University of Molise

Department of Biosciences and Territory

Bachelor Thesis

Global and Local Prediction in Automatic detection of Atrial Fibrillation

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Chapter 1

Introduction

1.1 What is the Atrial Fibrillation?

Atrial fibrillation, also abbreviated with AF or A-Fib, is an abnormal heart rhythm that happens when electrical impulses fire off in the atria (Figure 1.1), from different spots without being organized. Characterized by rapid and irregular beating, caused by the chambers of the heart twitching [1]. This arrhythmia is associated with an increased risk of stroke, in fact the proportion of strokes associated with AF increases from 6.6%, for ages 50 to 59 years, to 36.2% for ages 80 to 89 years [2]. Other risks are heart failure and even dementia [3]. The estimated number of individuals with AF globally in 2010 was 33,5 million and as the population ages globally, the burden of AF grows [4].

The disease is classified by doctors based on how long it lasts or based on the cause. The treatment will be different for each kind [5]:

- **Paroxysmal** (holiday heart syndrome): an episode of AF, the duration of whose maybe a few minutes or a few days, but which tends to be

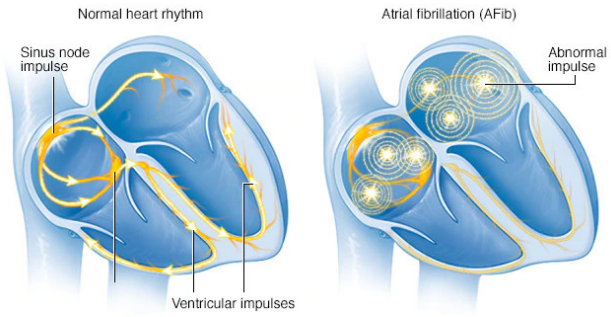

Figure 1.1: A normal heartbeat on the left, and AF heartbeat on the right. Image from mayoclinic.org

below the week. Usually, treatment is not needed;

- **Persistent**: the disease lasts longer than a week and it can stop on its own, or a specific medicine or treatment is needed. If the latter does not work, doctors opt for the electrical cardioversion, which is a low-voltage current used to reset the normal rhythm;
- **Permanent**: also called chronic, cannot be treated. The doctor decides for a long term medication to reduce the odds of associated health conditions.

1.2 Causes and Symptoms

There are many possible causes of the condition, some are controllable, others are not. Cardiovascular factors play a big role: high blood pressure, heart valve disease, congenital heart disease and even previous heart surgery. But difficulties in breathing are a key factor too, in other words, obesity and obstructive sleep apnea [6]. Alcohol consumption and tobacco smoking are associated with an increased risk of developing atrial fibrillation [7, 8]. Other factors are genetics, ageing, a sedentary lifestyle and diabetes [9, 10].

The person often feels an abnormal beating that starts to become longer and constant. There could be heart palpitations, shortness of breath, chest pain, light-headedness, or fainting [11]. But the biggest problem is that often these kind of episodes are asymptomatic [3], in fact sometimes first diagnosed when patients present a stroke [12].

1.3 Diagnosis

A doctor to diagnose AF could check your signs and symptoms, together with your medical history and conduct a different kind of tests [13]:

- **Electrocardiogram** (ECG or EKG) is the process through which a recording of the electrical activity of the patient's heart is made. To measure the electrical signals as they travel, multiple small sensors, called electrodes, are attached to the body. This test plays a key role among all the other tools used. A more in-depth explanation will be offered in Section 1.4.
- **Holter monitor** is a portable ECG device that can be carried in a pocket or even worn on a shoulder strap or a belt. The monitor will check the heart's activity for 24 hours, sometimes even longer. It is a

common practice to utilize the device when there is a strong suspect about a Paroxysmal-AF but an ECG during an office visit detects only a regular rhythm.

- **Event recorder** is another kind of ECG portable device that is meant to monitor the heartbeat over a few weeks to a few months. When the patient feels a symptom, then the button should be pressed to let the device memorize an ECG strip of the preceding few minutes and following few minutes.

- **Echocardiogram** is a non-invasive test that uses ultrasound waves to scan the heart and get moving pictures of the organ. The doctors aim to find problems in the valves, in the size of the left and right atrial or more general structural heart disease or blood clots.

- **Blood tests** are used to check any thyroid problems or other substances in the patient's blood that may lead to AF.

