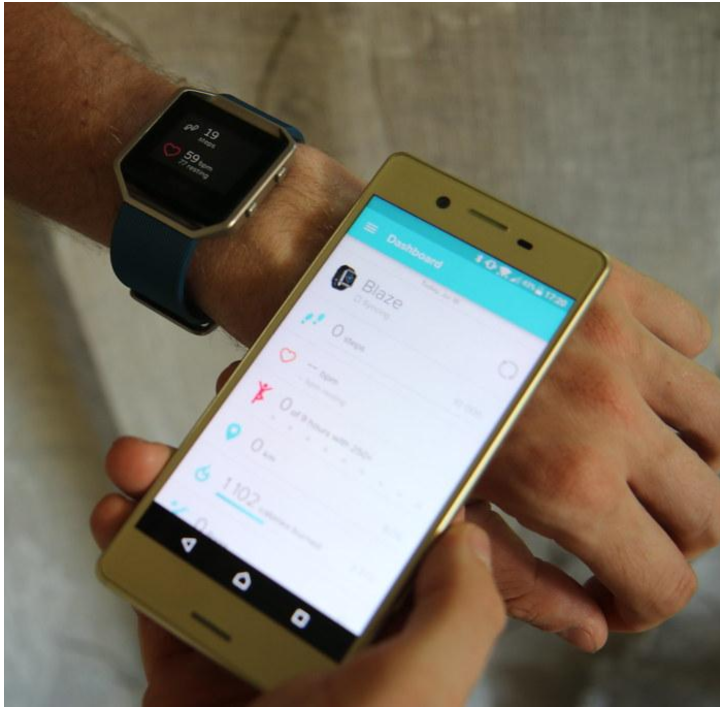


Figura 9: Wearable connected to Android

- Test **data augmentation** and learning transfer methods
- Increase accuracy for **minority classes**
- **Balance** the base
- Compress the model and ship it to a **wearable.**

Thanks for the attention

SOLI DEO GLORIA

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