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| **Contact:** | Stéphane GhozziRobert Koch InstituteGermany | Email: GhozziS@rki.de  |
| **Contact:** | Auss AbboodRobert Koch InstituteGermany | Email: AbboodA@rki.de  |

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| **Abstract:** | This document contains an outline of a topic description document (TDD) on Outbreak detection (TG-Outbreaks) |

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# Introduction

* Infectious disease outbreaks pose a major risk to public health
* Early detection of outbreaks can prompt fast interventions
* Case data are collected by diverse surveillance systems
* Artificial intelligence (AI) algorithms can be applied to detect aberrant case numbers based on these data collections
* AI algorithms have the potential to increase the timeliness and accuracy of outbreak detection

## Document Structure

This TDD will cover core topic-specific questions, including:

* Relevant definitions of the term and event of outbreaks for detection algorithms
* Label uncertainties (e.g. issue of unlabelled outbreak cases, no lab-confirmed outbreaks)
* Performance evaluation: relevant scores and metrics for benchmarking detection algorithms
* Test set(s) (undisclosed) to serve as a gold standard for benchmarking (based on different pathogens, time frames, demographic groups, and regional resolution)

## Topic Description

Infectious disease outbreaks pose a major risk to public health and are of global concern. Many established infectious diseases cause the death of millions of people every year and new infectious diseases are emerging. The risk and occurrence of infectious diseases is influenced by globalization, migration, and climate change. According to a World Health Organization (WHO) ranking, infectious diseases are ranked in the top 10 causes of death worldwide.

However, early detection of outbreaks can prompt fast interventions to limit spread of the disease or even prevent an outbreak altogether. Improved algorithms for outbreak detection can save lives, increase quality of life, and will benefit the overall health of the world population.

The aim of outbreak detection algorithms is to detect aberrant case numbers and conspicuous events within data streams, pointing to the emergence of infectious disease outbreaks, in a fast and automatic manner. To this, AI algorithms can increase the timeliness and accuracy of outbreak detection as well as improve the understanding of the warnings.

## Ethical Considerations

Relating to medical doctors having the Declaration of Geneva and the Nuremberg Code, analogue principles and quality standards need to be established for AI applications used in health enquiries.

* Best scientific practices need to be assured.
* Data protection: drawing references to an individual person has to be weight up.
	+ The integration of several and further data sources needs to assure that the personal identity is still protected.
	+ For the collection of labelled outbreak data, the levels of data aggregation need to be defined carefully.
* Balanced selection of test data: prevent discrimination of demographic groups, risk groups or even countries.

## Existing AI Solutions

There is a variety of published statistical approaches and machine learning methods ( (Unkel, Farrington, Garthwaite, Robertson, & Andrews, 2012) (Yuan, Boston-Fisher, Luo, Verma, & Buckeridge, 2019) (Allévius & Höhle, 2017) (Salmon, Schumacher, & Höhle, 2016)), which are used for the detection of outbreaks in given surveillance data.

At the Robert Koch Institute (RKI) we have applied both classical statistical methods as well as supervised learning methods to the problem of outbreak detection. The machine learning methods use outbreak labels, assigned from expert investigations. The main methods at hand are based on Hidden Markov Models and the improved Farrington method. We already see first improvements in the accuracy using machine learning (ML) approaches compared to classic statistical approaches (Zacher & Czogiel, 2019). E.g., when keeping the same sensitivity in outbreak detection, the false positives are considerably decreased. This reduces the number of alarms the experts have to assess.

For the future, since many of the previous approaches were time-series based, we expect further Hidden Markov Models and deep learning methods appropriate for sequential data such as Long Short Term Memory Networks (LSTM). However other methods, like multivariate Bayesian regression or all-purpose deep learning methods are conceivable.

## Existing work on benchmarking

Minimal benchmarking setup at RKI:

* Data: weekly reported infection cases and outbreaks for notifiable diseases in Germany
* Training of the algorithms on data of the past 5 years
* Testing on next week (prospective 1 week ahead: data available until last week)
* Scores calculated as functions of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN), such as sensitivity, specificity, precision, F1, …

# AI4H Topic Group

## Topic group structure

Topic Groups summarize uses cases of a certain health topic or problem and similar AI benchmarking requirements. However, inside a Topic Group (TG) different Subtopic Groups can be established to pursue different topic-specific specializations. TG-Outbreak will start without separate Subtopic Groups. However, it is possible that during the process subtopics will be introduced. Possible examples are:

* Outbreak detection for specific pathogens
* Different national outbreak detection methods for different nations based on different national reporting systems
* …

### Topic group participation

The topic group on outbreak detection algorithms currently includes members from the Robert Koch Institute (Federal Public Health Institute Germany), involving members from different groups within the institute

* Dr. Stéphane Ghozzi, Infectious disease epidemiology, Signale team (Robert Koch Institute, Unit 31)
* Auss Abbood, Infectious disease epidemiology, Signale team (Robert Koch Institute, Unit 31)
* Dr. Alexander Ullrich, Infectious disease epidemiology, Signale team (Robert Koch Institute, Unit 31)
* Dr. Benedikt Zacher, Infectious disease epidemiology, Nosocomial infections (Robert Koch Institute, Unit 37)

### Tools/process of TG cooperation

The TG will utilize ITU’s online collaboration tools to further its work (between FG meetings) which includes the cloud-based document storage and a meeting room for Zoom

### TG interaction with WG and FG

TBC

* Regular attendance of the Focus Groups meetings
* Regular attendance of the Working Groups (DAISM/DASH) to prevent redundancy in the development of AI tools

### Next meetings

The Focus Groups meets about every two months at changing locations. The upcoming meetings are:

* G: New Delhi, India; 11-15 November 2019
* H: Brasilia, Brazil; 21-24 January 2020
* I: Singapore, 16-20 March 2020
* J: Geneva, Switzerland, 4-8 May 2020 (TBC)

An up to date list can be found at the official [ITU FG AI4H website](https://www.itu.int/en/ITU-T/focusgroups/ai4h/Pages/default.aspx).