- **Stress test** can help the doctor in the task of finding AF. The reason is that some individual with the disease do well in normal activity, but not with exertion. Moreover, the nature of the symptoms can be understood.

- **Chest X-ray** help to see the condition of the lungs and heart of a specific patient. In general, it's used if a pulmonary cause of AF is suggested or if conditions like congestive heart failure are suspected.

The first type of test, the ECG, is an investigation performed routinely whenever an irregular heartbeat is suspected. And it can be done in the office and later even with a portable device, thus it's a relevant tool through which an automatic detection of atrial fibrillation can be implemented.

1.4 Diagnose AF using ECG

Electrocardiography produces an electrocardiogram (ECG), namely a recording which is a graph where the x-axis represents the time and the y-axis represents the voltage, of the electrical activity of the heart using electrodes placed on the skin [14, p.74]. In this way, small electrical changes can be detected, that are the normal consequences of cardiac muscle depolarization followed by a re-polarization during each cardiac cycle (Figure 1.2).

Normally the number of electrodes attached to the patient's limbs and on the surface of the chest is 10, this allows to form 12 ECG leads. Thus the

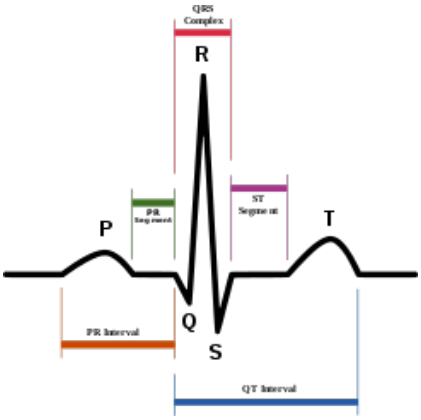

Figure 1.2: Cardiac cycle divided into different components. P, QRS and T.

Figure 1.3: ECG of a heart with atrial fibrillation on top and with normal sinus rhythm on the bottom.

overall magnitude of the electrical potential of the heart can be measured from twelve different angles (leads).

A single cardiac cycle can be divided into different components as in (Figure 1.2). The first is called P wave, which represents the depolarization of the atria. The second one is the QRS complex, that symbolizes the ventricles' depolarization. To finish with the T wave, which represents the re-polarization of the ventricles [14, p.80].

Knowing all this, to find atrial fibrillation heartbeats through the electrocardiogram is sufficient to run an investigation on the absence of P waves with disorganized electrical activity in their place and irregular $R-R$ intervals caused by irregular conduction of impulses to the ventricles [15]. Furthermore, problems over fast heart rates arise since A-Fib may look more regular, which could make it indistinguishable from other supraventricular tachycardias or ventricular tachycardia [16]. Besides QRS complexes should be quite narrow because it means that they are initiated by a normal flow of electrical activity through the intraventricular conduction system. Otherwise wide complexes are disquieting for ventricular tachycardia, albeit in cases where there is a disorder with the conductions system, wide QRS complexes may

be present in A-fib with a rapid ventricular response. A good example is shown in (Figure 1.3).

In Chapter 2 and Chapter **??**, two different automatic detection of AF approaches are described based on two public datasets offered by PhysioNet [17], respectively MIT-BIH Atrial Fibrillation Database [18] and Long Term AF Database [19].

Chapter 2

Global prediction

2.1 Introduction

In this Chapter, an automatic approach to detect Atrial Fibrillation is analyzed and an attempt to improve it is made through Machine Learning techniques. The state of art it's based on different public datasets offered by PhysioNet [17], among which MIT-BIH Atrial Fibrillation Database [18] and Long Term AF Database [19] are used. The method it's based on ECG, whose explanation it has been given in Section 1.4. The reason that lies behind the use of ECG, is its intrinsic simplicity, that cannot be found in methods like blood tests, chest x-ray, etc.

2.1.1 Description of MIT-BIH

The database includes 25 long-term ECG recordings of patients with atrial fibrillation, which is mostly paroxysmal. Each record is 10 hours in duration and contains two ECG signals sampled at 250 samples per second with $12-bit$ resolution over a range of ± 10 millivolts. The signals files `.dat` are available only on 23 records. But all of the records have `.atr` and `.qrs` annotations files. The former contains information about the kind of rhythm: atrial fibrillation, atrial flutter, junctional rhythm or other rhythms. The latter contains unaudited beat prepared using an automated detector and have not been corrected manually. In some cases, manually corrected beat annotations files `.qrsc` are present.

