Classification of Drinking-related Events at the Sensory Interactive Table

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ABSTRACT

Healthy eating is an important part of our lives. University of Twente recently created the Sensory Interactive Table to support healthy eating in a social setting. There has already been research done on classification, however, the classification of drinking-related events is missing. This research focuses on classifying different drinking-related events that happen at the table. These are: tracking and classification of putting a glass on the table, pouring water in the glass, and the drinking behavior of people. Supervised machine learning with two machine learning algorithms k-NN and SVM are used for classification. Results show high accuracies, with the highest accuracy measured using SVM being 0.938 and k-NN being 0.933. This research identifies how accurately drinking-related events can be classified and hence provides new insights on how to add more intelligence to the table.

Keywords

Dietary Support System, Sensory Interactive Table, Machine Learning, Human-Computer Interaction

1. INTRODUCTION

When it comes to health, one of the first things that come to mind is healthy eating. A healthy diet generally consists of vegetables and limits food that is processed [12]. Following a healthy diet is not always easy. An unhealthy diet can lead to severe health problems, such as cancer and heart strokes [5]. According to research from 2015, around 52 225 colorectal cancer incidents were related to malnutrition in the United States [15]. These consequences of an unhealthy diet highlight the importance of promoting a healthy diet, and thus thereby a healthy lifestyle. There are already smart systems availabe to support healthy eating of individuals, such as nutrition apps. However, social dimensions, such as the influence of food choices of others on a person, lacks in these smart systems [6].

The Sensory Interactive Table (SIT) [6] is a smart table that supports healthy eating in a social environment, taking into consideration social aspects that affect people and their food selection. The surface of the table has 199 hexagon-shaped modules, each consisting of a load cell for weight measurement on the table and a LED panel for feedback to the user of the table. Figure 1 shows the picture of the hexagon-shaped module. As the main goal in the creation of the smart table is to create a dietary support system, research in many different areas are possible. For example, people's eating behavior when dining with others, the socialization surrounding people's eating behavior, and the influence of the feedback from the LEDs on people's eating behavior [6].

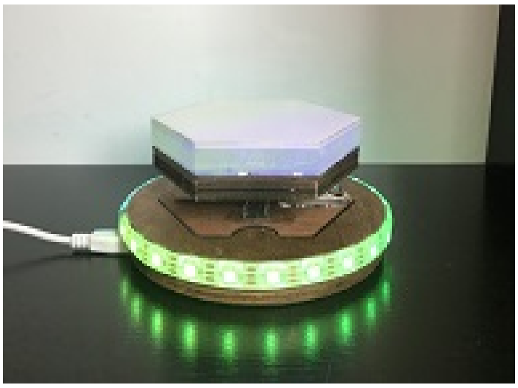

Figure 1. A picture of the hexagon-shaped module.

There is research available on how to classify different events happening at the table. In order to get more insights on these events and to make the table smarter, it is important to look at all eating and drinking-related events. In the end, the aim is to bring all classifications together such that the table is smart enough to automatically detect different events that take place at the table. One missing part is the classification of drinking-related events. This research will therefore focus on how to classify drinking events. Thereby, the focus will be on the following events: whether a glass is put on the table, whether water is poured into the glass and whenever a person takes the glass, takes a sip, and puts it back on the table. All these drinking-related events will be used to investigate whether classification can be done accurately.

It is possible to track all drinking-related events with the Sensory Interactive Table. However, as there is no research available in this area, it was decided to create a setup and collect data in a controlled environment, using a single module instead of the smart table itself.

2. RESEARCH QUESTIONS

This section describes the research questions. The main research question of this research is formulated as follows:

RQ How accurately can different drinking-related events be classified?

35^{th} *Twente Student Conference on IT* July 2^{nd}, 2021, Enschede, The Netherlands.

The main **RQ** will be answered through answering the following three sub-questions:

RQ1.1 How can a glass put on the table be tracked and classified?

