M.S. THESIS

Design of a Wearable-based Automated Monitoring and Reporting system in School Violence Scenarios

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Abstract

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School violence (including *cyberbullying*) represents an ever-present and complex problem that is difficult to address. Due to its accompanying detrimental short- and long-term consequences for the involved students, it is essential to enhance the monitoring and addressing aspects of these problems to guarantee a healthy development of the children. Research has shown that school violence cases remain undetected relying only on traditional approaches towards bullying [1]. To increase the monitoring capability, we present a system that leverages a combination of wearable technology (for the collection of student data) and machine learning techniques (sentiment analysis and random forest classification). Furthermore, we provided a feedback channel to the teachers to access their domain expertise and to have a possibility to improve the dataset over time. Moreover, this work proposes an initial visual design of a monitoring dashboard that reflects the design guidelines extracted from the teachers' interview. This research presents an approach to make the social issue of school violence measurable and set the starting point to disrupt the classical approaches of teachers.

Keywords: Decision Support System; Wearable Computing; Machine Learning; User-Centered Design; Education

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Chapter 1

Introduction

Bullying behavior is considered a severe problem among school children and adolescents that might have long-lasting detrimental impacts not only on the victims themselves, but also on the perpetrator(s), and the bystanders. According to Olweus, bullying is an act of aggression which is repeated over a certain time, and its trait is a power imbalance between the perpetrators and their victims [35]. It has been observed that bullying events tend to take place in educational settings more often [32]. Therefore, bullying constitutes a significant concern in the school context [36, 39]. According to the American Psychological Association, 40% to 80% of school-aged children reported to have encountered bullying at some point during their school career [19]. Though traditional forms of bullying, such as physical and verbal bullying, are still prevalent, the emergence of modern technical means (e.g. internet, text messaging, chat rooms, and social network services) provoked a new type of bullying, which is referred to as cyberbullying [28]. Its characteristics of anonymity, inability to see the perpetrators[28], and taking place off-school [9] make bullying even more complex. This complicates the process of grasping and subsequently handling these kinds of bullying events by the teachers [9].

The advancements in both wearable and machine learning technologies have the greatest impact in the fields of health and fitness in our modern-day lifestyle. However, the powerful capabilities of these technologies do not need to be confined to just the mentioned areas. We believe that using the capabilities of wearable technologies and machine learning techniques presents a feasible way to build a sophisticated school violence detection and intervention system and in turn even tackle social problems. Since wearable technologies enable gathering of physiological data on a large scale, both continuously and unobtrusively, machine learning algorithms can be applied to those physiological data to make inferences about the psychological states of the user. This technology interplay opens up the pathway for new processes, such as behavioral sensing and emotion recognition. This provides the possibility to make inferences and obtain insights about the psychological well-being of the human being. Several kinds of research have attempted to apply this technology to address school violence with the focus on school students [4, 16, 17, 37, 41, 45, 48]. In this research, we make usage of the following sensors, namely GPS sensor, microphone, and accelerometer, included in the Apple Watch, to trace and measure the heart rate (as bpm), outdoor location data (longitude and latitude), audio data (expressed sentences), and movement data (gravity, acceleration, rotation, and attitude). This work assumes that features extracted from the mentioned datasets have the potential to identify bullying events. The collected data will be transmitted to the back-end of the system that employs classical machine learning algorithms to predict bullying cases. In addition, since we regard teachers as the main decision-makers when it comes to bullying situations and the ones who perform the corresponding interventions, valuable system-related design implications can be extracted from the teachers' opinions. Therefore, to suggest an initial design of a monitoring dashboard to display and analyze the bullying incidents that occur between the students of the class, we firstly interviewed the teachers (primary, middle, and high school) to obtain an understanding of the teachers' obstacles and intervention remediations to derive design implications for the system and the system's monitoring dashboard. Afterwards, we implemented these design implications into the visualization dashboard.

This research makes the following contributions:

- Teachers' interview (Expert interview) conducted in a semi-structured manner to collect the teachers' views on the idea (technology adoption in the context of detection of school violence cases) and learn their pain points and intervention methods
- Extraction of design guidelines for the system, especially for the visual design of the monitoring dashboard component
- Construction of a pipeline with an internal sentiment analysis component, bullying prediction component, and an integrated feedback loop
- Design of the monitoring dashboard component

This work presents the implementation of a pipeline for a monitoring and reporting system. The system could be tested in real-life situations (inside and outside of schools) its suitability should be proved to improve the identification and handling of bullying situations in schools. With the feedback of experienced teachers, the system can be trained to identify bullying situations more accurately. This research can set the beginning to improve the classical approaches of teachers when it comes to addressing bullying situations.

Chapter 2

Related Work

Several previous studies in the research areas related to the detection of psychological well-being via wearables, approaches in emotion recognition, and first technical approaches to address school violence provide the context for the present study.

2.1 Detection of Psychological States using Wearable Devices

Nowadays, consumer-grade wearable technologies have found their way more and more into our daily life due to their unobtrusive and inexpensive characteristics. One key feature of those wearables is the alignment of physiological patterns with psychological traits. It is probable that more sophisticated measures will be implemented over time and at the same time, this accomplishment would provide assistance to yield a more precise matching of physiological data with mental states [18]. These consumer-grade wearable technologies are equipped with built-in sensors that make it possible to collect various forms of biometric data from the user. Previous research have leveraged this sensing capability of wearable devices and demonstrated that it is feasible to grasp and detect the psychological states of the users, such as mood, stress, anxiety, depression, and emotion[7, 11, 14, 20, 43, 50].

The EudaeSense system collects user data via wearable technologies in a non-invasive manner and subsequently leverages those data to detect and infer early signs of depressive mood [10]. It traces the following physiological data: heart rate, sweat, temperature, muscle tension, and breathing rate. Through combining a smartphone with wearable sensors the system monitors behavior related to mood changes, namely sleep quality, activity level, mobility, and social interaction, which are considered indicators for depression. It also prompts micro-interventions via a wearable interface to the users. The findings demonstrated that the best neural network results could be obtained with datasets comprising the heart rate data.

The fully automated mood recognition system HealthyOffice, which is employed in the working environment, utilizes wearable sensors to capture the physiological data to infer the moods of the employees [50]. The system leverages the heart rate data from the electrocardiogram (ECG) sensor, the pulse rate from the photoplethysmogram (PPG) sensor, the skin temperature, and 3-axial acceleration. To automatically recognize eight different types of moods, three standard classifiers were used, namely, i) k-Nearest Neighbour (k-NN), ii) Decision Tree (DT), and iii) Ensemble approach. The physiological data were unobtrusively collected through wearable technology while the employers performed their daily routines and over the time the system is trained through the provided moods of the users.

These aforementioned research approaches employ wearable technologies with their equipped sensors to derive inferences about the mental health of the users. Especially, those research approaches highlighted the importance of the physiological data heart rate which is also considered an essential indicator in our current approach. Since any type of bullying is significantly associated with impacts on mental health [15, 46], it is essential to detect these mental health issues of the involved persons. However, adolescents may not reveal their fears and distress; so these mental health problems are not apparent and can be overlooked by both the teachers and the parents[30]. This underpins the motivation of this research to find a way to capture tendencies of mental health problems, that are not directly visible, to have examples for the machine learning algorithm to identify cases of bullying.

