Machine learning for risk analysis of Urinary Tract Infection in people with dementia

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***Abstract*—The Urinary Tract Infections (UTIs) are one of the top reasons for unplanned hospital admissions in people with dementia, and if detected early, they can be timely treated. However, the standard UTI diagnosis tests, e.g. urine tests, will be only taken if the patients are clinically suspected of having UTIs. This causes a delay in diagnosis and treatment of the conditions and in some cases like people with dementia, the symptoms can be difficult to observe. Delay in detection and treatment of dementia is one of the key reasons for unplanned hospital admissions in people with dementia. To address these issues, we have developed a technology-assisted monitoring system, which is a Class 1 medical device. The system uses off-the-shelf and low-cost in-home sensory devices to monitor environmental and physiological data of people with dementia within their own homes. We have designed a machine learning model to use the data and provide risk analysis for UTIs. We use a semi-supervised learning model which leverage the environmental data, i.e. the data collected from the motion sensors, smart plugs and network-connected body temperature monitoring devices in the home, to detect patterns that can show the risk of UTIs. Since the data is noisy and partially labelled, we combine the neural networks and probabilistic neural networks to train an auto-encoder, which is to extract the general representation of the data. We will demonstrate our smart home management by videos/online, and show how our model can pick up the UTI related patterns.**

I. Introduction

Urinary tract infections (UTIs) symptoms occur more often in older adults, and around 150 million people are infected in a given year [2]. Nevertheless, the diagnoses of UTIs are often delayed due to the high prevalence of asymptomatic bacteriuria (AB) [3]. Furthermore, the current standard UTI diagnosis methods, such as urine and blood tests, are time-consuming and may cause unplanned hospital admissions. To provide early detection of UTIs, we have developed a digital platform to collect in-home sensory data. The system is deployed and tested in over 150 homes of people affected by dementia. All the participants have given their consent to participate in the study. The study protocol has been reviewed and approved by an Ethics Committee. The data is collected continuously from environmental monitoring sensors including Passive Infra-Red (PIR) sensors for detecting movement (deployed in kitchen, bedroom, bathroom, hallway and lounge), smart plugs (to monitor the use of kettle and microwave in the kitchen), door switch sensors (entrance, backdoor and fridge door). The participants have also been given network-enabled vital sign monitoring sensors to collect daily blood pressure, heart rate, body temperate, weight and hydration data. We have also deployed a smart bed mat to monitor sleeping patterns. The data is communicated via a secure network to a digital platform that we have designed in our study.

The continuous in-home observations and measurements data collected by network-enabled sensory devices are increasingly used to develop remote monitoring and risk assessment applications in healthcare. Some of the key challenges in processing and interpreting this type of data is dynamicity, quality variations and access to sufficient training samples. Partially labelled data and imbalance in the training samples limit the generalisation of the learning models in these applications. The models can also show lower performance in learning sporadic events. Creating a robust model that can continuously learn that can work with imbalanced data, learn to detect sporadic events and adapt to the changes in data (e.g. seasonal effects and environmental changes in the data) can significantly improve the performance of remote healthcare monitoring applications.

The existing works in this area focus on developing supervised or unsupervised models for activity recognition [6], pattern change detection [4] and adverse health risk analysis [1] based on environmental and vital sign data. Continual learning and handling the imbalance and generalisability issues are, however, among the key open challenges in this area. Semi-supervised models have the advantage of learning non-linear correlations in the data and extracted latent features from the unlabeled data. In this work, we use an adaptive model to train a classifier for UTI risk detection. Some of the symptoms of UTI can include increase body temperature, increase in bathroom visits and changes to activity and sleep patterns. Processing the environmental monitoring and vital sign data and using a small set of training samples, we have designed a model that can alert the clinicians when a risk of UTI is detected. The clinicians respond to the alerts generated by the algorithm and shown on the digital platform. The clinical team verify the alerts by contacting patients or their carers. This leads to early interventions and avoiding unplanned hospital admissions in people with dementia.

In this demonstration, we introduce the workflow including data collection and UTI risk analysis process in our digital