RQ1.2 How can pouring water in the glass be tracked and classified?

RQ1.3 How can taking a glass, taking a sip, and placing the glass back on the table of an average person be tracked and classified?

The sub-questions are about specific drinking-related events and hence contribute to answering the main research question. These events were chosen in particular because they are among the most common drinking-related events that happen during dining. This research focuses on a controlled environment to answer the research questions. Therefore, a protocol will be made beforehand for the set-up and data collection. The controlled environment is chosen in order to achieve consistency in the collected data and to analyze to what extent accuracy can be achieved for each sub-question in such an environment.

3. BACKGROUND

This section provides background about machine learning, as this is an essential part of the research, namely it will be used for the classification. The choice of machine learning method and algorithms for this research will be explained in 4.4.

3.1 Machine Learning

Machine learning is a topic that has been gaining popularity over the years. It is an important part of Artificial Intelligence and is about computer systems that learn through experience [8]. Machine learning is widely deployed and has many applications in real life. For example, the traffic alerts in Google Maps through prediction, virtual personal assistants that make use of speech recognition, and product recommendations that are based on machine learning applications in Amazon [9]. These are just a few of the many popular applications of machine learning in real life. There are two main methods within machine learning, namely supervised and unsupervised machine learning which will be described in 3.1.1 and 3.1.2, respectively.

3.1.1 Supervised Machine Learning

Supervised learning makes use of labels in the datasets. These labels are used to train algorithms for the accurate prediction of outcomes and also for classification [14, 8]. Therefore, supervised learning can mainly be split into two categories, namely classification, and regression. For classification, test data is categorized into different classes using an algorithm, for example classifying an email into spam or not spam, whereas in regression an algorithm is used to get the idea of how dependent and independent variables relate to each other [14, 8].

3.1.2 Unsupervised Machine Learning

Another method in machine learning is unsupervised learning. In this approach, datasets do not have labels. A label is sort of a tag that is attached to a sample and is meant to be the final output [2]. Within unsupervised learning, for example, clustering and association can be done. In clustering, the aim is to find groups that are similar and in association to find links between variables in data [11]. Hence, the main purpose of unsupervised learning is to derive insights from a huge amount of data [11].

3.1.3 Main Differences

It can be assumed that labeling is what mainly differentiates supervised learning from unsupervised learning. Moreover, both methods can be used for different purposes. The choice of which one should be used depends heavily on the research itself.

3.2 Machine Learning Algorithms

There are many machine learning algorithms available that can be used. These algorithms can also be split based on which method is being used, thus supervised machine learning or unsupervised machine learning [14]. This section describes briefly some of the known machine learning algorithms.

3.2.1 Support-Vector Machine (SVM)

One of the algorithms is the Support-Vector Machine. This algorithm [14, 7] creates a hyperplane or hyperplanes and divides the data, if possible, into binary classes. The support vectors (data points) that are the nearest to the hyper-plane(s) are taken into account and the hyper-plane is chosen based on the maximum distance between the closest data point and the hyperplane [14, 7]. Even though Support-Vector Machine is based on binary classification, it can also be used for multi-class classification by using various binary classes [10]. Hence, multi-class classification allows the data to be categorized into several classes [1].

3.2.2 K-Nearest Neighbors (k-NN)

Another algorithm is the k-Nearest Neighbors. K-Nearest Neighbors algorithm is a simple algorithm [7]. It calculates the distance, using for example the Euclidean distance, and classifies data points based on the k-nearest neighbors [14, 1]. The value for k is fixed and represents the number of neighbors [4].

3.2.3 Artificial Neural Networks (ANN)

This is an algorithm that is based on the biological term neural networks and uses mathematical motifs [1]. As is also the case in the biological neural networks, the artificial neurons are connected to other artificial neurons by the so-called edges. In this algorithm, the structure changes based on the data from the input and output flowing over the network [1].