2.2 Emotion Recognition for Detection of School Violence Events

Existing research shed light on the emotion recognition by leveraging physiological data, such as heart rate/ heart rate variability, galvanic skin response (GSR), electromyogram signals, and changes in respiration. Well-known classifiers like kNN, multilayer perceptron, and Support Vector Machine (SVM) were applied to recognize the different emotions [16, 17, 45]. However, the application of emotion recognition based on physiological data in the context of school violence is still in its infancy. The emotion recognition approaches undertaken so far rather consider the analysis of the speech of the involved people in bullying events to recognize the related emotions [21, 23]. Han et. al [21] developed and tested a system to recognize emotions based on voice signals. Some tendencies of negative emotions, such as anger, fear, anxiety, and sadness could be identified based on voice signal. By using these voice signals, we would be able to give assistance to detect cases of school violence. An emotion recognition algorithm with the consequential eliminating process (CEP) has been applied. Subsequent optimization of the parameters was made with SVM. In order to conduct a verification of the emotion algorithm, the Berlin database with emotional speech is analyzed by the algorithm. The findings of this research have shown that the CEP procedure could yield a rather high accuracy for speech emotion recognition. This work motivated us to consider speech data as a feasible approach to recognize students' emotions. Emotion recognition itself is one of the factors to identify school violence.

2.3 Technical Approaches for Detection and Prevention of School Violence

Several approaches [4, 21] have attempted to set a starting point to address the issue of insufficient monitoring in school facilities. These approaches proposed a design of a bullying detection/alert system to notice teachers and staff about potential bullying situations. Brahnam et al. [4] suggested system leverages varied technologies, such as smart ID badges, wearables with integrated heartrate sensors, surveillance cameras, state-of-the-art machine learning systems, cloud computing, and mobile devices. The system relies on the interplay of many diverse technologies, meaning that a malfunction of one technology in that technology network would eventually affect the overall accuracy of how the system detects school bullying episodes. Our approach, indeed, shows similarities with the mentioned work, however, it differs in the aspect that the data collection is carried out with just the smartwatch device and therefore it is detached from other technologies. In addition, our research explores further data types that may have the potential to indicate bullying situations/tendencies, namely audio and movement data.

Since the system is intended to be used by students, teachers, and parents (its target users), it is essential to seek their opinions towards the system. By reflecting the views of the target users, the usability of the system could be definitely enhanced. This aspect was not sufficiently addressed in the mentioned research approach.

Chapter 3

Design Implications for Monitoring System

Since it is essential for us to create a monitoring and reporting system to detect cases of school violence, that is intended to be eventually used by students, teachers, and parents, it is crucial for us to follow a user-centered design approach. To achieve this, it is necessary to get input from the users already at an early stage of the design process. Since teachers take on a significant role in terms of managing and mediating school violence [49], we find it appropriate to have a direct exchange of opinions with the teachers to build a foundation for our system based on the given insightful views. This chapter provides insights about our initial vision, the user interview, and the extracted design guidelines and suggestions from the teachers' answers.

3.1 Our Conceptualization

School bullying depicts a pervasive worldwide social issue, including South Korea [26, 27]. Previous studies/case studies demonstrated the negatively affected outcomes that come along with sustained bullying: low psychological well-being, poor social adjustment, psychological distress, and physical illness [31, 38]. It has been acknowledged that the monitoring aspect should be further enhanced to reach a more effective tool to address and prevent bullying. This constitutes a high priority for schools [47].

Through researching the literature, we concluded several difficulties/problems in terms of school violence:

- Victims do not have the courage to communicate the bullying cases. Bullying cases are well known by the peers, however, they are rarely reported due to pressure of involvement and fear of becoming the victim. This means there is a difficulty to communicate the bullying situation[47]
- Some bullying cases in school still remain undetected by the teachers [1]
- Difficulty to grasp cyberbullying due to its nature of being online

Therefore, we have come up with the vision to enhance the process of detecting school bullying situations by offering a self-acting and automated mechanism to identify bullying signals. We can attain this objective by using the technology interplay of wearable technologies and advanced machine learning techniques. If the system is sufficiently automated, it is expected that trends of bullying can be discovered at an early stage, a quicker reaction towards the problem, better adjustments of the applied interventions, and eventually better prevention could be reached.

With this system, we intended to provide support to the victims who have difficulties to express their problems and also to give an option to not rely on the reporting actions of their peers. Through the automatic recognition of bullying tendencies, they would no longer be dependent on the reports of the classmates. Furthermore, this system would provide additional support and reference to adequately address school violence.

Our focus is on the following types of bullying: physical, verbal, and cyberbullying. The target users of our project consist of students (primary, middle, high school students), teachers, and parents.

3.2 User Interview with Teachers

We conducted a user interview about school violence in a semi-structured manner with 35 teachers [25]. Through the literature research conducted beforehand, we identified five technologies, namely wearable technology, in-/outdoor localization, audio capturing, activity, and emotion recognition, that might have the potential to mitigate school violence. The posed questions revolved around the following topics: school violence, their applied intervention techniques, their experienced obstacles, the mentioned technologies intended to use, and our conceptualization. The objective of the user interview was to develop an understanding of the teachers experienced problems (with the applied methods regarding bullying), opinions/attitude towards the adoption of wearable and monitoring technology, and to gather suggestions to create a useful monitoring and reporting system.

Participants

In total, we interviewed four elementary, thirteen middle, seventeen high school teachers, and one former teacher (21 women, 14 men; age 27-60; with experience as a teacher ranging from 1-36 years; 2 Germans (with teaching experiences both in Germany and Korea), 33 Koreans; all teaching in South

Korea). Among these teachers, thirty teachers hold experience as a homeroom teacher.

Procedure

The user interview with the teachers was approved by the institutional review board (IRB) of Seoul National University. Subsequently, we forwarded the recruiting documents via mail and fax to the school principals. We answered further questions regarding the interview via phone. After recruiting the participants, we set up appointments with the teachers to conduct a semi-structured user interview (see interview questions in appendix). The interviews took place in their classroom or office. Since we needed to take into account the limited time at hand, we conducted a group interview with fifteen out of thirty-five participants (2-3 participants per session, a total of 6 sessions). Before we started the interview, we provided a short briefing to convey the project's objective and explanations regarding the proceeding of the interview. During the interview, the teachers answered questions regarding school violence inside/outside of school, their used detection/intervention methods, their obstacles in terms of coping with school violence cases. Furthermore, we explained our conceptualization in combination with the five potential technologies that can be used for the detection of school violence. We gathered their views on these matters. Afterwards, we concluded the user interview by providing a debriefing session and rewarded the participants with $8.6 (10,000 KRW). Each interview took about one hour.