2.2 State of the art algorithm

Most of the algorithms work on the processing of the ECGs components (P wave, QRS complex, ...) and the poorly coordinate atrial activation (AA) of heart and rapid cardiac beating. Although these pieces of information can lead to the identification of Atrial Fibrillation, noise must be taken into consideration. Especially with P waves which in general is of very low-intensity magnitude. Whereas the approaches based on the RR interval (R wave peak to R wave peak) irregularity, nonetheless the component is a more prominent feature of ECG and thus less subject to noise, tend to be quite complicated and not so efficient to make them suitable for real-time applications [20, p. 2]. For this reason, a real-time and low-complexity but robust method for the discrimination of AF episodes is taken as reference. The algorithm is composed of three steps and is based on the heart rate (HR).

2.2.1 Heart rate sequence

Let hr_n be the heartbeat rate sequence obtained from,

$$hr_n = 60\,\mathrm{s} \cdot \frac{250}{R_n - R_{n-1}} \tag{2.1}$$

where 60 are the seconds, R_n is the sequence that denotes the R peak in the QRS complex and 250 is the number of samples per second. From an implementation point of view, here one bpm is lost. The `.qrs` files contain a registration where the first sample does not represent the R peak, therefore all the part before the first R peak cannot be used to compute the first bpm. An example of the sequence hr_n can be found in (Figure 2.2 (a)). The following implementation of the function is done in Python 3.7

```
def compute_bpm(qrs_ann_list, frequency=250):
 bpm_list = list()

 for i in range(0, len(qrs_ann_list) - 1):
   dist = qrs_ann_list[i + 1] - qrs_ann_list[i]
   bpm = 60 / (dist / frequency)
   bpm_list.append(bpm)

 return bpm_list
```

2.2.2 Symbolic dynamics of hr_n sequence

Let sy_n denote a symbolic dynamics that encodes the information of hr_n to a series with fewer symbols, where the mapping function is given by [20, p.

3],

$$sy_n = \begin{cases} 63 & \text{if } hr_n \geq 315 \\ \lfloor hr_n/5 \rfloor & \text{otherwise} \end{cases} \tag{2.2}$$

where $\lfloor \cdot \rfloor$ is a floor operator. In this way the raw sequence hr_n is transformed in a sequence $sy_n \in [0, 63]$, with 64 instantaneous states (Figure 2.2 (b)). Here below the implementation

```
def compute_sy(bpm_list):
  return list(map(lambda x: 63 if x >= 315 else floor(x / 5),
                                  bpm_list))
```

2.2.3 History sequence of sy_n

A 3-symbols template can be applied to get a window of information that acts as a history (Figure 2.2 (c)), in this case on 3 successive symbols. Through a novel operator defined below [20, p. 3], the word value can be calculated.

$$wv_n = (sy_{n-2} \times 2^{12}) + (sy_{n-1} \times 2^6) + sy_n \tag{2.3}$$

A major intrinsic property to be explained is the following,

$$|wv| = |sy| - 2 = |hr| - 2 = |qrs| - 3 \tag{2.4}$$

where wv denotes the set of words in a specific moment. The set qrs is composed of all the QRSs complexes provided by the ECG, in this case in the `.qrs` files. To sum up, a tiny bit of information is lost, precisely 1 R peak to compute the heartbeat sequence hr and 2 bpm to compute the word sequence wv. Here follows the implementation of the above

```
def compute_wv(sy_list):
  wv_list = list()

  for i in range(2, len(sy_list)):
    wv = (sy_list[i - 2] << 12) + (sy_list[i - 1] << 6) +
                                    sy_list[i]
    wv_list.append(wv)

  return wv_list
```

2.2.4 Shannon entropy

A coarser version of Shannon entropy is employed to discriminate the AF arrhythmias (Figure 2.2 (d)). Without loss of generality, let $\mathbf{A} = (A|P)$

denote a dynamic system. The unique elements in this set can be defined as $A = \{a_1, \ldots, a_k\}$ with the interrelated probability set $P = \{p_1, \ldots, p_k\}(1 \leq k \leq N)$, where N is the total number of elements and k are the unique elements in space $\mathbf{A}$. Each element a_i has the probability $p_i = N_i/N(0 < p_i \leq 1, \sum_{i=1}^{k} p_i = 1)$, where N_i is the total number of the specific element a_i in space $\mathbf{A}$. Hence the coarser version of Shannon entropy can be defined to quantitatively calculate the information size of wv_n,

$$\mathcal{H}''(\mathbf{A}) = -\frac{k}{N\, log_2 N} \sum_{i=1}^{k} p_i\, log_2 p_i \tag{2.5}$$