4. METHODOLOGY

4.1 Data Collection

The first step in the methodology is the data collection with the module. Before starting the data collection the main issue was to decide on how the data should be collected, as many methods can be used for each sub-question in real life. It was decided to use three common methods for each sub-question, resulting in a total of nine methods for the data collection. See Figure 2 for the example graphs for all methods per sub-question. Moreover, to have consistency in the collected data, a protocol had to be set up in advance. This protocol can be found in Appendix A.

Firstly, the module is connected to the laptop using a mini USB cable. Secondly, the open-source software Tera Term is used to collect and save the data from the module. To determine the starting point of each saved sample, there has been tapped five times on the module before collecting the data. The data collection for each sub-question is done in a row, according to the protocol.

4.2 Data Pre-Processing

The data collected was in its raw form, as there had been no pre-processing done yet. There were failed attempts for each sub-question, which had to be removed. The module occasionally gave erroneous measurements in the form of large peaks, which were considered as noise. This noise happened sometimes, regardless of putting any weight on the module, which indicates that the problem was likely caused by the load cell. These large peaks are also excluded from the data. The five times tappings before collecting data, which is mentioned in subsection 4.1, had to be cut from each sample as well. In total 80 samples have been collected for sub-question 1, 69 samples for sub-question 2, and 75 samples for sub-question 3. Resulting in a total of 224 samples.

4.3 Feature Selection

The feature selection is made based on features that were visible and calculable in each method of each sub-question. We have used three different methods for each sub-question and saw that methods show different results in the graphs. This caused selection to be made based on the features that were present in all the methods in a sub-question.

RQ1.1 How can a glass put on the table be tracked and classified?

For this sub-question, the common features of the three methods in the dataset were the minimum value of the graph, the maximum value of the graph, and the shift caused by the peak in the x-axis, as x-delta. Moreover, the sample variance is also used as a feature. The maximum value corresponds to the peak height in the sample. The minimum and maximum values of each sample are calculated using the min() and max() functions in Excel. The shift in the x-axis of each sample was calculated based on the maximum shift caused by the peak. Sample variance is calculated using the var.s() function.

RQ1.2 How can pouring water in the glass be tracked and classified?

For this sub-question, the common features of the three methods in the dataset were also the minimum value of the graph, the maximum value of the graph, and sample variance. Minimum and maximum value have been computed using min() and max() functions and the sample variance using var.s() function. Furthermore, the slope of the graph has also been used as a feature. The slope() function in Excel has been used to calculate the slope in each sample of method 1. For method 2 and method 3, the slope() function could not be used, as the slopes of the graphs were not linear. Therefore a trendline is made for each sample and then the slope of each trendline is used.

RQ1.3 How can taking a glass, taking a sip, and placing the glass back on the table of an average person be tracked and classified?

The features for this sub-question are also the minimum and maximum value of the graph and sample variance. For these features again the min(), max() and var.s() functions have been used, respectively. Another feature is the the shift caused by the peak in the x-axis, denoted as x-delta.

4.4 Classification

After data collection, pre-processing and feature selection, the datasets are ready for classification. In total three datasets were created for each sub-question. All the samples of the three methods in each sub-question have been added to the corresponding dataset.