Data Collection

In order to ensure the extraction of insightful and accurate answers from the user interview, we asked the participants for permission to record their given answers. Therefore, we recorded each of the interviews through an audio file. In total, twenty-two hours of audio data were gathered from twenty-six interview sessions. Subsequently, the gathered audio files were transcribed.

Data Analysis

For the extraction of the themes in the given answers of twenty-six interviews, we applied the thematic analysis method [5]. Three coders, the researchers, read and continuously refined the extracted cues. They generated initial codes from the interviews through the application of open coding. Lastly, they clustered the codes to find patterns created from the themes.

3.3 Results and Discussion

Based on the twenty-six interviews, we extracted eleven themes. Table 3.1 shows a listing of the extracted themes. We took into account the recurrent codes that appeared in most of the teachers' given answers.

Themes	Codes
Conduct consultation	Having teatime with students, Gently approaching students, Discuss with other teachers
Relying on observation	Observe class atmosphere, Observe facial expressions
Through reports from students (victims or classmates)	Ask students, Report from victims
Invisible student's mental state	Introverted, Difficulty of self expression, Suppression of feelings
Passive observer rather than an active conciliator	Wait and see, Do not take sides, Letting students solve the problem, Leave problem as it is
Physiological responses of mental states	Eating disorder, Speak less
Exclusion from group activities	Difficulty to find team
Expression of mental states	Depressed facial expression, Steadily lying on desk
Unusual behaviors	Frequent absence, Late to school, Poor academic achievements
Strange atmosphere	No responses from classmates at the time of presentation

Table 3.1: 11 Themes Describing Teachers' Intervention Methods, their Relied Cues, and Encountered Obstacles

Depending on indirect cues and students' reports

Most of the teachers mentioned the following course of action. Firstly, they make suppositions based on the students' external cues (e.g. facial expressions or whether the student is oftentimes alone), their own teaching experiences, and intuitions. Subsequently, they check their suppositions by listening to the students and victims who report the bullying incidents. P22 has stated, "Mostly I figure out students' mental state through their facial expressions". Notwithstanding, it has to be considered that there are students who tend to not show their character/behavior to their surroundings. Consequently, this would make it more difficult for the teachers to grasp the bullying case. P32 states, "I can still remember about one case where everyone thought both were best friends, but after several years, we have come to realize that the child was involved in a severe bullying case.". Moreover, due to the pervasiveness of smartphone devices and the popularity of SNS messengers relying primarily on indirect indicators complicate the fact of noticing incidents of school violence.

Indirect more preferred over direct intervention

Teachers tend to demonstrate a somewhat cautious behavior towards the conduction of direct interventions, since the students may show adverse reactions in response to direct interventions. They may react sensitively and may have the feeling that the teachers do not believe in their abilities to solve the problems on their own. Therefore, teachers often tend to conduct indirect intervention methods where they slowly and gently approach the students and try to find possibilities to listen to the students. P16 stated her proceeding in the following matter, "When I sense that something is wrong with the student, I begin to observe her a bit more. I let some time pass and wait and see. Immediate intervention is not always desired by us teachers."

Teachers' attitude about modern technologies

The teachers suppose that wearable computing devices, including the smartwatch, would constitute an obtrusive approach to the students. Further aspects were pointed out, such as the high price tag of the device and the possibility of damage. Still, since the teachers do not constitute the users who are going to wear the wearable device, it is relevant for us to verify this supposition with the answers of the students. Most of the teachers confirmed the usefulness of emotion recognition, and that the results can be used as a basis to conduct further consultations with the students. However, knowing the emotions of the students constitute a rather privacy-intrusive approach. In terms of tracing the location of the students, the teachers stated that this technology is more applicable to primary students. Students of higher grades could have a defensive attitude towards tracing their locations. However, to our surprise, the teachers were not averse to gathering the audio data of the students. P6 stated, "I would agree on having a recording of a student in order to give a better explanation about the experienced problem and to better converse with the parents." The teachers mentioned that through the audio data, it would be possible to judge the current situation of the student directly.

Nevertheless, additional burden may be placed on the teachers. P17 stated the following, "I think teachers will encounter an extra burden when a school violence detection and intervention system that consists of the mentioned technologies is introduced (e.g. Sending too many notifications or full exposure of the students' emotions).".

Based on the teachers' given answers we extracted design considerations to eventually create a proper school violence monitoring and reporting system.

Data Collection

The application of school violence detection and intervention algorithms makes it necessary to collect a vast amount of student data. Indeed, the use of wearable devices constitutes a plausible approach to achieve the mentioned objective. However, the teachers pointed out the high price tags of the current off-the-shelf devices and their obtrusiveness. Therefore, it is required that the used device should be both affordable and unobtrusive. The majority of teachers agreed on the beneficial aspect of leveraging biometric data and machine learning techniques to reach a better judgement revolving around incidents of school violence. Still, the exposure of student data depicts a privacy concern. Hence, it is relevant to obtain the consent of both the parents and the students beforehand.

Teachers as the ultimate decision makers Some of the teachers stated that they fear that through the system they get into the situation of improper intervention. Therefore, they remain skeptical. The system should not put pressure on the teachers to intervene, instead, it should be used as a reference system to convey further relevant information to support the teachers' decision-making process. The ultimate decision, whether or not to intervene, should always lie with the teacher.

Imbalance of work and private life

Since teachers have a considerable workload and hold high responsibilities, it is essential to not place further burden on them. The participants have voiced their concerns that through the employment of the technology, further burden may be placed on them in the form of increased stress or intrusion into their private life. For this reason, appropriate moments should be figured out to send the warning signals to the teachers. However, the majority of teachers have agreed on the fact that there is a necessity to notify them about severe cases of school violence.

Data conveyance

Indeed, providing teachers with necessary information about the students helps the teachers to make a better judgment about cases of school violence. The teachers reacted positively towards the visual representation of the students' mental state. However, full exposure of the students' emotions would raise privacy concerns for parents and students. Addressing this concern, a partial visual representation of the students' mental state, indeed, depicts a reasonable approach. However, there is a necessity to report severe emotional states to the teachers in order to prevent devastating consequences, such as suicide attempts, substance abuse, or rampage.

Disclosing invisible bullying problems

Several teachers reported difficulties to grasp bullying incidents. There can be diverse reasons: students suppressed emotions in the presence of teachers, hesitation and shyness to talk about the bullying events, etc. Cyberbullying, especially, has much lower visibility than face-to-face bullying, which makes it even more difficult for the teachers to sense these kinds of bullying events. Therefore, the system must expose the invisible properties of bullying to the teachers.

Effectiveness of applied remediations towards bullying

Some of the teachers pointed out that it is beneficial to have suggestions and recommendations on how to cope with the bullying events. The system should go beyond the aspect of notifying the teachers about bullying cases/tendencies. It should also include recommendations on how to deal with the bullying case or assessments about the applied intervention methods.

Chapter 4

Model for Detection of School Violence Situations and Tendencies

First of all, we will discuss the problems we would like to solve. Subsequently, we will describe the two applied methods (sentiment and bullying classification).