The dynamic $\mathcal{A}$ is characterized by a bin size of $N = 127$ consecutive word elements from wv_{n-126} to wv_n. By defining the characteristic set A and the corresponding probability set P, the entropy $\mathcal{H}''(\mathbf{A})$ can be calculated. A specific cardiac beat hr_n is labelled as AF if the coarser entropy meets or exceeds a discrimination optimal threshold equal to 0.639. The threshold was obtained through an investigation of various thresholds in the range $[0.0, 1.0]$ with an increment of 0.001 from the receiver operating characteristic (ROC) on training databases. The computational challenges that are found in the Equation 2.5 can be overcome with a pre-calculated map of $-\frac{1}{log_2 N} p_i\, log_2 pi_i$ [20, p. 4]. Here follows an implementation where a constant value 1000000 it's used to get decimal floating points as integers through a floor operator.

```
def get_pimap(n, cons):
  pi = lambda i: int(-cons / log(n, 2) * i * log(i, 2))
  return [pi(p / n) for p in range(1, n + 1)]

pi_map = get_pimap(127, 1000000)

def compute_entropy(wv_list):
  nu = list([0] * 127)
  sh2 = list()

  for i in range(0, len(wv_list)):
    nu.pop(0)
    nu.append(wv_list[i])

    # Number of occurrences of an element are counted
    a = dict()
    for j in nu:
      a[j] = (a[j] + 1) if j in a else 1

    k = len(a)
    sh1 = sum([pi_map[a[element] - 1] for element in a])
    sh2.append(k / 127000000 * sh1)
```

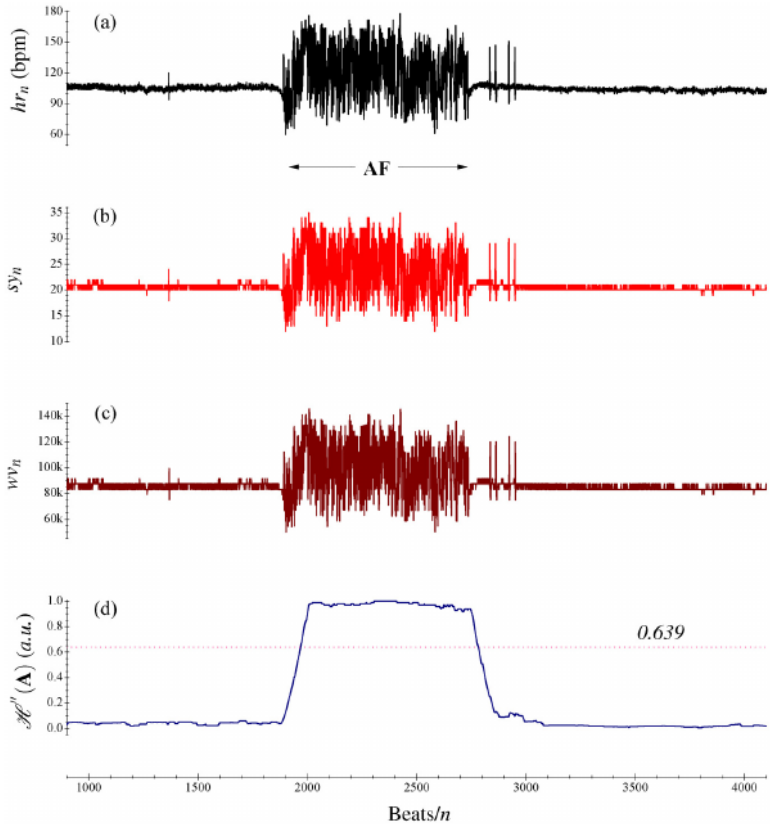

Figure 2.1: Application of the method to detect AF. (a) is the original sequence hr_n; (b) is the symbolic dynamic sy_n; (c) the word sequence wn_n; (d) the distribution of $\mathcal{H}''(\mathbf{A})$.

```
    return sh2
```

2.2.5 Results and comparisons

Performance metrics

The work under consideration measures the performances using sensitivity (Se), specificity (Sp), positive predictive value (PPV), and overall accuracy (ACC) [20, p. 6].