The important part here is to decide whether supervised or

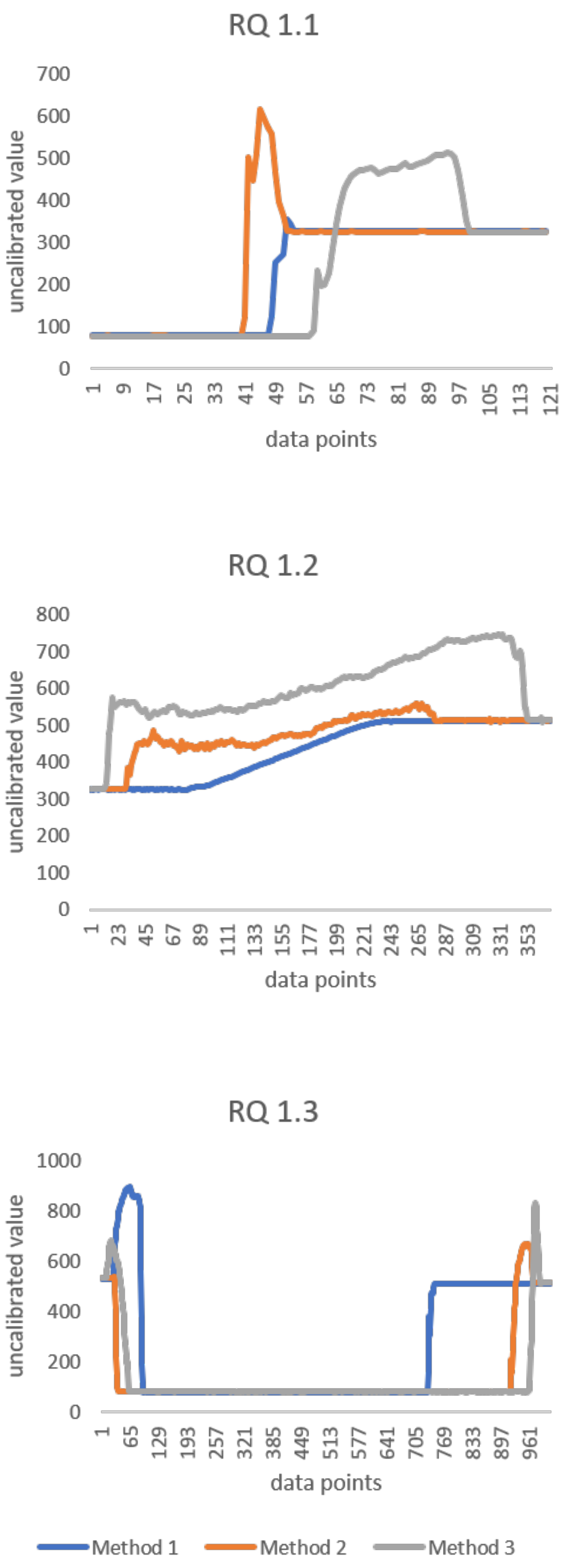

Figure 2. The example graphs of all the methods in each sub-question.

unsupervised machine learning is the right fit and thereby which algorithms are suitable for this research. The decision is made on supervised machine learning, as this research is about a classification problem in which labeled data will be used. In order to classify, a dataset is provided, machine learning algorithms are used, and finally, the dataset is categorized into three classes. Two machine learning algorithms have been used, namely Support-Vector Machine and k-Nearest Neighbors. The choice for these two algorithms is based on their suitability for multi-class classification and because a small dataset is being used.

As labeling is a part of supervised machine learning, each dataset contained a column for the label. This value was either 1, 2, or 3, representing the method to which the sample belongs. So, we look into how accurately data can be classified into methods 1, 2 and, 3 each time, using the Support-Vector Machine algorithm and the k-Nearest Neighbors algorithm. For the classification, Jupyter Notebook software has been used along with Python libraries. Moreover, libraries for the two machine learning algorithms Support-Vector Machine and k-Nearest Neighbors have been used, such as sklearn.

5. RESULTS

RQ1.1 How can a glass put on the table be tracked and classified?

For this sub-question, three different methods were used for placing a glass. Based on the method, especially the maximum peak observed, the x-delta and the sample variance showed differences among the methods.

The Support-Vector Machine gave an accuracy of 0.938, meaning that 93.8% of the 80 samples were classified accurately. The k-Nearest Neighbors gave accuracy of 0.875. Thus, 87.5% of the 80 samples were classified accurately for placing a glass on the table.

RQ1.2 How can pouring water in the glass be tracked and classified?

For this sub-question, three different methods were used for pouring water into the glass. This especially showed a difference in the maximum value and the slope of the graphs. Whereas method 1 showed a linear slope, the other two methods resulted in a non-linear slope.