4.1 Definition of Problem

Four types of sensor data which may be beneficial to recognize bullying incidents will be collected, namely heart rate as beats per minute (BPM), outdoor location (longitude and latitude), audio data (expressed phrases as text), and movement data (gravity, acceleration, rotation, and attitude). In this study, we solve the two following classification problems that build the basis for the bullying recognition functionality of our system. In terms of the audio data, we primarily focus on the expressed phrases of the students in order to predict whether each of the phrases is emotionally positive, negative, or neutral. As the system is developed to be used in Korean schools we explored audio files in the Korean language. In order to conduct sentiment analysis based on text classification, it is required to change the audio data format into text. This means we need to generate transcriptions from the audio files. Furthermore, the sentiment analysis algorithm has to learn from examples to extract the information from the text and subsequently assign it to specific classes (positive, negative, or neutral). This makes it necessary to have a corpus with labeled Korean text. Afterward, we need to determine a suitable machine learning algorithm to perform the specified classification task. The generated labels from the sentiment analysis again will be used to mark our audio files in the input table. The obtained sentiment will serve as a feature and will be combined with the other data mentioned earlier.

The second classification task is to make a prediction based on the four attributes, sentiment, heart rate, location, and movement of the student, to make a decision whether there is a bullying situation or not. In our case, we both have numerical and categorical features. Therefore we should find an algorithm that can work with these types of features. It can also be the case that there is missing data when the wearable device is not able to capture the data accurately. Even if there is missing data, the algorithm should still carry out its classification task.

4.2 Description of Classification Components

Sentiment Analysis

To infer whether the expressed sentences from the student are either positive, negative, or neutral, we made usage of the machine learning framework fastText [24]. FastText is a three-layer neural network (NN) that provides efficient learning for both word representations and text classification. Additionally, it can be trained on a variety of corpora. These properties are suitable for our task to classify the sentiments from the students' expressed phrases (in Korean). In order for fastText to make inferences about the conveyed sentiments, it is required that it learns from examples. Therefore, we use the representative annotated Korean Sentiment Analysis corpus (KOSAC) [40] based on 8050 sentences extracted from news articles to train fastText on it. We focused on the polarity label to make the inferences about the sentiment of the specific sentence. We tested the resulting model and could observe that the recall part shows a satisfactory rate, with values revolving around 0.89. At times the model did not perform well, most often because of the difference between oral and written language, i.e. missing pronouns or additional pronouns that we use in the everyday language. Thus, we thought about extending the corpus with the pronouns from our daily speech to improve the overall data quality.

Random-Forest-based Bullying Recognition

The aim of the bullying recognition component is to detect bullying and non-bullying incidents in the aggregated dataset (consisting of information about the sentiment, heart rate, location, and movement). The dataset that is collected with the wearable device consists of numerical and categorical data. Also, it has to be taken into account that sometimes missing data is expected to occur. Therefore, we chose the random forest algorithm [6] that is an ensemble learning method mostly applied to classification and regression tasks. It combines a huge number of decision trees, these are individually generated based on bootstrapped samples of the data. The random forest model has the advantages of being robust towards various data types and dealing with the issue of missing data and data artifacts. Most of the time the random forest algorithm is able to achieve relatively good results and have a rather low bias. The issue of overfitting can be prevented with both bagging and constantly selecting a subset of features randomly. Therefore, compared with other algorithms, we regard the random forest algorithm as a suitable candidate to perform the distinction of bullying from non-bullying cases. We applied the algorithm on the aggregated data (sentiment, heart rate, location, movement) to classify whether the data bundle depicts a bullying event or not. Until now there is no labeled dataset available to recognize bullying cases, therefore it is expected that the achieved precision would be rather low and might tend to be inaccurate. Due to the fact that there is no existing available dataset, it was necessary to label the data bundles by ourselves and apply the random forest algorithm on these labeled data bundles. Nevertheless, through this approach, we would be able to label the data, in order to associate the examples with the corresponding labels.

Chapter 5

Monitoring and Reporting System Prototype

In what follows, we discuss the technical realization of our approach. To give an understanding of how the technical components are wired with each other, we explain the system pipeline and its implementation. Lastly, we suggest an initial design for the monitoring dashboard interface that reflects the extracted opinions and considerations of the teachers.

5.1 System Pipeline

Our proposed system pipeline for the detection of school violence cases is illustrated in Figure 5.1 and comprises of seven major components:

- An Apple Watch (Series 4) as a wearable device to collect the physiological (heart rate, audio data, movement data), environmental (audio and movement data), and location data (outdoor location; GPS) of the students.

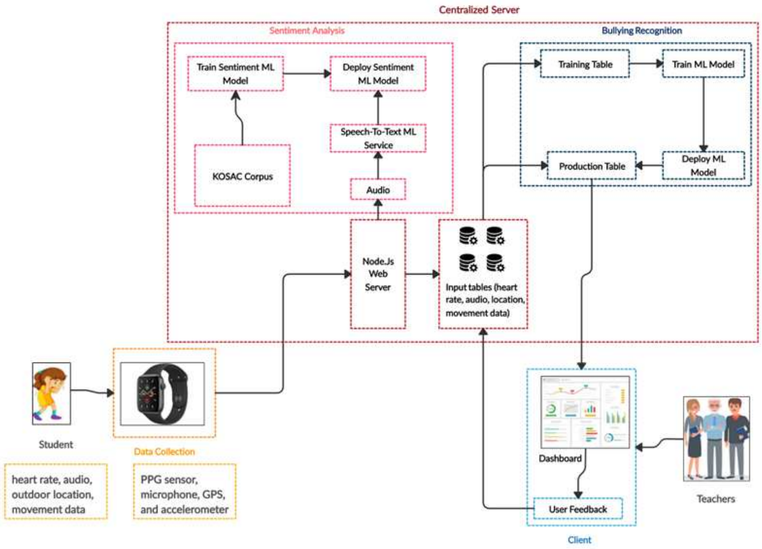


Figure 5.1: System Pipeline with Internal Sentiment Analysis and Bullying Recognition

- An integrated automated speech to text component to generate text transcription based on the Korean audio input from the users.
- A sentiment analysis component to figure out the polarity (positive, negative, or neutral) regarding the expressed sentences of the students
- A bullying recognition component that generates predictions about bullying cases based on the extracted sensor data and provides notices via the monitoring dashboard
- A monitoring dashboard that represents the visual component of the bullying recognition system
- A feedback loop component which uses the predicted outputs from the machine learning model and gives the teachers the possibility to correct the applied labels from the model (acquiring the ground truth).

- A manual bullying reporting mechanism which the student can use to report the bullying case by him- or herself with the button integrated in the smartwatch interface

In our system, the wearable smartwatch (Apple Watch) is used to conduct the continuous passive data collection of the users (students). Through the use of wearable smartwatches we are able to collect the physiological, environmental, and location data from the students in an unobtrusive manner while they are able to conduct their daily activities. Furthermore, through this usage, it is possible to gather a significant amount of data from the users.

