Atrial Fibrillation Risk Prediction in Pacemaker Patients Using Artificial Intelligence Methods

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Abstract

This research covers various methods to predict Atrial Fibrillation (AF) risk in pacemaker patients, including creating a specialized dataset for AF prediction in Senegal, comparing data augmentation techniques, setting up an effective MLOps workflow, and building an AF prediction model using transfer learning. Challenges include limited data affecting model performance and class imbalance causing prediction biases. In Senegal, scarce medical resources hinder extensive ECG data collection. Future steps include collaborative data collection, incorporating clinical variables, and implementing MLOps best practices for model management and data governance.

Keywords : Atrial fibrillation prediction, Conditional data generation, Data augmentation, Transfer learning, Electrocardiograms, Senegal, MLOps

Background

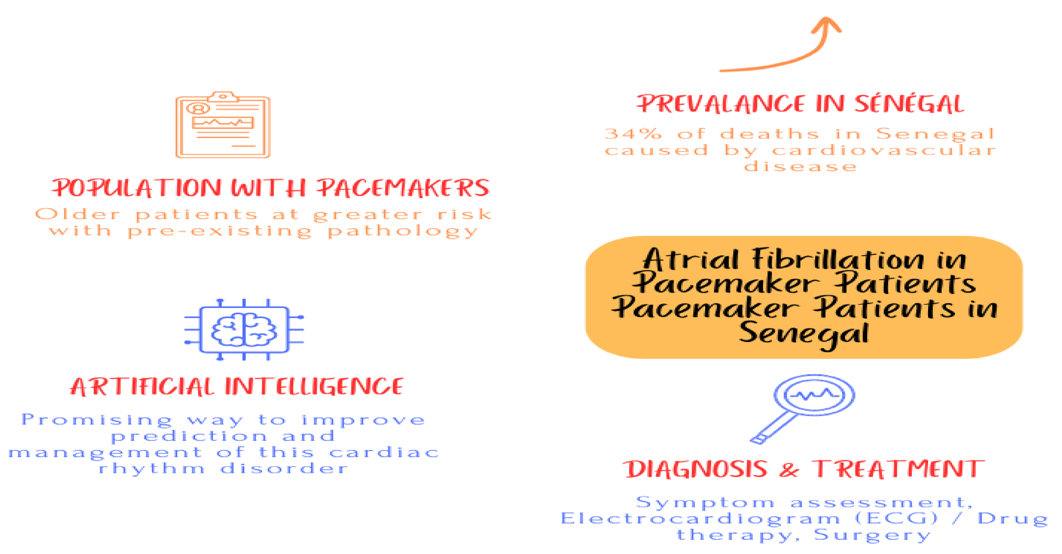


Figure 1. Background

Issues

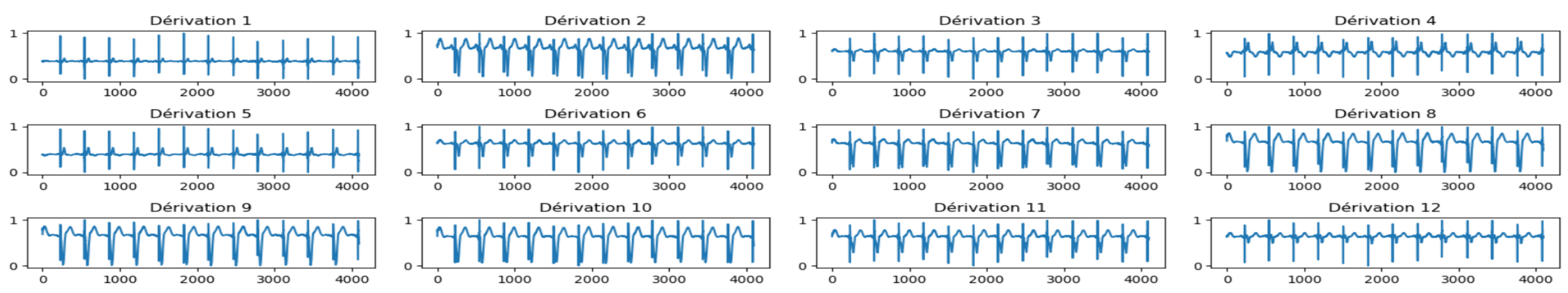
- Impact of pacemakers on ECG patterns
- Challenges due to lack of digital data
- Adapting artificial intelligence models to patients' cultural and ethnic differences patients
- Evaluation of the adoption of artificial intelligence models by healthcare professionals in Senegal

Atrial Fibrillation (AF)

Atrial fibrillation (AF) risk factors include age, underlying heart disease, etc. Symptoms include palpitations, tiredness, shortness of breath and dizziness. Diagnosis is based on the patient's medical history, pacemaker monitoring and electrocardiograms (ECG).