### Next steps

Future contributions expected for the TG will revolve around:

* Collection of labelled test data from different sources: Any data stream (case reporting systems, surveillance systems, etc.) directly linked to outbreak labels (expert/lab confirmed) is of high value. The ultimate goal is to cover outbreak data from different systems and countries.
* Provision of AI models, metrics and approaches for outbreak detection: Contributing to the development of a viable and accepted benchmarking framework
* Support on various aspects (data, methods, benchmarking, etc.) of this topic

# Method

TBC

## AI Input Data Structure

### Available Data

There are different potential data sources which can be used for outbreak detection and serve as input for the detection algorithms. Possible data input sources can be based on different surveillance systems, such as national mandatory reporting systems or syndromic surveillance systems. Further, input data sources, particularly accessible in near real-time, are online sources (Wikipedia, Google Trends, HealthTweets, Twitter) or data from symptom-assessment apps, healthcare providers, hotlines etc. Real time data sources have a high potential of significantly improving the outbreak detection particularly in accuracy and/or timeliness.

## AI Output Data Structure

TBC

## Test Data Labels

TBC

German SurvNet data

The labels ‘outbreak’ and ‘no outbreak’ are given by experts from actual outbreak investigations. Hence, the information that a case, which is labelled as an outbreak case, was actually part of an outbreak is highly trustworthy. However, it is not clear to which extent all true outbreak cases are labelled as an outbreak, since not all outbreaks are found or investigated by the local health agencies. An independent and external study on gastrointestinal diseases by the food safety agencies, e.g., confirmed that most of the larger outbreaks reported by them were also found in similar case numbers in the SurvNet dataset.

## Score and Metrics

TBC

Standard statistical metrics

* + sensitivity
	+ specificity
	+ precision
	+ F1

Outbreak detection specific metrics

* time-to-event characterizations (e.g. by time (days/weeks) passed, by number of occurred cases before detection)
* cost functions that interrelate false positives (false alarms) and false negatives (missed true alarms)
* cost functions for outbreak size detection and incorporated prediction uncertainty.

## Undisclosed Test Data Set Collection

German SurvNet data

In Germany, data from the German mandatory reporting system, collected since 2001 at the Robert Koch Institute (RKI), contains 8 million infectious disease cases and undergoes constant data quality checks by data engineers and review by epidemiologists. The data contains expert labels indicating which cases are related to specific disease outbreaks. All of the data is collected through the national reporting system via a web service and stored in a structured relational SQL database. The data arrives pseudonymized at the RKI from about 400 local health agencies. The data holds expert labels relating cases to specific disease outbreaks. For each case, information is given on the pathogen, demographics (age, sex), location (NUTS-3 level, county) and additional features such as hospitalization, fatality, affiliation with care facilities, and others. Some data is publicly available in an aggregated form, e.g., by counts for a specific disease, by week, and county. However, further details and single cases are not published. Most importantly, the expert outbreak labels have not been disclosed so far. In this document this set is referred to as German SurvNet data.

## Benchmarking Methodology and Architecture

### Benchmark Tasks

At present, outbreak detection algorithms are commonly parametrized and benchmarked on small sets of data or on simulations. These simulations are very simplistic representations of outbreaks, which capture only few aspects and often reduce benchmarking to the task of detecting elevated case count levels. By creating solutions for using real outbreak data from mandatory surveillance system, e.g., by “sending the algorithm to the place of the data”, algorithms could be benchmarked on the actual task of detecting real world outbreak events.

The topic of outbreak detection is of national and international concern. The development of most detection algorithms is, however, naturally executed on national level. Thereby, each country relies on individual national disease surveillance systems.

To create a standardised benchmarking for output detection algorithms, the topic group aims to address all aspects, which are relevant and shared across countries.

## Reporting Methodology

TBC

# Results

TBC

# Discussion

TBC

# Declaration of Conflict of Interest

TBC

In accordance with the ITU rules in this section working on this document should define his conflicts of interest that could potentially bias his point of view and the work on this document.

Robert Koch Institute (RKI)

One of the main responsibilities of the Robert Koch institute is to detect, prevent and control the spread of infectious diseases in the population. For this purpose, the RKI has established a traditional surveillance system, collecting lab confirmed cases for around 80 infectious diseases as well as several syndromic surveillance systems using data from, e.g., emergency departments and general practitioners. An automated outbreak detection system, utilizing this data, is in use for early detection of infectious disease outbreaks.

While assessing more and more external data sources to improve RKI’s mandate to support outbreak detection through a Syndromic Surveillance System, a strategy for a comprehensive exhaustion of the full information content is under development.

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