Audio data holds a rather multifaceted nature, and we do believe that audio can be a beneficial source of information that can be segmented in varied ways to provide essential indicators for bullying cases. However, since this research should instead set a foundation for a possible automated reporting system of school violence events, we initially placed the focus on the sentiment in the expressed sentences from the students. This is achieved by the extraction of the polarity in these sentences (application of sentiment analysis), meaning that labeling those as positive, negative, or neutral. This sentiment again will be used as a feature and it will be combined with the remaining data (heart rate, outdoor location, movement data) to infer bullying cases.

These aggregated data will be fed into the bullying recognition component where the classical machine learning algorithm are applied to the data to predict whether the present case is a bullying incident or not. It then generates feedback that will be displayed via the monitoring dashboard to notify the teachers.

The monitoring dashboard component displays these feedbacks related to the detected bullying cases. Furthermore, it provides initial design suggestions on how the bullying-related data can be visualized, in order to raise the awareness for bullying cases while the teachers are using the monitoring dashboard. Since it is intended that the teachers use this dashboard as a further assistive reference source on their desktop computer in the school, this dashboard is realized as a web-based dashboard.

Furthermore, the integrated feedback loop obtains the verification of a potential bullying situation. This verification is made by the teachers (domain experts) through the dashboard, he or she can confirm the bullying notification provided by the recognition system. Otherwise, he or she can deny the bullying situation based on his or her judgment. With the aid of this teacher feedback the machine learning models of the bullying recognition system can learn from better examples (ground truth), the system would be able to achieve a better labeled dataset as time goes by. We regard this way as a reasonable pathway to correct the poorly labeled data. Still, we have to take into account that teachers might misinterpret the present bullying cases. In that specific case, the recognition system is not able to learn from good examples and is not able to perform well.

We do not want to deny the need and importance of passive detection of bullying cases in assisting both the students and teachers. Nevertheless, it should still be possible that the students (victims or bystanders) could report the bullying situation by him- or herself. That is the reason for including a manual mechanism which provides the student with the possibility to press a button on the smart watch interface to report a bullying situation. In that case, all the data (heart rate, location, audio, and movement data) will be transferred to the system to notify the teachers about a bullying incident (see Figure 5.2).

Figure 5.2: Watch App Interface

5.2 Implementation

Data Collection component

The data collection part of our system was created for the iOS platform, using both the iPhone and the Apple Watch Series 4. The sensor data (heart rate, location, audio, and movements) was obtained through the usage of the following APIs, frameworks, and libraries:

- In order to access the heart rate sensors in WatchOS and to retrieve heart rate data near real-time, we used the HealthKit API. To sample heart rate data, it was required to start a workout session and to initiate a streaming query from Healthkit.

- The current locations of the student were obtained through the Core location framework that provides the geographic location of the device. The system is currently limited to the outdoor location (GPS location) of the student. At a later point in time, it is conceivable to infer the indoor location of the student by using and processing Wi-Fi signals.

- We obtained the audio data via the AVFoundation framework. In order to transmit the generated audio file to the server, we used the Alamofire (5.2) library.

- Through leveraging the Core Motion framework, information related to the motion and environmental data including acceleration, attitude, rotation, and gravity could also be obtained.

- In order to ensure a robust transmission of the aforementioned captured data, we also leveraged the Watch Connectivity framework to build communication between the smartwatch and the phone.

To ensure a lower depletion of the battery, since battery drain can be an issue due to our usage of the sensing capacity, we inserted buttons into the watch app application that gives users the possibility to switch off the data capturing process. Figure 5.2 shows the data collection interface of the watch app.

Back-End

The sensor data captured by the Apple Watch is transmitted to a centralized server for storage and processing. Each captured data point is bound to a specific student id and a certain timestamp for later reference. Both the watch application and the monitoring dashboard communicate with the server via a RESTful API built up with the Node.js framework. The server receives the different data and stores these in input tables realized via mySql. The training table and output table for further data processing by applying machine learning techniques were also created with mySql.

Sentiment analysis component

Since this work looks at whether the expressed sentences are emotionally negative, neutral, or positive (the polarity of the words in each of the sentences), it is at first required to have transcriptions from the audio recordings that are in Korean. This is achieved by using the NAVER Speech Recognition API to access the Clova Speech Recognition (CSR) engine which states to have the highest speech recognition rate for the Korean language. It is expected that time delays occur due to the computation of the speech input to generate the transcripts. As the teachers stated (see chapter 3), even if they receive a warning notification about the current bullying incident, depending on the severity of the case, they would not intervene immediately. Therefore, we regard this constraint of the time delay as not too aggravating. Nevertheless, we still want to keep the impact of time delay to a minimum, therefore we determined to record the speech of the user every thirty seconds to minimize the issue of time delays and feed those short recordings to the speech recognition component. Furthermore, to avoid a time mismatch, i.e. a difference between the time of data capturing and the time of the recorded transcription, we marked each of the audio recordings with a beginning- and an ending-timestamp. In order to automatize the transcription process and the creation of the corresponding timestamps, we use the built-in Node.js child process module to call the python script responsible for the transcription.

Subsequently, the transcribed text needs to be categorized as either emotionally negative, positive, or neutral. Therefore, we leveraged the three-layer neural network (NN) fastText to perform this kind of predictive sentiment analysis. FastText will be trained by using the labeled Korean Sentiment Analysis Corpus (KOSAC) with supervised classification. Through the training of fastText on the labeled data provided by the corpus, it is possible for us to extract sufficient information from the text to assign this information to specific classes. The previous chapter four provides a more in-depth explanation about the training and optimization process of the model regarding both the internal sentiment analysis component and the prediction component with the aggregated data.

Monitoring dashboard component (Front-End)

The suggested design for the monitoring dashboard that is planned to be eventually used by the teacher is realized with the following web technologies and frameworks: React.Js, JavaScript, D3.js, Material UI, and Node.js (for the visualization of the teachers' remediations regarding bullying events). A more detailed discussion about the design of the monitoring dashboard and the connections made to the teachers' needs and opinions is given in the following section.