Electrocardiogram (ECG

ECG comprises 12 leads, 6 in the frontal plane (I, II and III, aVR, aVL and aVF) with electrodes placed on the arms and legs, and 6 in the horizontal or precordial plane (V1, V2, V3, V4, V5, V6) at specific locations on the chest.



ECG Preprocessing

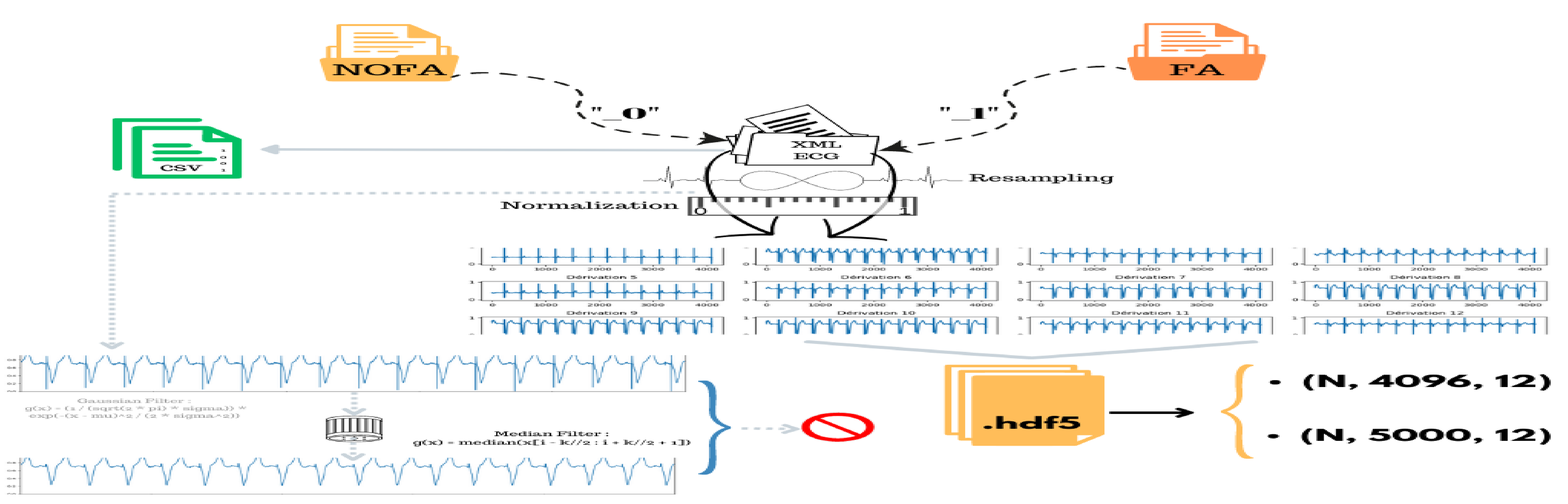


Figure 2. Preprocessing Process

ECG Data Generation : Results and Discussions

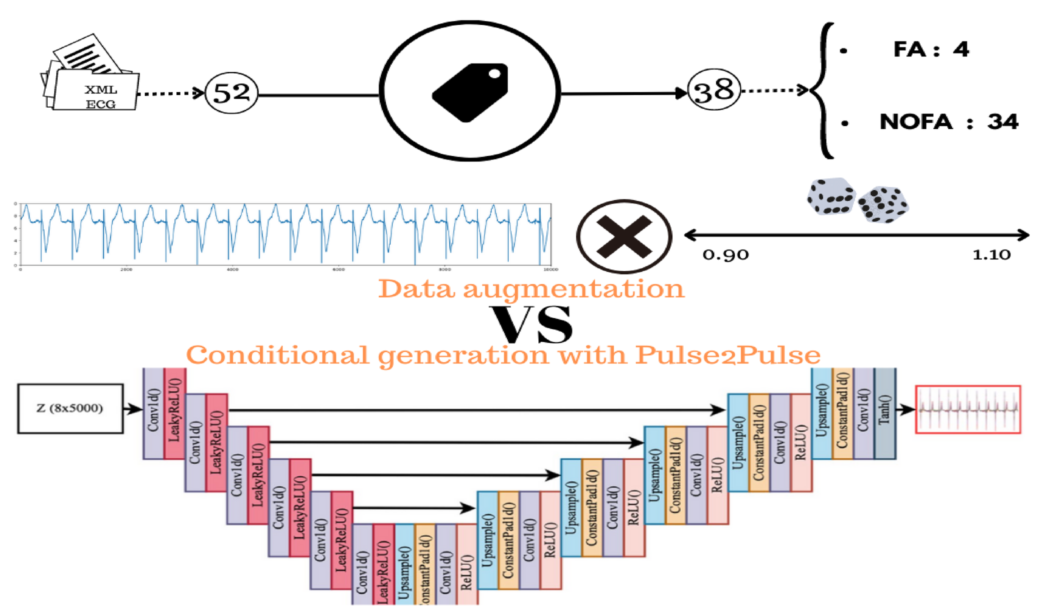


Figure 3. Comparison of two data generation techniques [1]

Conditional Generation with DeepFake vs Data Augmentation:

MMD measures the distribution dissimilarity(DeepFake MMD value > Data Augmentation MMD value)

Table 1. Patients without FA - MMD Value [1]

Methods	MMD Value
DeepFake vs Real ECG	0.008404
Augmentation vs Real ECG	0.010263