The Support-Vector Machine gave an accuracy of 0.857, meaning that 85.7% of the 69 samples were classified correctly. The k-Nearest Neighbors algorithm gave an accuracy of 0.786, thus 78.6% accuracy out of 69 samples.

RQ1.3 How can taking a glass, taking a sip, and placing the glass back on the table of an average person be tracked and classified?

Three methods have been used for carrying out how to take a glass, take a sip and place it back for an average person. This showed that the methods give different results in some features in the graphs, such as the maximum peak and the maximum change in the x-axis.

The Support-Vector Machine algorithm gave an accuracy of 0.933, hence 93.3% of the 75 samples were classified accurately. Moreover, the k-Nearest Neighbors algorithm gave the same accuracy: 0.933. Thus 93.3% of the 75 samples were classified accurately.

6. DISCUSSION

We are interested in how accurately different drinking-related events can be classified. For this matter, the classification of the three sub-questions has been done in a controlled environment. Results for each sub-question show that high accuracies can be achieved. Overall, the highest accuracies were obtained for RQ1.3, resulting in an accuracy of 0.933 for both Support-Vector Machine and k-Nearest Neighbors algorithms. The high accuracy could be caused by the less variety within the features of RQ1.3. For SVM the highest accuracy achieved among the three sub-questions is 0.938 in RQ1.1 and 0.933 for k-NN in RQ1.3. In general, the results show that different drinking-related events can be classified very accurately.

The variety and number of features and the chosen machine learning algorithms are elements that played an important role in the achieved accuracies. For example, classification can be harder when there are many features with high variety and this will likely result in lower accuracy. Moreover, a controlled environment was used for this research, which caused the data to have consistency and led to high accuracies. The lowest accuracy among all the sub-questions was for RQ1.2, for this sub-question the slope was used as a feature, which was not used for RQ1.1 and RQ1.3. The slope feature caused the dataset to have variety, which made it a bit harder to classify. Despite that, it still resulted in high accuracy.

Furthermore, related research [3] was conducted that also used Support-Vector Machine algorithm and k-Nearest Neighbors algorithms, but for the classification of water quality. In this research, an accuracy of 92.40% is achieved for SVM and 71.28% for k-NN. So, in this research, also high accuracies have been achieved. However, the approach in this related research differs from this research. For example, in the related research, 120 datasets have been used and classification was done based on four categories of water quality.

Another research [13], was conducted which compared classification models for water quality. In this research, three different machine learning algorithms have been used, namely Naive Bayes, SVM and, Decision Tree. An accuracy of 98.50% has been achieved using Decision Tree. This indicates that if the Decision Tree algorithm would have been used for classifying different drinking-related events, this could also possibly result in such high accuracy.

7. CONCLUSION

The goal of this research is to determine how accurately different drinking-related events can be classified. Firstly, a background on machine learning has been given, as this was a vital part of this research. Data is collected using a hexagon-shaped module and then pre-processed. Afterwards, feature selection was done for classification. To classify, supervised machine learning is chosen along with two machine learning algorithms, k-NN and SVM. Results show high accuracy in each sub-question, with the highest accuracy achieved for RQ1.3 with 0.933 for both SVM and k-NN. This research provides new insights on the classification of drinking-related events and thereby contributes to how to make the Sensory Interactive Table smarter.

8. FUTURE WORK

This research uses only a limited number of different drinking-related events in a controlled environment. For future research, the same research can be conducted in an uncontrolled environment. Moreover, different methods and drinking-related events can be researched using other machine learning algorithms. With a larger dataset, more features and more methods can be used for classification. Another future research can be mixing eating and drinking-related events and see how these can be classified. To add more intelligence to the table, it is of course essential to do a lot of research to many events that happen at the table, regardless of drinking and eating habits. For example, the classification of plate or glass shifts that happen at the table.