$$\begin{aligned} Se &= \frac{TP}{TP+FN}, & PPV &= \frac{TP}{TP+FP} \\ Sp &= \frac{TN}{TN+FP}, & ACC &= \frac{TP+TN}{TP+TN+FP+FN} \end{aligned} \tag{2.6}$$

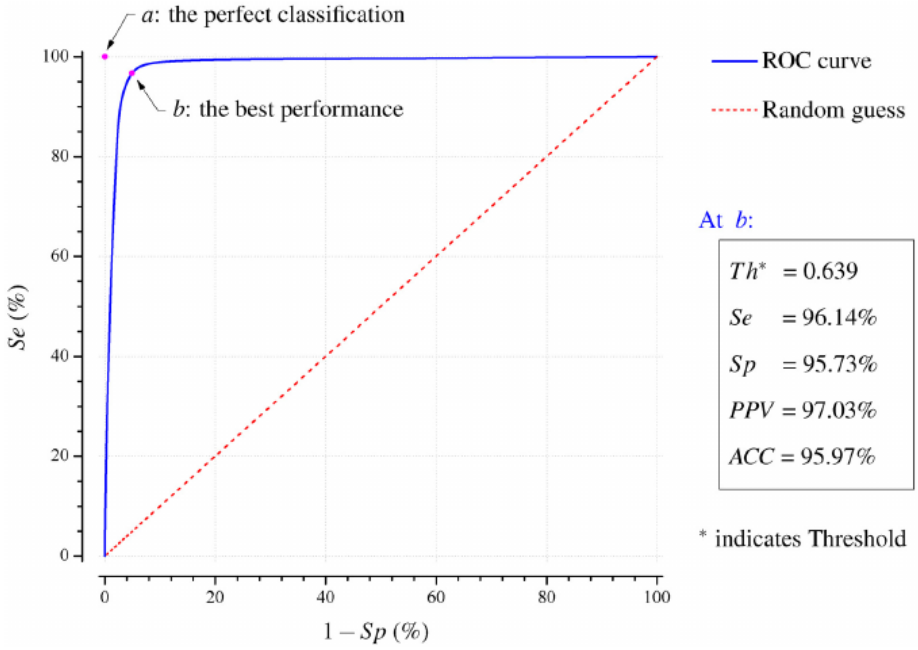

Figure 2.2: Application

where TP stands for true positives, TN true negatives, FP false positives and FN false negatives.

Training phase

The training phase was executed on LTAFDB which consists of 84 long-term ECG recordings (commonly 24 to 25 hours duration) of patients with paroxysmal or persistent/permanent AF. The number of cardiac beats is around 9 million of which 59.2% are annotated as AF. The threshold, as already mentioned in the previous section 2.2.4, is tested from 0.0 to 1.0 with an increment of 0.001. ROC curve is defined based on the metrics Se and $1 - Sp$, where a point on the graph is formed by the couple $(Se; 1 - Sp)$ of a specific threshold. Thus the best-case scenario, namely perfect classification, is the couple $a = (Se = 1; 1 - Sp = 0)$, hence the best performance can be found trivially using the Euclidean distance of a generic point from the point a. In (Figure 2.2), the best performance point b is found at threshold 0.639, with distance 0.0576 from the perfect classification, an area under the ROC curve that is 0.9845 and the corresponding values of Se, Sp, PPV and ACC are 96.14%, 95.73%, 97.03% and 95.97% respectively [20]. In other words, a slight improvement is made compared to RRI based method Zhou, et al[21].

Testing phase

This phase uses the threshold 0.639 across all testing databases: AFDB, MITDB[22] and NSRDB[23] set. A complete overview of the results of the state of art method explained and others can be found in Table 2.1. AFDB[1] is experimentation without the records `00735` and `03665` for which the `.hea` files are not existent. While AFDB[2] excludes the record `04936` and `05091` because many incorrect manual AF annotations are contained [24]. To be sure about experimentation, edge cases are needed. Hence dataset like MITDB which contains many coexisting various types of complex arrhythmias and NSRDB without any AF annotation, are perfect for this purpose.

Table 2.1: Classification performance of different methods based on three different testing databases [20, p. 8].