Table 2. Patients with FA - MMD Value

Methods	MMD Value
DeepFake vs Real ECG	0.000497
Augmentation vs Real ECG	0.000772

Evaluations of conditional generation in relation to Minas Gerais baseline :

Table 3. Patients without FA - Pacemakers Patients [1]

Metrics	FD	MMD	PRD	RMSE
Minimum	16.18	0.008	3.32	0.21
Maximum	44.34	0.008	6.41	0.42
Mean	31.19	0.008	5.21	0.32

Table 4. Patients without FA - Minas Gerais [1]

Metrics	FD	MMD	PRD	RMSE
Minimum	9.69	0.002	3.13	0.14
Maximum	45.51	0.002	9.61	0.38
Mean	17.66	0.002	4.90	0.23

Table 5. Patients with FA - Pacemakers Patients [1]

Métrics	FD	MMD	PRD	RMSE
Minimum	23.68	0.0004	4.36	0.24
Maximum	40.09	0.0004	6.11	0.37
Mean	31.64	0.0004	5.34	0.31

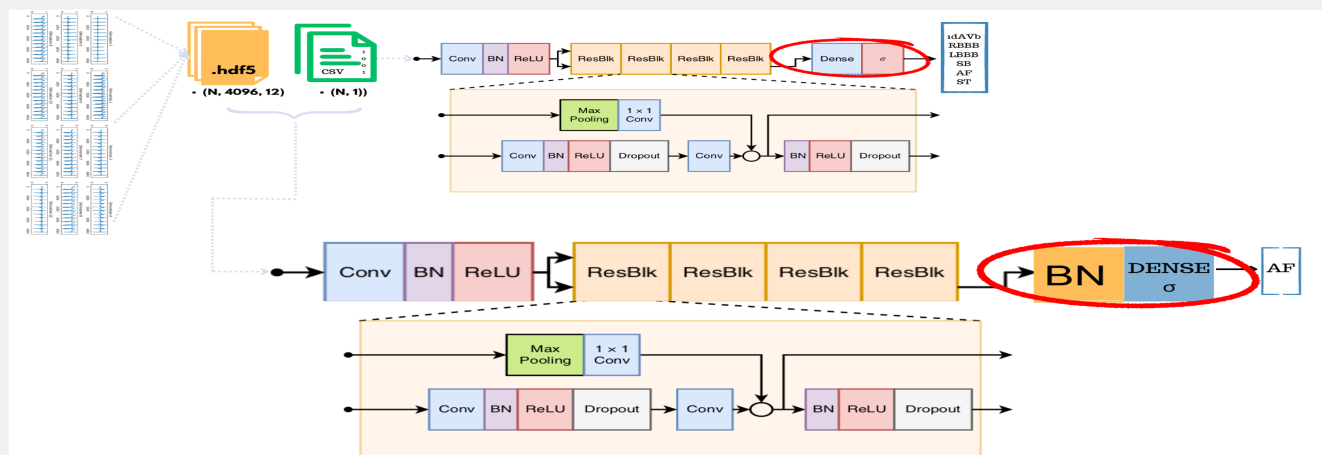
Table 6. Patients with FA - Minas Gerais [1]