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APPENDIX

A. THE STANDARD PROTOCOL

Materials

-Water glass of 8.7cm x 8.7cm x 9.2cm (LxWxH) (275 ml)

-Measuring spoon of 5 ml

-Plastic carafe with a capacity of 500 ml

-Water 300 ml

-Paper and pencil

-Scissors

Methodology

RQ1.1 How can a glass put on the table be tracked and classified?

1. Standard step

1.1 Take a piece of paper on which the module fits

1.2 Draw the outline of the module on the paper

1.3 Cut the paper in the shape of the module

1.4 Take the glass and put it in the middle of the paper and draw the glass outline

1.5 Place the paper on the module and attach it with adhesive tape on the sides of the module so that the paper does not move

The methods should be carried out without extra pressure/hand touching/shifts, unless stated.

Method 1: only glass touches the module

1. Take the glass

2. Put the glass as much as possible on the glass outline on the paper.

3. Let go of the glass once placed (after step 2)

Method 2: pinky and glass touches the module

1. Take the glass

2. Hold the glass such that the pinky is at the same level as the bottom of the glass

3. Put the glass on the outline, such that both glass and the bottom of the pinky touch the module at approximately the same time.

Placing: the glass should be approx. on the glass outline, and the pinky approx. outside the glass outline

4. Let go of the glass once placed (after step 3)

Method 3 : as in method 1, now with the shift.

1. Take the glass

2. Put the glass on the edge of the module, such that the glass is totally on the module, but the level of the edge of the glass and edge of the module is the same.

3. From there shift it to the glass outline, such that the glass ends up on the glass outline

Steps 2 and 3 are done in a sequence, thus without stopping after step 2.

4. Let go of the glass once placed (after step 3)

RQ1.2 How can pouring water in the glass be tracked and classified?

2. Standard step

2.1 Take a carafe and fill in until 300 ml

2.2 Use the paper from sub-question 1 and do standard step 1.5

2.3 Put the glass on the module on the glass outline

Method 1: pouring while the carafe does not touch the glass

1. Take the carafe

2. Keep the carafe about 2 cm above the glass when pouring

3. Use about 6 seconds to fill the glass

Method 2 : pouring while carafe is held against the glass constantly

1. Take the carafe

2. While filling the glass, hold the carafe against the glass

3. Use about 6 seconds to fill the glass

Method 3 : pouring while the carafe does not touch the glass and the glass is being held on the module

1. Take the carafe

2. Hold the glass, while resting your pinky on the module

3. While pouring water into the glass, make sure the carafe is about 2 cm above the glass.

4. Make sure the carafe does not touch the glass.

5. Remove hand from the glass, once filled

6. Use about 6 seconds to fill the glass

RQ1.3 How can taking a glass, taking a sip, and placing the glass back on the table of an average person be tracked and classified?

3.Standard step

3.1 Use the paper from sub-question 1 and do standard step 1.5

3.2 Fill in the glass and place it on the glass outline

3.3 Keep the measuring spoon ready

3.4 Use an average sip size of 22.5 ml[1]

Method 1: First hold the glass for a while then take a sip, then place the glass back

1. Hold the glass for 3 seconds

2. After 3rd second, take the glass off the module.

3. Use the measuring spoon to take water from the glass (do it 4.5 times for the average sip size)

4. Place the glass back on the glass outline on the module (as in Method 1 of sub-question 1)

Method 2: Take the glass directly, take a sip, and place it back on the glass while shifting

1. Take the glass from the module

2. Use the measuring to take water from the glass (do it 4.5 times for an average sip size)

3. Place the glass back on the glass outline on the module (as in Method 3 of sub-question 1)

Method 3 : Shift, take the glass, take a sip and place it back on the module

1. Shift the glass from the module until the glass is totally off the module.

2. Hold the glass

3. Use the teaspoon to take water from the glass (do it 4.5 times for an average sip size)

4. Place the glass on the module, (as in Method 2 of sub-question 1)

[1] Average sip is based on average sip of a woman and a man. Retrieved from: https://doi.org/10.1007/s00455-002-0105-0