Detecting Loneliness in People Using Technology

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Abstract

Loneliness has a negative effect on both physical and mental health, which increases the risk of both morbidity, including heart conditions, and death. Poor social bonds have been linked to a 29% rise in coronary heart disease and a 32% rise in strokes in a study that looked at thousands of people.[2] Loneliness can have a serious impact on the brain, and it can also weaken the body's immune system, which can cause many health problems. Loneliness can reduce a person's life expectancy by fifteen years, which is equivalent to being overweight or smoking 15 cigarettes per day.[9] That's why early detection of chronic loneliness is very important to avoid its long-term health problems.

Keywords: loneliness, passive sensing, detection, social isolation.

The most terrible poverty is loneliness and the feeling of being unloved.

— Mother Teresea

Introduction

Humans are social beings, so having a healthy and meaningful social relationship with other humans is essential for survival and growth.[1] Loneliness is a subjective state where the desired level of closeness and affection with significant others, close friends or family is not met.[4] Loneliness is a common experience; up to 80% of those under the age of 18 and 40% of adults over the age of 65 report feeling lonely at least occasionally, with levels of loneliness gradually decreasing through the middle adult years and then increasing in older age (i.e. 70 years).[2]

Why is loneliness detection important?

Loneliness has a negative effect on both physical and mental health, which increases the risk of both morbidity, including heart conditions, and death. Mental health is a prerequisite for physical health and is strongly interconnected with other development factors such as poverty, employment and economic growth, and peace and justice.[9] Although feeling lonely is not a mental health issue in and of itself, the two are strongly linked. Loneliness can cause a number of mental health issues, especially if it persists for an extended period of time. Poor social bonds have also been linked to a 29% rise in coronary heart disease and a 32% rise in strokes in a study that looked at thousands of people.[9] Loneliness can have a serious impact on the brain, and it can also weaken the body's immune system, which can cause many health problems. Loneliness can reduce a person's life expectancy by fifteen years, which is equivalent to being overweight or smoking 15 cigarettes per day.[5] That is the reason why early detection of chronic loneliness is very important to avoid its long-term health problems. In the context of our project, early detection refers to identifying a person's behaviours through passive sensing (the collection of data through smartphone and fitness band sensors without the user's active engagement) that are associated with loneliness or can cause loneliness in the future. Early recognition of loneliness by the person may help them to put strategies in place that will prevent chronic loneliness, and provide opportunity for early intervention by support services.

How can technology be used in loneliness detection?

People's daily lives have changed a lot over the past decades because of technology. Smartphones have become an integral part of our everyday lives, and in addition to communication, we have access to a huge range of applications that can greatly ease our lives. A smartphone can serve as a portable camera, navigator, fitness tracker, and personal assistant.[3] As modern smartphones are equipped with a variety of potent sensors, they have become powerful monitoring devices. As a result of the stigma associated with loneliness and other mental health conditions, most individuals avoid visiting clinics. Passive sensing and machine learning have created new avenues for the early detection of loneliness. There is a variety of applications for this technology that are available to end users. Different smartphone and smartwatch manufacturers, such as Apple and Samsung, already offer core fitness applications for mobile and watch. They are collecting numerous health-related data for their fitness applications via various sensors. In the future, they may be able to incorporate loneliness and other mental health-related insights and detection into their mobile and watch applications.

We can use smartphone sensors to track the daily activities of users. For instance, we can obtain location data on a periodic basis to determine the mobility patterns and locations visited by users. Similarly, we can use call and SMS logs to determine the number and duration of users' daily communications. Using these behavioural patterns, we can assess the health and well-being of users. Fitness trackers are another promising device for collecting data on the health of users. In addition to behavioural patterns, modern fitness trackers can measure heart rate, number of steps, detect sleep patterns, and other health-related data that can be used to determine users' health and well-being. Recently, this approach has produced highly encouraging results for detecting loneliness in individuals.[7] Many studies have used passive sensing in order to identify behavioural indicators and digital biomarkers associated with loneliness.[11,12] We have used machine learning in order to train models and identify loneliness in individuals.