Method	**Feature**	**Year**	**Database**	**Temp**	**Results**		
				SE(%)	**SP**(%)	**PPV**(%)	**ACC**(%)
Zhou, et al[20]	HR	2015	AFDB	97.37	98.44	97.89	97.99
			AFDB[1]	97.31	98.28	97.89	97.84
			AFDB[2]	98.43	98.46	97.92	98.45
			MITDB	97.83	87.41	47.67	88.51
			NSRDB	NA	99.68	NA	NA
Petrênas, et al[25]	RRI	2015	AFDB	97.12	98.28	-	-
			AFDB[1]	97.1	98.1	-	-
			AFDB[2]	98.0	98.2	-	-
			MITDB	97.8	86.4	47.67	88.51
			NSRDB	NA	98.6	NA	NA
Zhou, et al[21]	RRI	2014	AFDB	96.89	98.25	97.62	97.67
			AFDB[1]	96.82	98.06	97.61	97.50
			AFDB[2]	97.83	98.19	97.56	98.04
			MITDB	97.33	90.78	55.29	91.46
			NSRDB	NA	98.28	NA	NA
Lee, et al[24]	RRI	2014	AFDB[2]	98.22	97.68	-	97.91
			MITDB	91.1	89.7	-	-
			NSRDB	NA	99.7	NA	NA

[1] Records `00735` and `03665` excluded.
[2] Records `04936` and `05091` excluded.
'NA' indicates not applicable because there is no beat with AF reference annotation in this database.

Thus the method performs statistically better than the others [20, p. 11] with a very low computational complexity [20, p. 14]

2.3 Using machine learning techniques

The state of the art algorithm just described could be improved using machine learning (ML) techniques. To make a complete experimentation, multiple ML algorithms should be used in the investigation. But first a replication of Zhou, et al[20] is needed.

2.3.1 State of the art replication

The replication was made with Python 3.7 and its most popular libraries for data science, such as Numpy and Pandas. Wfdb library to manipulate the different databases introduced in Section 2.1. The core part of the work has been shown in pieces in the previous sections that explain the steps of the algorithm.

Table 2.2: State of the art algorithm replication performance.

Method	**Database**	**Results**			
		SE(%)	**SP**(%)	**PPV**(%)	**ACC**(%)
Zhou, et al[20]	AFDB	97.37	98.44	97.89	97.99
A	AFDB	96.03	97.49	96.59	96.87
	AFDB[3]	96.04	97.50	96.60	96.88
B	AFDB	95.99	97.50	96.60	96.86
	AFDB[3]	96.00	97.50	96.62	96.86
C[4]	AFDB	96.03	97.53	96.64	96.89
	AFDB[3]	96.04	97.53	96.66	96.90

[3] File `.qrsc` (qrs complexes corrected manually) used when available.
[4] Hybrid heartbeat rate were introduced. 584 *hr* not classified.

In Table 2.6 the performance of the replication are reported. The predicted values were compared with an oracle. To define the matching oracle oa_n of a specific record, a binary sequence bs_k was used to keep track of the samples that are AF (bit 1) and non-AF (bit 0), between the peaks R_i and R_{i+1}. The correct labels were obtained from the `.atr` files. Then the percentage of AF bit in the interval RR was counted,

$$\text{AF}\% = \frac{\#\text{ of ones}}{RR\text{ length}} \tag{2.7}$$

In order to be able to carry out as complete trial as possible, the oracle oa_n was defined based on the percentage in three different ways:

- Method A: oa_n is AF $\iff$ $AF\% = 1$, else non-AF
- Method B: oa_n is AF $\iff$ $AF\% > 0.5$, else non-AF
- Method C: oa_n is $AF\%$

In the method C 584 beats were not classified, because hybrids (not 1 and not 0). In Table 2.3 the number of AF and non-AF beats classified per method are showed. An artefact was introduced in the implementation of algorithm or in the definition of the oracle. Further investigation are needed, but the difference between the methods applied on the same database is negligible.

Table 2.3: Number of beats comparison between state of the art and replication.

Method	Database	AF	NON-AF	TOTAL	Difference from SOA*
Zhou, et al[20]	AFDB	519687**	701887**	1221574	0
B	AFDB	516515	704969	1221484	−90 beats
B	AFDB[3]	518082	705013	1223095	+1521 beats

* Difference from state of the art method.
** [20, p. 9].