Metrics	FD	MMD	PRD	RMSE
Minimum	12.92	0.000047	4.46	0.20
Maximum	23.21	0.000047	6.64	0.27
Mean	15.97	0.000047	5.59	0.24

Average values of conditional generation metrics slightly different from those used as a reference base (Minas Gerais database).

Atrial Fibrillation Prognosis : Results and Discussions

Model Architecture based on a DNN architecture [2] :



- 1st Experience : with only 38 real samples and 100 generated samples from Deepfake for each class (238) :

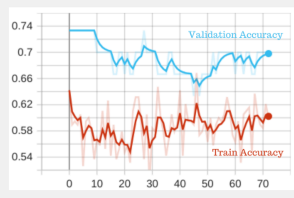


Figure 4. Accuracy

Table 7. Evaluation metrics

Class	precision	recall	f1-score
Patients without FA	0.80	0.67	0.73
Patients with FA	0.60	0.75	0.67


Figure 5. Loss

The results show encouraging performance of transfer learning on a limited dataset, with moderate precision and recall scores. - 2nd Experience : with 238 samples from Minas Gerais telehealth network :

Table 8. Evaluation metrics

Class	precision	recall	f1-score
Patients without FA	0.8	0.0	0.89
Patients with FA	0.00	0.00	0.00

With the same protocol applied (hyperparameters and model structure), and the same data size, this time from the Minas Gerais telehealth network database, we obtained the same poor results. - 3rd Experience : with 1024 samples from Minas Gerais telehealth network :

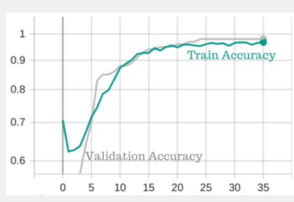


Figure 6. Accuracy

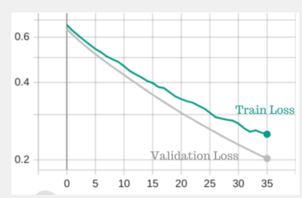
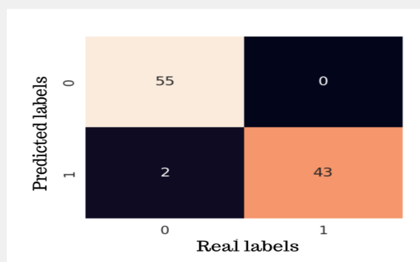


Figure 7. Loss

Table 9. Evaluation metrics

Classes	precision	recall	f1-score
Patients without FA	0.96	1.00	0.98
Patients with FA	1.00	0.96	0.98



- The performance of the model on a large dataset was better than previous experiences, with an AUC score of 0.97 and improved precision and recall scores.

Conclusion

Some insights of our work might be :

- Creation of a specific dataset for AF prediction in Senegal.
- Rigorous comparative approach for validation of the best data augmentation method.
- Demonstration of the effectiveness of transfer learning for small-sized datasets.
- Lack of data and class imbalance limited model performance and increased predictions biases.
- Not evaluating subgroups can lead to inadequate prediction analysis and outcome disparities.
- Efforts in ECG and clinical data collection and from healthcare centers must be made
- And Implementation of good MLOps practices for model management and data governance.

References

[1] C. A. Ngom, M. Ba, S. A. Sarr, I. Diop, A. Bah and M. Diao, "Data Generation Strategies for Enhanced Atrial Fibrillation Prediction in Pacemaker Patients," 2023 First International Conference on the Advancements of Artificial Intelligence in African Context (AAIAC), Arusha, Tanzania, United Republic of, 2023, pp. 1-10, doi: 10.1109/AAIAC60008.2023.10465446.

[2] C. A. Ngom, M. Ba, S. A. Sarr, I. Diop, A. Bah and M. Diao, "Deep Learning Approaches for Predicting Atrial Fibrillation Risk in Pacemaker Patients" 2024, IEEE Open Journal of the Computer Society, Under Review