electronics

Correction

Correction: Billeci, L.; et al. Automatic Detection of Atrial Fibrillation and Other Arrhythmias in ECG Recordings Acquired by a Smartphone Device. *Electronics* 2018, *7*, 199

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The authors wish to make the following corrections to our published paper [1].

The scores, shown in the last column of Table 3, refer to the follow-up phase of the CinC 2017 challenge, and may have been obtained with methods and features different from those shown in columns 3 and 2, which refer to Challenge phase and are described in the cited articles published on CinC 2017 Proceedings. In particular: The score $F_1 = 0.848$ of Teijero et al. was obtained not using 79 features, as shown in the table, but 42 features and the score $F_1 = 0.8278$ of Plesinger et al. was obtained using not 277, but 60 features. These data are extracted from their recently published articles on *Physiological Measurements*.

Furthermore, it must be specified that the applied classification method of Teijero et al. is not a Recurrent Neural Network, but an ensemble of a Gradient Boosting classifier and a Recurrent Neural Network.

As for the other two items in the table (Kropf et al., Datta et al.), we have no information on any changes in the follow-up respect to the challenge phase.

In summary, on page 9, Table 3 should be changed from:

Table 3. Comparison of the results of the proposed methods with that of the other algorithms proposed for the Physionet Challenge 2017 obtained in the follow-up phase.

Reference	Number of Features	Classification Method	Overall Performance
Teijeiro et al. [40]	79	Recurrent Neural Network	$F_1 = 0.848$
Kropf et al. [41]	380	Random Forest	$F_1 = 0.832$
Billeci et al. (proposed method)	30	Least Square-Support Vector Machine	$F_1 = 0.830$
Datta et al. [42]	150	Multi-layer Cascaded Binary	$F_1 = 0.8294$
Plesinger [43]	277	Neural Network + Bagged Tree Ensemble	$F_1 = 0.8278$

Notably, our performance on the hidden test set of the official challenge phase was: $F_{1n} = 0.911$; $F_{1a} = 0.784$; $F_{1o} = 0.739$ and $F_1 = 0.812$ (obtaining the 12th place in the official ranking list). The increase in performance achieved from the official phase to the follow-up phase suggests the importance of having reliable annotations for the algorithm training and evaluation.

to the following correct version:

Table 3. Comparison of the results of the proposed methods with that of the other algorithms proposed for the Physionet Challenge 2017 obtained in the follow-up phase.

Reference	Number of Features	Classification Method	Overall Performance
Teijeiro et al. [40]	42	Gradient Boosting classifier and Recurrent Neural Network	$F_1 = 0.848$
Kropf et al. [41]	380	Random Forest	$F_1 = 0.832$
Billeci et al. (proposed method)	30	Least Square-Support Vector Machine	$F_1 = 0.830$
Datta et al. [42]	150	Multi-layer Cascaded Binary	$F_1 = 0.8294$
Plesinger [43]	60	Neural Network + Bagged Tree Ensemble	$F_1 = 0.8278$

Notably, our performance on the hidden test set of the official challenge phase was: $F_{1n} = 0.911$; $F_{1a} = 0.784$; $F_{1o} = 0.739$ and $F_1 = 0.812$ (obtaining the 12th place in the official ranking list). The increase in performance achieved from the official phase to the follow-up phase suggests the importance of having reliable annotations for the algorithm training and evaluation.

On page 14, reference 40 and reference 43 should be changed from:

40. Teijeiro, T.; García, C.A.; Castro, D.; Félix, P. Arrhythmia Classification from the Abductive Interpretation of Short Single-Lead ECG Records. *Comput. Cardiol.* **2017**, *44*, doi:10.22489/CinC.2017.166-054.

43. Plesinger, F.; Nejedly, P.; Viscor, I.; Halamek, J.; Jurak, P. Automatic Detection of Atrial Fibrillation and Other Arrhythmias in Holter ECG Recordings using PQRS Morphology and Rhythm Features. *Comput. Cardiol.* **2017**, *44*, doi:10.22489/CinC.2017.364-057.

to the following correct versions:

40. Teijeiro, T.; García, C.A.; Castro, D.; Félix, P. Abductive reasoning as the basis to reproduce expert criteria in ECG Atrial Fibrillation identification. *Physiol. Meas.* **2018**, *39*, 084006, doi:10.1088/1361-6579/aad7e4.

43. Plesinger, F.; Nejedly, P.; Viscor, I.; Halamek, J.; Jurak, P. Parallel use of a convolutional neural network and bagged tree ensemble for the classification of Holter ECG. *Physiol. Meas.* **2018**, *39*, 094002, doi:10.1088/1361-6579/aad9ee.

The authors would like to apologize for any inconvenience caused to the readers by these changes. The changes do not affect the scientific results. The manuscript will be updated and the original will remain online on the article webpage, with a reference to this Correction.

Reference

1. Billeci, L.; Costi, M.; Lombardi, D.; Chiarugi, F.; Varanini, M. Automatic Detection of Atrial Fibrillation and Other Arrhythmias in ECG Recordings Acquired by a Smartphone Device. *Electronics* **2018**, *7*, 199. [CrossRef]