5.3 Dashboard Interface Design for Monitoring

As mentioned in chapter two, in the earlier stage of our research, we conducted a semi-structured interview with the teachers (N=35) to learn their way to detect/intervene in school violence cases and obtain their views about the adoption of technology (usage of wearable devices) as a new potential method to address bullying cases. Based on the teachers' needs, obstacles, and suggestions, we were also able to extract several design considerations which could be applied to the design of the monitoring dashboard:

Imbalance of work and private life

As stated in chapter three, a number of teachers pointed out that they experience a work-life imbalance due to their high responsibilities as being a teacher. They fear that with the adoption of technology to address bullying events, additional burdens would be placed on them in the form of intrusion into their private life and increased stress. Indeed, receiving warning notifi-

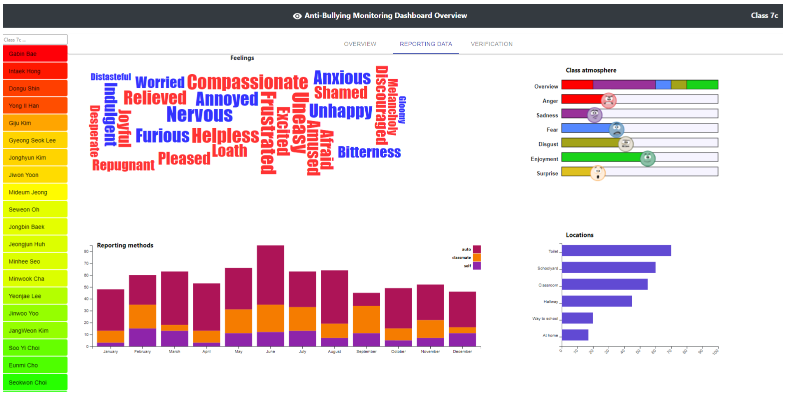


Figure 5.3: View with aggregated data of students

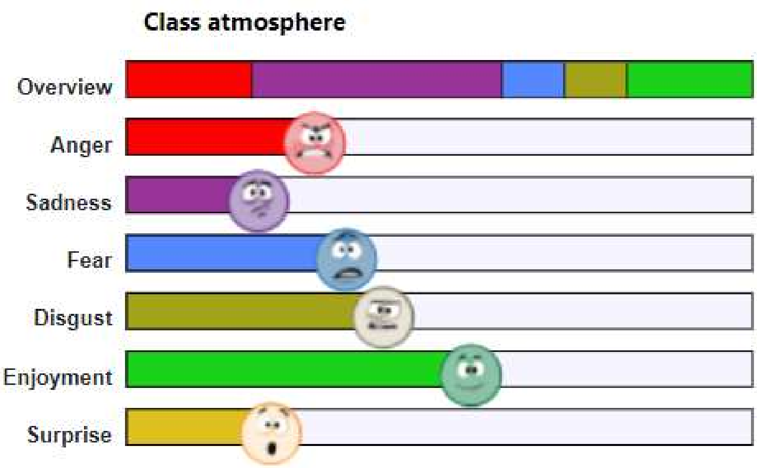


Figure 5.4: Class Atmosphere Chart

cations on the smartphone after work constitutes an intrusive approach into teachers' private life. In this sense, we regard the opportunity of providing a monitoring dashboard as a reasonable additional reference source to detect and analyze bullying cases.

Exposure of mental/emotional data

Teachers do not deny the assistive effect of knowing the emotions of the students in order to achieve a better judgment regarding school violence. However, they stated that knowing the exact emotion of students might be rather privacy-intrusive. The teachers suggested that the polarity of the emotion on its own, either positive or negative, could already be insightful and could provide sufficient information so that they can pay attention to the involved students regarding the bullying incidents. For this reason, it is essential to call into question the extent of exposure of the students' emotional data. We consider a visual representation that comprises a partial exposure of the student's emotional data as a more reasonable approach to implementing this design guideline. Accordingly, as can be seen in Figure 5.3 in terms of the overview it includes the aggregated information of the student from the class. The emotional data is shown in a collective manner (word cloud and the class atmosphere's multiple bar chart (Figure 5.4)) where the emotions cannot be attributed to any particular student. Whereas, the individual view (vertically stacked bar chart of positive and negative emotions) shows the mental state of the student in an abstracted manner, just presenting the accumulated polarity of the emotional data (Figure 5.5). In the overview under the *tab overview* we show the overall warning frequency line graph that plots all the accumulated notifications about bullying events on each day. If the user -in that case the teacher- clicks on the reporting data, he or she will have access to four various graphs, namely the word cloud, the class atmo-

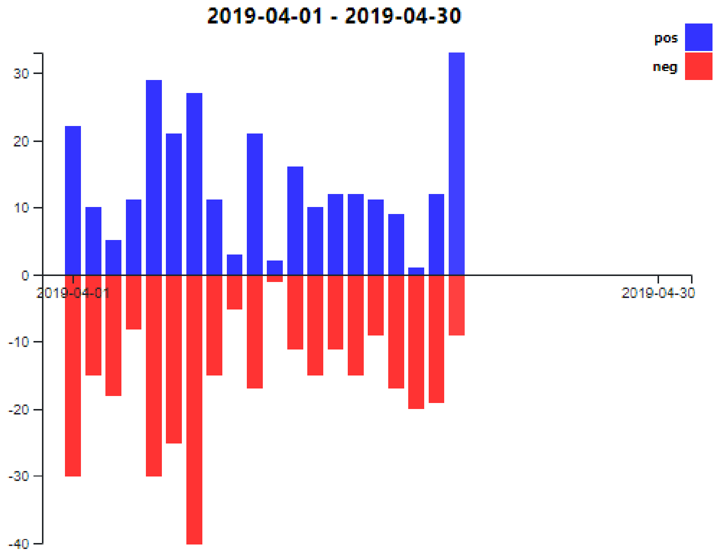


Figure 5.5: Vertically stacked bar chart of positive and negative emotion

sphere multiple bar chart, a stacked bar chart of the used reporting methods, and a horizontal bar chart showing the locations of bullying events. The word cloud is employed to show the feelings of the students in the class. By hovering over a word, the user is shown the number of students who have felt that specific emotion. We tried to keep the colors consistent to the colors used for the vertically stacked bar chart that demonstrates the positive and negative accumulated feelings of a specific student in the individual view. We decided to employ a word cloud due to its strength to draw the attention of the user. Especially, altering the font size, font-weight, and color of the tags has an visual impact on the users and consequently, the terms can be found quickly within a word cloud [2, 22, 29]. Regarding the considerable workload and the time constraint of the teachers, a word cloud reveals the essential feelings and can be scanned quickly by the teachers. Furthermore, we provide the opportunity to have insights about the overall atmosphere by showing the extent of the felt emotions. We used the representative basic emotions according to Paul Ekman [13] and we regarded anger, sadness, fear, disgust, surprise, and enjoyment as applicable to both show the overall class atmosphere as well as to have high-level emotions related to bullying. In order to show the reporting methods, i.e. automated, manual, or reporting conducted by the classmates, we used a stacked bar chart. We intended to provide the user with the opportunity to compare the reporting methods against each other. But, also to have the possibility to see how well each of the methods does which is achieved through leveraging the strengths of stacked bar charts, namely part-to-whole comparisons [42]. Lastly, in order to show the locations where most of the bullying cases happened, we incorporated a bar graph to have both the ratio of each location and to have a comparison between of the locations [42].

Exposure of depressive tendency

Even though the teachers have stated that full exposure of students' emotional data is not necessarily desired, the teachers stated that it is relevant to capture the depressive tendency/state of the student to be able to take appropriate measures on time. Therefore, in the individual student view, it is desirable to have a visual component that demonstrates the student's depressive tendency and its duration. We realized this component by integrating a progress bar into the individual view that shows the progression of the negative state of the specific student. Accordingly, the student can be in the following states: normal, mild, help needed, or depressive. Additionally, underneath the progress bar the duration of the negative state, which the student experiences, is displayed. Figure 5.6 illustrates the component that can provide insights about the depressive state.

