Qumphy

Newsletter

July 9, 2026

What is QUMPHY About?

Need Photoplethysmography (PPG) signals are rich in information and easy to measure passively without any physical or mental limitations of the subject. As it is impossible for physicians to infer physiological parameters from the PPG signal by themselves, they need to rely on algorithms based on machine learning (ML) techniques for diagnosis. As of today, no regulations specifying how these ML algorithms have to be applied, how their performance has to be measured or how their associated uncertainties have to be specified exist.

Aim At the core of this project stands the development of measures to quantify the uncertainties associated with ML algorithms applied to medical problems, in particular the analysis and processing of PPG signals. To achieve this the following tasks will be addressed: (i) benchmark datasets will be generated using publicly available in vivo, and synthetic data (ii) different ML models and uncertainty quantification (UQ) methods will be used to analyse the processing of the PPG signals and specify the associated uncertainty and (iii) a good practice guide with accompanying software repository showcasing the used models, methods and benchmarks will be developed and made publicly available.

Objectives

The overall objective is to provide trustworthy machine-learning models for analysing photoplethysmography signals in a medical context, by developing methods for the quantification of uncertainty in supervised machine learning and deep-learning models applied to photoplethysmography signals and generating reference datasets to benchmark those models, supported by software being developed that will be publicly available for independent review of the models.

The specific objectives are:

1. To develop methods for quantifying the uncertainty for at least 3 existing classification and 3 existing regression supervised machine learning and/or deep-learning models using photoplethysmography (PPG) data, considering the effects of both aleatoric (data) uncertainty and epistemic (model) uncertainty on model predictions.

2. To generate at least 5 measurement problems and their corresponding 5 datasets, using real and/or synthetic photoplethysmography data, that can be used to benchmark accuracy and uncertainty of supervised machine learning and deep-learning models. In addition, to make those reference problems and datasets available to the medical device and digital health communities via an online repository.

3. To validate the uncertainties obtained for existing machine learning and deep-learning models of Objective 1 and to compare the accuracy and uncertainty of at least 3 classification and 3 regression machine learning

and/or deep-learning models in order to identify models and methods which have high accuracy and low uncertainty for a wide range of tasks.

4. To engage with the medical device, digital and health communities to (a) promote the use of the good practice guide and the accompanying software repository through conference contributions, peer-reviewed journal articles and stakeholder workshops, (b) support the adoption of the benchmarking problems and datasets by providing guidelines for their use, and (c) develop a framework for independently reviewing machine learning models proposed by industry to assist them in getting regulatory approval.

5. To facilitate the take up of the technology and measurement infrastructure developed in the project by the measurement supply chain (NMIs, DIs, medical device calibration services), standards developing organisations (IEC, ISO), and end users (clinical practitioners, digital experts within the health communities, manufacturers of medical and healthcare products).

The Consortium

The consortium brings together the leading European metrology institutes (NMIs and DIs) in the fields of Machine Learning, Uncertainty Quantification and Medical Imaging, and they are complemented by a number of leading research institutes and companies that bring their specific knowledge and experience. In total, 6 NMIs/DIs, 8 universities or research institutes and 2 companies are involved in the project.

Final Project Meeting

The QUMPHY consortium recently gathered for its final meeting, hosted at the National Physical Laboratory's (NPL) historic Bushy House, beautifully situated next to Bushy Park in Teddington, UK. The event was a wonderfully cordial affair, bringing many project partners together in person to reflect on the project's journey and map out the remaining tasks. It proved to be a highly pleasant and uniquely memorable experience for everyone involved, especially as it marked the final time the consortium members would meet in this exact constellation. Between productive sessions, attendees enjoyed delicious food and enriching, entertaining discussions, all while walking the same halls once occupied by King William IV and looking out over a park alive with rabbits, parrots, and deer. With all critical matters thoroughly discussed and final steps officially agreed upon, the path forward is perfectly clear as QUMPHY enters its successful final stage.

Uncertainty Validation

The consortium has officially submitted its highly anticipated Deliverable D3 report. The deliverable focuses on validating uncertainty quantification across existing machine learning and deep-learning models. Led by NPL, the comprehensive study evaluates and compares the accuracy and uncertainty of classification and regression models. Notably, the report introduces a robust benchmarking framework for PPG signal analysis, introducing a cutting-edge 1D Vision Transformer (ViT) classifier alongside established 1D variants of AlexNet and XResNet. By rigorously testing these models, the consortium aims to pinpoint the exact architectures that yield high accuracy paired with low uncertainty, a critical milestone for dependable, data-driven healthcare diagnostics.

You can find the complete report at: https://www.qumphy.ptb.de/downloads

Good Practice Guide

The QUMPHY project is proud to announce the official release of its Good Practice Guide (GPG) for quantifying uncertainties for machine-learning models applied to photoplethysmography (PPG) signals. Developed under the leadership of the National Physical Laboratory alongside 15 contributing European partners, this comprehensive guide serves as a crucial roadmap for reliable and understandable quantification of uncertainties associated to machine-learning methods when applied to PPG signals. It bridges the gap between complex artificial intelligence and reliable medical decision making by outlining state-of-the-art machine-learning architectures, including deep learning on raw signals, features and image representations, and pairing them with robust uncertainty quantification methods like deep ensembles and conformal prediction. By detailed mapping of evaluation metrics (such as ECE and ENCE), standardisation of clinical benchmark problems (ranging from blood pressure estimation to atrial fibrillation detection), and rigorous examinations of ethical aspects and potential model misuse, the GPG establishes a framework to ensure AI-driven applications are reasonable, precise and trustworthy. In tandem with the guide's release, the project has made its accompanying software repository fully open and publicly available, accelerating the translation of continuous PPG-sensing technologies into practice.

Give the good practice guide a quick look at:
https://www.qumphy.ptb.de/downloads

New Software Release

We are thrilled to announce the upcoming release of the first full version of our QUMPHY software version v1.0, which will be released shortly. Built with transparency and accessibility at its core, the repository features a completely open development history and comes with straightforward installation instructions to get you started quickly. The software provides a highly modularised framework for implementing machine-learning models and uncertainty quantification methods, complete with standard evaluation scripts to effortlessly reproduce our research results. Users can interact with the code through an intuitive graphical user interface (GUI) and via easily customisable configuration files. Adhering to strict software engineering and formatting standards, the repository boasts clean, heavily documented code. Comprehensive, multi-version documentation is also hosted online and is downloadable in PDF and EPUB formats for offline use. Finally, the repository serves as a central hub, providing direct links to all relevant publications and related QUMPHY project work.

Check out the software and its documentation:
gitlab.com/qumphy/qumphy-software
qumphy-software.rtfd.io

Publications

Peer Reviewed Articles

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That's All

Thank you for reading. If you want to stay up-to-date with the project, you can always visit our project website:

www.qumphy.ptb.de

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