2.4 Applying machine learning

During this phase, machine learning algorithms were applied on enriched feature datasets using Weka 3.8. The method B on the corrected AFDB is the base of the experiment. Furthermore to make comparison more immediate, Matthews correlation coefficient (MCC), a measure of the quality of binary classification, was introduced

$$\mathrm{MCC} = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \tag{2.8}$$

From here on, a bespoke entropy be_n is introduced on each dataset and is defined as follows. Let hr_n be the heartbeat rate sequence.
1 step. Filter the hr_n sequence by labelling beat 1 if is stable otherwise 0 or 2:

$$\mathrm{x_n} = \begin{cases} 0, & \text{if } hr_n \leq 50 \\ 1, & \text{if } 50 < hr_n < 120 \\ 2, & \text{otherwise} \end{cases} \tag{2.9}$$

2 step. Count number of stable beat (1) in a window of 10 elements $[x_{n-9}, x_n]$:

$$\mathrm{be_n} = \sum_{i=n-9}^{n} [x_i = 1] \tag{2.10}$$

Explicit and encoded entropy dataset

As already explained in 2.2.4, hr_n is labelled as AF if the coarser entropy meets or exceeds a discrimination optimal threshold equal to 0.639. This will be referred as encoded entropy, while the value itself of the Shannon entropy is the explicit entropy.

The first experiment consisted in using a dataset with encoded/explicit entropy, custom entropy and of course the oracle as a label (Table 2.6). In

Table 2.4: Machine learning algorithms applied on dataset with explicit and encoded entropy, compared with the replication of Zhou and Zhou, et al [20] itself.

Dataset	**Algorithm**	**Results**				
		SE(%)	**SP**(%)	**PPV**(%)	**ACC**(%)	**MCC**(%)
Explicit	j48	96.01	97.19	96.21	96.69	93.22
	ibk	94.95	96.09	94.74	95.60	91.01
	logistic	**96.93**	96.58	95.47	96.73	93.33
	bayesnet	96.05	96.72	95.61	96.43	92.71
	adaboostm1	95.57	97.34	96.39	96.59	93.01
	randomforest	95.19	96.10	94.78	95.71	91.24
	reptree	95.38	97.32	96.36	96.49	92.83
Encoded	j48	96.48	97.27	96.33	96.93	**93.73**
	ibk	96.48	97.27	96.33	96.93	**93.73**
	logistic	96.03	97.04	96.01	96.61	93.06
	bayesnet	96.07	97.45	96.56	96.86	93.59
	adaboostm1	96.03	97.53	96.66	96.89	**93.64**
	randomforest	96.48	97.27	96.33	96.93	**93.73**
	reptree	96.48	97.27	96.33	96.93	**93.73**
Both	j48	95.98	97.19	96.21	96.68	93.20
	logistic	96.67	96.91	95.87	96.81	93.48
	bayesnet	96.05	97.53	96.65	96.90	**93.65**
	adaboostm1	95.57	97.34	96.39	96.59	93.01
	randomforest	95.15	96.05	94.71	95.66	91.14
	reptree	95.32	97.28	96.31	96.45	92.73
AFDB	**replication**	96.01	97.51	96.62	96.87	93.59
AFDB	**zhou**	97.37	98.44	97.89	97.99	NA

'NA' indicates not applicable because there the metric is not offered by the reference [20].

the case of the explicit dataset (explicit and custom entropy with the oracle), the overall performance is lower than in the case of the replication. But a remarkable result is obtained in the case of the `logistic` algorithm in term of SE around 0.92. The MCC though of the `logistic` is quite low compared to the replica. All in all, expected result, since the threshold was not used to discriminate against the Shannon entropy.

As for the encoded case, an increase in performance was hypothesised, which proved to be true. In fact, five out of seven algorithms are able to obtain an increase in MCC (+0.14) compared to the replica. It is important to underline that `j48`, `ibk`, `random forest` and `reptree` have the same performance and `logistic` compared to before is the algorithm with the worst performance.

Instead for the last case where both entropias were used, a performance to report is certainly that of the algorithm `bayesnet` with an increment in terms of MCC equal to (+0.06). In any case, the experiment in question is placed in the middle between the two previous ones.

Experimentation with the encoded dataset can be considered successful.

If we consider that it has been applied on a basis that does not reach Zhou, we can assume that applying it on the latter, we should achieve improvements.

Fast Fourier Transform and AR Coefficients

The explicit and encoded datasets of the previous experimentation were used as a base, on which signal analysis was done excluding records `03665` and `00735` (no `.hea` file). Each interval $[R_i, R_{i+1}]$ was divided into two blocks. For every block Fast Fourier Transform was applied obtaining 16 values and 4 Autoregressive model's coefficients estimated through Yule–Walker equations.