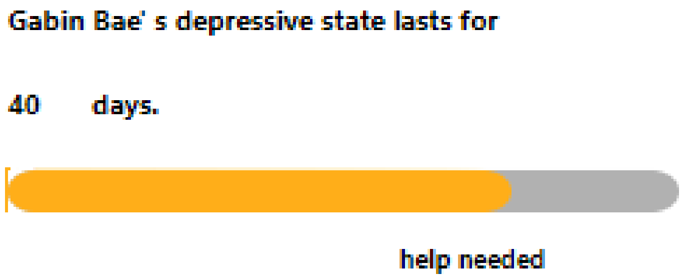


Figure 5.6: Progression of negative state

Disclosing invisible bullying problems

Most teachers stated that it is difficult to grasp the problems between the students, and sometimes they are far too late to know about the bullying issues (e.g. after one year). As stated, the difficulty of grasping the students' problems has diverse reasons: students suppressed emotions in the presence of teachers, discouragement, and shyness to talk about the bullying events, students' prior experiences with the teacher being involved in the bullying issues, and finally, the teachers are not always present with the students (especially the case for middle and high school teachers). For this reason, the dashboard should highlight the students who have issues in terms of bullying and distinguish them from the other students in the class. The overview as well as the individual view show on the very left side all the students from the class. Each of the students is displayed in a color that represents the number of received warnings. We leverage traffic light coded (TLC) labeling, as previous research has pointed out the impact of these labels on the evaluation, perception, and decision making of the users [44]. Hence, the students marked with red represents the ones from whom many bullying notifications have been obtained. Conversely, students marked with green indicates that they barely have bullying notifications. Yellow, orange, and variations of these colors convey the meaning that the teachers should pay attention to these marked students. By clicking on one specific student, the teacher can assess the particular information related to that student. Under the overview tab, the overall warning frequency line graph with the particular graph of that student comprising of his or her aggregated bullying warning notifications is shown.

Effectiveness of applied remediations towards bullying

Several teachers highlighted the aspect that the system should go beyond the aspect of just sending warning signals about bullying situations. The system should, in addition, comprise of the ability to give recommendations on what actions should be taken when a bullying situation takes place or when a bullying tendency is sensed by the system. A conceivable approach is to provide the user with the possibility to visually see the relationship between his or her applied intervention methods and the tendency of the bullying events in the class. In other words, there should be a visual opportunity to see whether the trend of bullying is either going up or down with the applied methods, in order to properly assess the effectiveness of the method. Thus, as illustrated in Figure 5.7, we integrated into both the overview and individual view an editable table, where the intervention methods (direct interventions or consultations) and the information related to the bullying case can be typed in by the teacher. This information will be stored in the background in the database. It will also be plotted on the overall warning frequency line graph when the user selects the corresponding method from the legend. The teacher can retrieve his or her used remediation method from the table, inspect, and compare the method in relation to the overall obtained

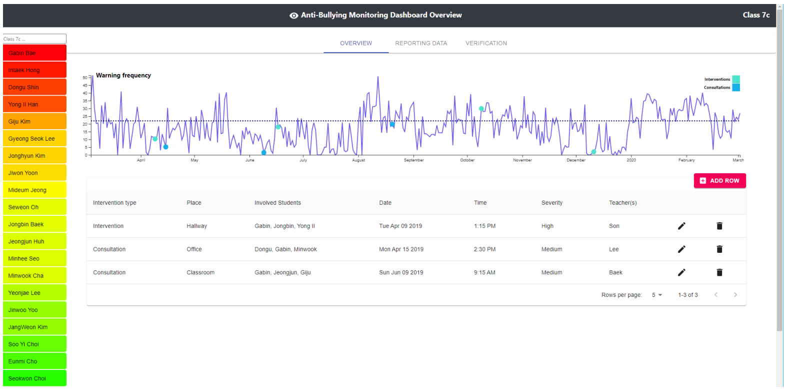


Figure 5.7: Inspection and Assessment of conducted Remediations

reported bullying cases over time. This also makes it possible for the teacher to compare the intervention methods conducted at different time periods against each other and evaluate the efficiency of the methods.

We have taken into account the aspects of visual clutter, simplicity, and consistency with the objective to achieve a good user experience [33, 34]. To have a simple structure and to split the number of visualized graphs, we have used tabs to show a maximum of four graphs on one page. Both the page connected with the overview tab in the overview and the page with the individual view is shaped in a consistent manner. In the overview, as well as in the individual view, the teacher is able to navigate between the overview and the reporting tab to inspect the different graphs related to the student data (see Figure 5.8).

However, it has to be noted that the current suggested design of the dashboard reflects only the views of the teachers. The students' views could diverge from the teachers' views. It might even be the case that the students hold different views towards the extent of revealing their data within the

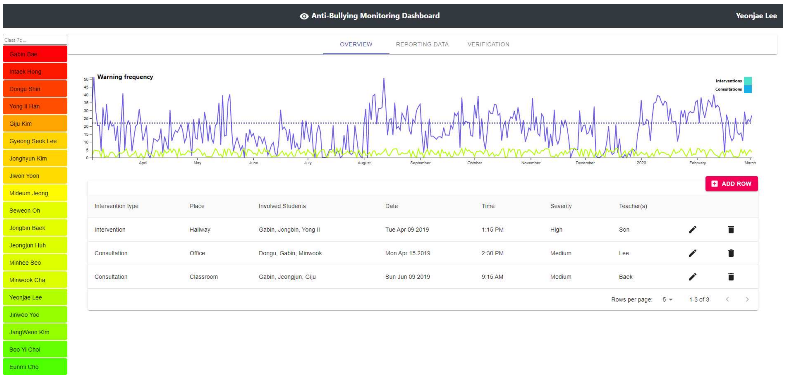


Figure 5.8: Navigation through different views (Inspection of individual student)

dashboard which would be beneficial to address bullying incidents. Therefore, it is relevant to consider the opinions of the students, as well.

Chapter 6

Technical evaluation

This chapter provides a brief verification of the system pipeline's functionality. In order to test the pipeline, we asked laboratory members and friends to create a small simulated dataset.

6.1 Test with Simulated Data

We asked the four participants to wear the Apple watch for a minimum of four hours and also asked them to take notes of the activities that they carried out at specific times. The notes are planned to be used as a possibility to verify the classifications made by the system. The participants were asked to wear the watch while performing their daily tasks and in between bullying incidents were staged for about five to ten minutes. Due to the time constraints of the participants, we were only able to stage four bullying cases in total.

First of all, we were able to confirm that the data collection and data transmission part function properly and are solid. The Speech to Text component to generate the transcripts based on the audio files, however, is not always able to grasp the speech content from the users properly. Additionally, we also noted mistakes in the transcriptions, punctuations were not added to the sentences, and word fillers and sounds from laughter were also transcribed. These aspects have an impact on the result created by the sentiment analysis component. Therefore, an additional manual review was required.