What is machine learning?

Machine learning (ML) is a computing method that uses data and algorithms to explore patterns within the data and predict certain outcomes based on the data, such as depression and wellbeing scores. Many of the biggest companies, like Facebook, Google, and Twitter, utilize ML extensively.

Each ML model has been taught to recognize specific types of patterns in data. Researchers train a model on a collection of data by providing it with an algorithm that can be used to train on different scenarios and then the trained model can predict outcomes for future unseen data. For instance, suppose one wishes to develop an application capable of identifying an apple among different fruit images. A model can be trained by feeding it with photographs of different fruits including apples that are each labelled with apple or other fruit, and then one can use that model to create an application that can identify images of apples. We are using supervised machine learning for detecting loneliness in which an algorithm is trained on input data that has been labelled for a particular output (lonely or not lonely). In this way, the model is fed with labelled data in the training phase, which instructs the model on what output is related to each specific input value. The trained model is then presented with test data: This is data that has been labelled, but the labels have not been revealed to the model before. The aim of the testing data is to measure how accurately the model will perform with unseen data. This procedure is shown graphically in Figure 1. ML is utilized in our work because, once trained, a system can work on its own and continuously monitor individuals for loneliness, alerting them, their family, or friends in the event of loneliness detection. Consequently, the ML-based loneliness detection system can be utilized by users themselves or their relatives/friends to monitor loved ones. Psychiatrists can also use these technology-based detection systems for continuous monitoring of their patients, which can assist them in diagnosing the problem and then administering a more effective treatment.

Centralised vs. Federated Machine Learning

Traditionally, machine learning has been implemented by sending all data from each user's device to a central computer (server) in order to build a general model that can be applied to all devices. This approach is known as centralised machine learning and is shown in Figure 2.

Centralized machine learning has some limitations, like data privacy issues, because all user data has to be sent to a central machine. This can make it harder for users to keep their data

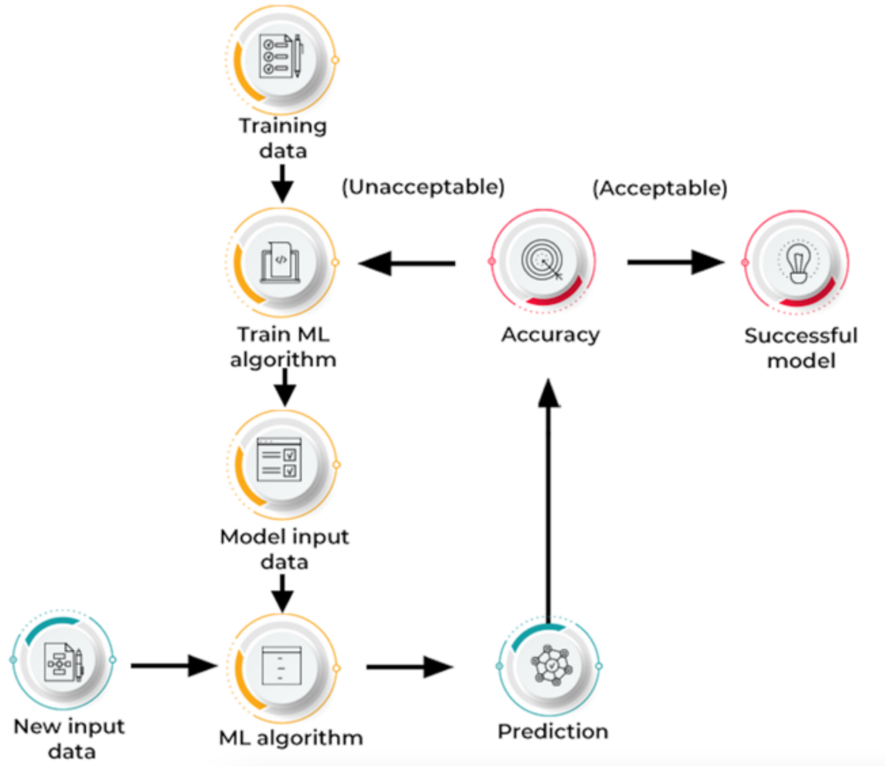

Figure 1: How does machine learning work? Sourced from.[10]

