Improving biomedical diagnosis through light–based technologies and machine learning

Doctoral Networks (MSCA-DN)

HORIZON - MSCA - 2022 - DN

Grant Agreement Nº 101119924

WP2: Cardiovascular diseases

Deliverable D2.3

ML model for heart dynamics

Khizar Abbas, MPI

Prof. Stefan Luther

Date: 28 02 2026

Type: OTHER

Dissemination Level: PU-Public

DELIVERABLE IDENTIFICATION SHEET

Document version	Date	Editor	Change(s)
1	28-02-2026	Khizar Abbas	First version

Funded by the European Union

Grant Agreement Nº	101119924
Call Identifier	HORIZON - MSCA - 2022 – DN
Acronym	BE-LIGHT
Full title	Improving biomedical diagnosis through light-based technologies and machine learning
Project URL	http://www.belightproject.eu/

Deliverable Nº and Name	Deliverable D2.3 – ML Model for Heart Dynamics
Work Package	WP2: Cardiovascular diseases
Lead Beneficiary	MPI
Type	Other
Dissemination Level	PU-Public
Due date	Month 29 (February 2026)

Authors (Partner)	Khizar Abbas, MPI			
Responsible Author	Khizar		**Email**	Khizar1010@gmail.con
	Partner	UPC	**Phone**	4915750453590

Abstract (for dissemination)	This deliverable proposes a **real-time feedback control system** for regulating cardiac dynamics in optogenetic cell cultures. The system integrates optical imaging of cardiomyocyte monolayers, predictive machine learning models, and optogenetic stimulation to detect and suppress arrhythmic patterns. Due to ongoing data collection from cell cultures, the full implementation of the ML-based control code is not yet completed. The current deliverable describes the system architecture, control strategy, and experimental framework, with full code and validation pending additional datasets.
Keywords	Keywords: Cardiac arrhythmia, machine learning, spatio-temporal modeling, optogenetics, electrophysiology, reinforcement learning

Table of Contents

EXECUTIVE SUMMARY

Deliverable D2.3 reports the development of a machine learning framework designed to capture and control nonlinear spatio-temporal cardiac dynamics. The system combines convolutional neural networks (CNNs), recurrent neural networks (RNNs), and reinforcement learning (RL) for predictive modeling and potential control of arrhythmias.

Key outcomes include:

- Design of hybrid ML architecture for spatio-temporal modeling
- Definition of preprocessing and feature extraction pipelines
- Integration with electrophysiological and optical mapping datasets
- Simulation framework for in silico validation

Note: Full code implementation is pending due to incomplete experimental datasets. The framework and algorithms are ready to be applied once sufficient data has been collected.

INTRODUCTION

Cardiac arrhythmias arise from complex nonlinear interactions across spatial and temporal scales in cardiac tissue. Traditional mechanistic models are computationally intensive and require precise parameterization. ML approaches provide efficient approximations of high-dimensional dynamics while enabling predictive and control capabilities.

Deliverable D2.3 focuses on:

1. Modeling cardiac electrical propagation
2. Detecting arrhythmia precursors
3. Supporting data-driven control strategies

The deliverable also addresses partial implementation: while methods and architectures are defined, the complete ML code depends on acquiring additional data from experimental protocols (Langendorff-perfused hearts, optical mapping, and electrophysiological recordings).

1 DATA AND PREPROCESSING

1.1 Data Sources

The model design uses:

- datasets from HL1 experiments of cell culture.
- Multivariate electrophysiological time-series data
- Simulated cardiac tissue data
- Optogenetic stimulation response datasets

1.2 Preprocessing

The preprocessing pipeline includes:

- Motion artifact correction
- Temporal filtering
- Baseline normalization
- Spatial alignment
- Phase reconstruction
- Time-delay embedding

1.3 Feature Extraction

Planned features:

- Action potential duration (APD)
- Dominant frequency
- Phase singularity density
- Conduction velocity
- Spatial entropy
- Early warning signals

The feature extraction is designed but will be fully applied after complete dataset acquisition.

2 Machine Learning Model

Cardiac arrhythmias arise from abnormal spatio-temporal electrical propagation. While predictive ML models (like in D2.3) can forecast arrhythmogenic events, **real-time control** is necessary to suppress these events actively. Optogenetic cardiomyocytes provide precise, light-mediated control of electrical activity, making them ideal for **closed-loop feedback systems**.

The system combines sensing, prediction, and actuation in a **feedback loop**:

1. **Sensing**: Real-time optical mapping or voltage-sensitive fluorescent signals from optogenetic cardiac cells.
2. **Prediction**: ML model predicts potential arrhythmic events using current and historical data.
3. **Control/Actuation**: Controller determines optimal light stimulation pattern (intensity, duration, spatial location) to stabilize rhythm.
4. **Feedback**: Response of tissue is continuously monitored, and control actions are adjusted in real time.

Optical Mapping → ML Prediction → Controller → Optogenetic Stimulation → Cardiac Response → Feedback

3 Validation and Results

3.1 Predictive Performance

Metrics:RMSE,SSIM,ROC-AUC
Results: Pending full dataset. Preliminary testing confirms workflow feasibility.

3.2 Experimental Validation

- Implemented in optogenetic cardiomyocyte cultures
- Full validation to follow additional data acquisition

3.3 Generalization

- Framework designed to generalize across experimental and simulated datasets
- Domain adaptation planned to improve robustness

4 Summary

Deliverable D2.X presents a **feedback control system** for regulating cardiac dynamics in optogenetic cell cultures. The architecture, preprocessing, ML prediction, and control strategy are fully designed; full code implementation and experimental validation are pending additional datasets.

Future Work:

- Complete ML code implementation and training
- Integration with real-time optical mapping data
- Experimental validation in cell cultures
- Extension to tissue-level or ex vivo cardiac systems

REFERENCES

R. Majumder, V. Krinski, S. Luther – *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 2024

C. Richter, J. Christoph, S.E. Lehnart, S. Luther – *Optogenetics: Methods and Protocols*, Springer, 2016

L. Diaz-Maue, S. Luther – *Optogenetics and Optical Methods in Cardiac Research*, SPIE Proceedings, 2018

ANNEX

- Feedback control system architecture diagram
- Preprocessing pipeline diagram
- Hyperparameter configuration for ML model
- Ethical compliance statement
- Planned datasets and pending acquisition