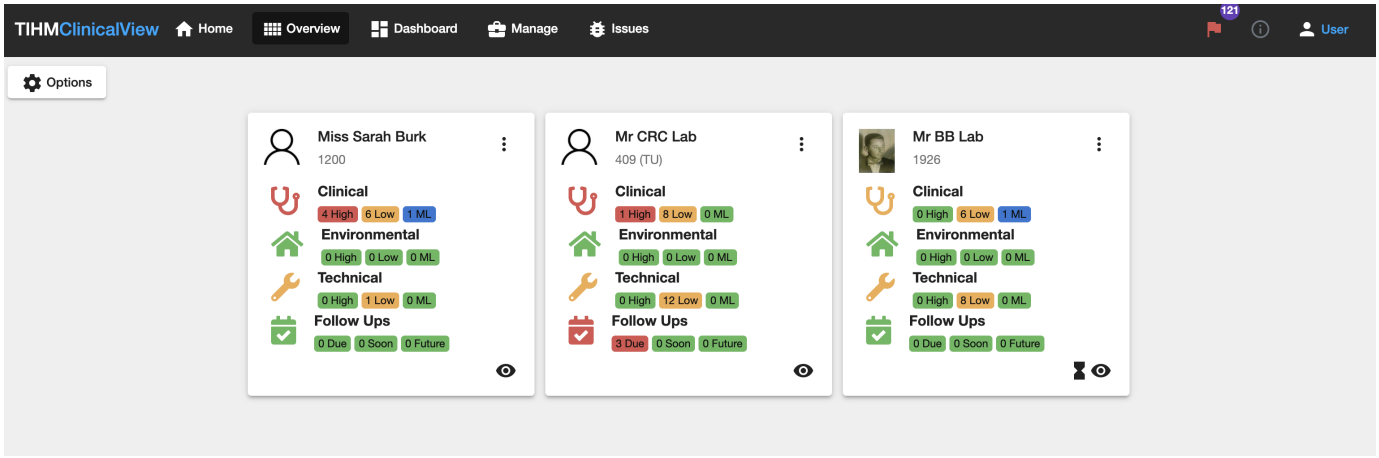

Fig. 1: Overview of the developed digital platform

platform.

II. Data Collection and Digital Platform

https://tihm-iot-dev.ee.surrey.ac.uk. The username and password for the demo are: demo@tihm.co.uk and ICPR2020_demo (please type the password, direct copy and paste from PDF may change the characters in the password).

The link above is our testing site and provide an overview of our digital platform, shown in Figure 1. Due to the privacy, the data shown in this demo is only collected from our living lab. We also show how the movement data in our living lab is collected by the sensory devices and communicated to our digital platform. Furthermore, the audience can also interact with the system and see the data collection process. An overview of the whole process is also available at https://github.com/UKDRI/CML-UKDRI. A user experience video of the UTI algorithm is available at: https://www.youtube.com/watch?v=JWekOaBkNXg

III. UTI Analysis

To analys the risk of UTI, we have developed a semi-supervised learning model using an auto-encoder and a probabilistic neural network (PNN) [5]. Different from existing semi-supervised learning approaches, we train an auto-encoder with the PNN simultaneously to increase the margin between positive and negative samples. Using the PNN model, we estimate the density of the samples. The encoder learns the mapping the labelled samples and unlabelled sample into similar distributions.

The analysis is performed based on a large set of unlabelled data representing 3864 days (for 110 participants) and a smaller set of labelled data collected over 60 days (for 18 participants). The labelled data contains 36 days defined as non-UTI and 24 days labelled as UTI. For each UTI case in a patient, we have selected the day that UTI was diagnosed along with three consecutive days (as the UTI symptoms could lasts for a few days). Since the sensors that are used to collect the environmental observation data may trigger multiple times

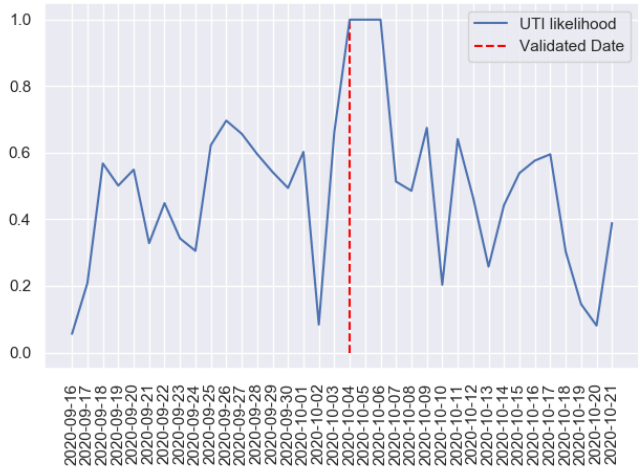

Fig. 2: UTI likelihood changes for a patient over several days

a day, we aggregate the values of each sensor within one hour to pre-process the data. Each data point is a 24*8 matrix.

The key results are shown in Table I. All the methods use the same auto-encoder (AE), which contains 6 fully-connected layers and with the Adadelta optimiser [7]. Each layer contains 256 neurons function, except the latent layer, which contains 100 neurons. The output of the latent layer is fed to the classifier. The activation function is hidden layers is ReLU; a sigmoid function is used in the last layer of the auto-encoder.

The model can also produce the likelihood of the UTIs, shown in Figure 2

	Evaluation			
	Precision	Recall	F1-Score	Accuracy
DE + LR	0.79	0.75	0.72	0.80
DE + GNB	0.72	0.63	0.62	0.67
DE + PNN (proposed)	0.83	0.82	0.81	0.83

TABLE I: A comparison of the conventional semi-supervised model with the proposed model

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