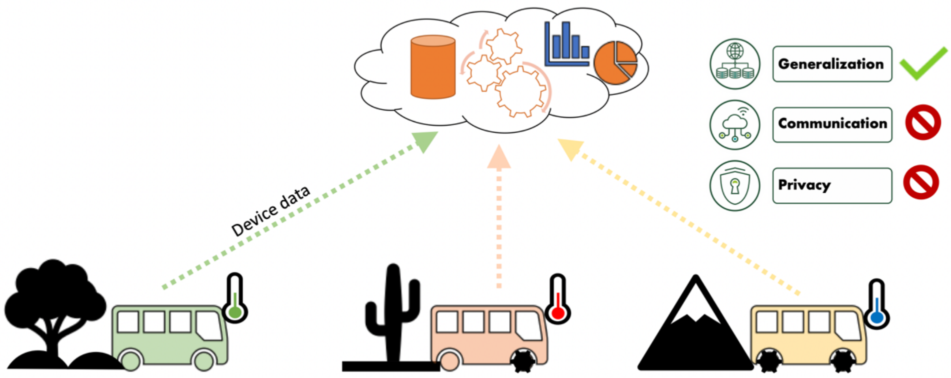

Figure 2: Traditional centralised ML - model training runs at a central machine while collecting data from all the devices which compromises data privacy and more communication cost.

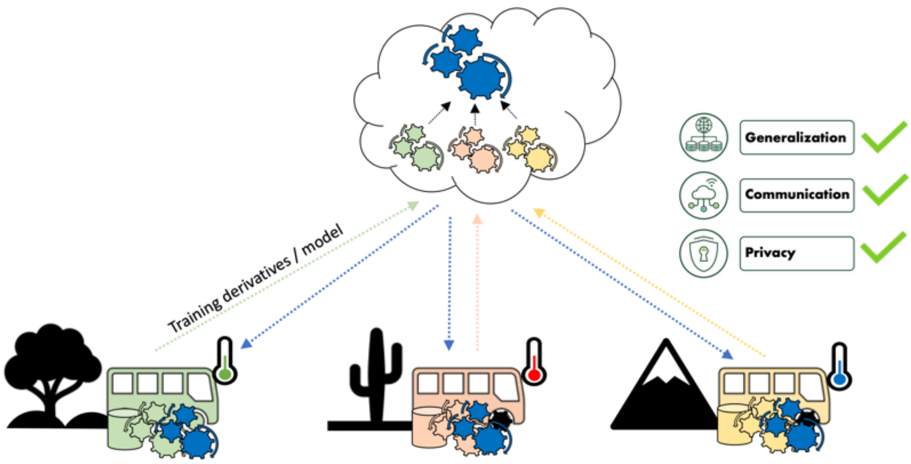

Figure 3: Federated ML - model training runs on local devices and then the model parameters are only being shared at central machine, which aids less communication cost while preserving data privacy.

private since all the personal data of users will be transferring to a central machine. Another problem with this method is that it can be hard to transfer and store data, since each device might generate a lot of data that could be very expensive to send to the server. In order to overcome these issues, the Federated Learning (FL) concept was invented. In FL, each user trains their own model independently on their own device.[13] In other words, each user's device goes through a model training process that is unique to that user. The model trained to each device is called as local model. Only local model parameters that have been learned are sent to a central server machine and not all the data from which the model has learned. After the central server gets the local model parameters from all the users, it combines them into a new model, which is called a ”global model.” As shown in Figure 3, the server then sends the global model back to these clients for training further on the new data, and this process is repeated.