Table 2.5: Machine learning algorithms applied on dataset with Fast Fourier Transform and AR coefficients, compared with the replication of Zhou and Zhou, et al [20] itself.

Dataset	**Algorithm**	**Results**				
		SE(%)	**SP**(%)	**PPV**(%)	**ACC**(%)	**MCC**(%)
Explicit FFT	j48	84.38	95.48	93.88	90.47	80.93
	logistic	**97.00**	95.73	94.92	96.30	92.56
	adaboostm1	95.49	97.06	96.39	96.35	92.63
	randomforest	88.78	96.82	95.83	93.19	86.36
	reptree	84.82	95.06	93.39	90.44	80.82
Encoded FFT	j48	89.01	93.36	91.68	91.40	82.61
	logistic	96.27	96.61	95.89	96.46	92.85
	adaboostm1	95.97	97.26	96.65	96.68	**93.29**
	randomforest	92.44	94.95	93.78	93.82	87.51
	reptree	90.85	93.40	91.89	92.25	84.34
Explicit FFT with AR	j48	86.74	94.96	93.40	91.25	82.40
	logistic	96.85	95.66	94.83	96.19	92.35
	adaboostm1	95.49	97.06	96.39	96.35	92.63
	randomforest	92.30	97.18	96.42	94.98	89.89
	reptree	89.86	95.23	93.94	92.81	85.49
AFDB[1]	**replication**	95.94	97.23	96.61	96.65	93.23
AFDB	**zhou**	97.37	98.44	97.89	97.99	NA

[1] Records `00735` and `03665` excluded.
'NA' indicates not applicable because there the metric is not offered by the reference [20].

Table 2.5 shows results of the process. First clarification to do is that some algorithms were removed for performance issues.

In the case of explicit FFT dataset, 16 values were added to the previous dataset with explicit entropy and custom entropy. A several drop in overall performance, compared to the explicit dataset, occurred for most of the algorithms except for `logistic` and `adaboostm1` where it was just slight. The `logistic` tended to find a great amount of true positives and in this case it reached its best performance in terms of SE that was equal to 97.00%, facilitated by a dataset richer in information.

But as for encoded FFT dataset, the state of the art is outdated again but the increment in terms of MCC is just a marginal (+0.06) with the `adaboostm1`. And if we consider the additional layer of complexity and an increment that is smaller than the previous one of (+0.14) achieved by four algorithms, then we can say that is not successfull at all.

In the last case, coefficients of autoregressive model were used in addition to FFT over the explicit dataset. A general increment in the worst performing algorithms was achieved, but the `logistic` decreased of (−0.21) in terms of MCC and the `adaboostm1` remained completely unchanged.

Thus because of the inconsistency in the statistical margins and the increase in complexity compared to the basic version of the datasets, this path can be considered as a failure.

Transient values

Table 2.6: Machine learning algorithms applied on dataset with explicit and encoded entropy, compared with the replication of Zhou and Zhou, et al [20] itself.

Dataset	**Algorithm**	**Results**				
		SE(%)	**SP**(%)	**PPV**(%)	**ACC**(%)	**MCC**(%)
Explicit	j48	96.08	97.19	96.23	96.72	93.29
	ibk	94.99	96.14	94.83	95.65	91.11
	logistic	96.97	96.60	95.50	96.76	93.40
	bayesnet	96.12	96.73	95.64	96.47	92.79
	adaboostm1	95.65	97.33	96.39	96.61	93.07
	randomforest	95.23	96.16	94.87	95.77	91.35
	reptree	95.44	97.29	96.33	96.50	92.84
Encoded	j48	96.56	97.26	96.34	96.96	93.79
	ibk	96.56	97.26	96.34	96.96	93.79
	logistic	96.11	97.53	96.66	96.92	93.71
	bayesnet	96.13	97.45	96.57	96.89	93.64
	adaboostm1	96.11	97.53	96.66	96.92	93.71
	randomforest	96.56	97.26	96.34	96.96	93.79
	reptree	96.56	97.26	96.34	96.96	93.79
AFDB	**replication**	96.01	97.51	96.62	96.87	93.59
AFDB	**zhou**	97.37	98.44	97.89	97.99	NA

'NA' indicates not applicable because there the metric is not offered by the reference [20].

2.5 Further developments

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