How have we used ML for loneliness detection?

As previously indicated, smartphones and fitness trackers have been widely employed in recent years to detect mental health and well-being. Our recently published scoping review showed the efficacy of smartphones to detect loneliness too.[7] In the present study, we utilized a subset of the Dartmouth College Student Life dataset.[10] This data was extracted over 10 weeks from 48 students. The StudentLife project gathered smartphone sensing data, including from accelerometers, the microphone, light sensor, GPS, and Bluetooth connections. Since the sensor data is in its raw form, it must be cleaned and processed to make sense of it and then converted into various behavioural patterns of students' daily lives. This is referred to as data pre-processing and feature extraction. We have utilized software that has allowed us to perform this process more efficiently. We have retrieved more than 200 behavioural characteristics from various sensor data, such as for calls we have total count, mean duration, minimum duration etc. Similarly, for location features we have features like total distance travelled by a person during some part of a day, number of significant locations visited by a person, etc.

In supervised machine learning (a type of ML), we must label raw data with informative labels to offer context so that a machine learning model can learn from the data. In other words, data labelling represents the outcome you want your machine learning model to predict. In our case, for instance, if a student exhibits a particular behavioural pattern at a specific time of day, he or she is either lonely or not lonely. Therefore, we must classify this behavioural pattern for that certain time of day so that the machine learning model can learn the student's activity pattern and predict whether future patterns will indicate loneliness or not. For this purpose, we require real-time measurements of loneliness from users. There are numerous methods for assessing loneliness. One of these are clinical loneliness measurement scales. These scales are well-established and have demonstrated promising outcomes in detecting loneliness. The University of California Los Angeles (UCLA) loneliness measurement scale is a 20-item questionnaire that is one of the most commonly used scales in the general population and health care settings to measure the frequency and severity of loneliness and social isolation in an individual.[8] Participants rate each item as either 'often', 'never', 'rarely', or 'sometimes'.

The StudentLife dataset contains the pre-post UCLA survey responses from students to assess loneliness levels. We have used those survey responses to label the sensor data and then trained the ML models. Additionally, we have used the Reproducible Analysis Pipeline for Data Streams (RAPIDS) to calculate behavioural features for each student for example number of significant places a student visited in a day, number of incoming/outgoing calls etc. We have used both a centralised and a federated learning approach to make comparison between them and see which one performs better in certain situations.[6] The primary objective of our work was to investigate the effectiveness of using federated learning to identify loneliness using data collected from smartphone sensors, while maintaining privacy. Machine learning models results (accuracy, precision and recall) indicated that centralised machine learning models perform better than FL models but federated learning has great potential for loneliness detection via passive sensing since it can train models on a user's device without asking the user to disclose data, thereby enhancing privacy. So, there is no need for users to disclose any data in FL and the data never leaves the user's smartphone. Data privacy could be more important as compared to best models performance in some sensitive scenarios like loneliness detection due to stigma associated with loneliness. However, the acceptability of these technologies for loneliness requires further investigation. The performance of both approaches are very close in some specific models. The reason for low performance of federated models could be due to the small dataset size for each client and output label class imbalance issue on some clients in which data has only single class representation; lonely or not lonely.

Conclusion and future work

Our research investigated the viability of using technology, particularly smartphone sensors and machine learning, to detect loneliness. The results indicate that this method has significant potential for early detection of loneliness, which could be useful in many situations for prompt intervention and assistance. We are currently conducting a proof of concept study with 30 younger and 30 older participants because many older adults are at high risk of loneliness. By including both younger and older participants we can identify the differences in detecting loneliness in both groups. We are collecting sensor data from their smartphones, as well as health-related data from fitness trackers and then use machine learning approaches to assess loneliness. In the future, we will investigate other important dimensions of this approach to the identification of loneliness including user acceptability, privacy, sensitivity across diverse groups and other potential limitation and barriers to adoption.

Declaration of Interests

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