For now, the sentiment analysis component is not automatized yet, since we wanted to test its functionality beforehand with text input.

For the application of the random-forest bullying recognition component, it was necessary to combine the collected data that are stored in separate different input tables. Moreover, since we work with the polarity of the expressed sentences of the collected audio files as a feature, it was necessary to apply the sentiment analysis on the transcription first and subsequently, obtain the sentiment. After we calculated all the corresponding sentiments of the audio files, we aggregated these with the heart rate, locations, and movement data. Since all the collected data were stored in separate different input tables, it was required to combine all the data points from the input tables to a huge training table. We noticed some missing data points in the input tables and not all the staged bullying situations could be grasped properly. Therefore, additional cleaning was required by removing non-useful data points from the training table. Due to the fact that there is no available labeled data set, we needed to label the data points by ourselves, marking the data bundle as "0" for a non-bullying situation and "1" for a bullying situation. Since we have both the numerical and categorical data, it was needed to convert the categorical data (i.e. the sentiments and the transcripts) into numerical data to have consistent data before applying the random forest algorithm to the data. We computed the performance of the random forest model by using the metric for classification accuracy. The fraction of samples that are predicted correctly are calculated as follows:

TP = True Positives
TN = True Negatives
FP = False Positives
FN = False Negatives

$$\underset{\text{Fraction predicted correctly}}{\text{Accuracy}} = \frac{TP + TN}{TP + TN + FP + FN}$$

Figure 6.1: Accuracy metric for classification (Fraction of samples predicted correctly)

We took into account the actual and the predicted labels and got the accuracy score from scikit-learn. The accuracy score for the inserted data bundles were consistent and showed a score of 0.9604 (rounded up; actual score: 0.9603960396039604). The model achieved a rather high score. Additionally, we attempted to examine the score in more detail by letting out the sentiment. We still could receive a high score of 0.9604. Still, it has to be noted that simulated data were used and the data collection was carried out in a controlled manner (i.e. the participants strictly followed our instructions and the bullying situations were staged). Lastly, we fed the verified data back into the recognition component. The feedback component to obtain the verification of the teacher is depicted Figure 6.2 as follows.

Additional essential aspects were noticed during the data collection. First, the audio data gathered demonstrates a rather good quality, even though the participant was not close to the smartwatch while talking. Also, even though all the participants were aware of the fact that they were monitored through the device, most of them showed a rather natural behavior, and their activities and conversations were not restrained, as if they were not monitored at all. Indeed, this aspect needs to be explored in more detail, however, it gives us the impression that wearable devices can be feasible measurement de-

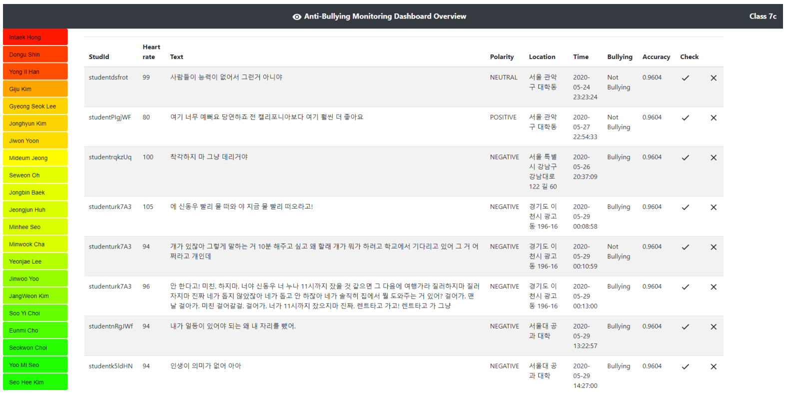


Figure 6.2: Feedback loop to acquire the ground truth (Obtaining Teachers' verification)

vices to gather insightful data that could be beneficial for explaining school violence cases.

Chapter 7

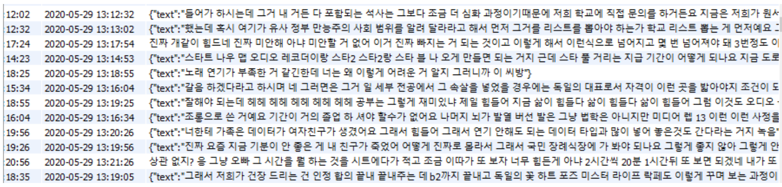
Limitations and Future Work

It is also essential to recognize potential limitations of this study. First of all, this study had to use simulated data in order to test and verify the flow of the overall system. The reasons for the usage of simulated data are twofold: Currently, available bullying identification techniques focus on cyberbullying and therefore do not contain information about the behavior, physical and mental reactions, and activities of the users involved in school violence scenarios as needed for the current approach. In addition, the current coronavirus (COVID-19) pandemic further complicates the data collection of school students. When the situation calms down and is more stabilized, data should be collected in school in order to generate a labeled dataset. The smartwatches could be distributed to the students and the data collection could be conducted in a similar manner as presented in this work [12].

The data collection in future studies should go hand in hand with the development of the machine learning algorithm under consideration of the gathered data and the teachers' input. It is required to validate the outcomes of the machine learning algorithm with the evaluation of the teachers. This validation is accomplished through the integrated feedback loop mechanism.

We assume that bullying scenarios could be defined by the given examples through the teachers' feedback regarding the bullying cases. However, it has to be considered that the teachers might misinterpret the bullying incident. As a consequence, our system would have to work with unreliable feedback and would not be able to detect the bullying cases accurately. Furthermore, we still have to define the relative importance of the different features: heart rate, outdoor location, audio, and movement data in relation to the detection of bullying cases. Future studies will have to verify the relevance of these features for the detection of bullying cases. Subsequently, further analysis is required to identify the proper model with reliable prediction accuracy. When an appropriate model is found, it could be integrated into the system to identify new cases of bullying.

Another aspect of improvement of the quality/performance would be to include other features as candidates to characterize bullying scenarios, such as breathing or heart rate variability. Additionally, as previous research stated that mobility traces have a correlation with both the depressive state and stress-related situations, it is worthwhile to explore the aspects of mobility data more in-depth and leverage its strengths in combination with the remaining data [3, 8]. In this work, sentiment analysis is applied to the extracted sentences from the recorded audio files to identify the polarity (positive, negative, or neutral). However, language might not be the only audible indicator for bullying situations. Since audio data comprises further properties that could function as potential indicators for bullying tendencies/situations, it may be appropriate to include more audio properties, such as loudness, the different speakers, and surrounding sounds included in the audio files.



12:02	2020-05-29 13:12:32	{"text":"들어가 하시는데 그거 내 거든 다 포함되는 석사는 그보다 조금 더 심화 과정이기때문에 저희 학교에 직접 문의를 하거든요 지금은 저희가
12:32	2020-05-29 13:13:02	{"text":"했는데 혹시 여기가 유사 정부 만능주의 사회 범위를 알려 달라라고 해서 먼저 그거를 리스트를 뽑아야 하는가 학교 리스트 뽑는 게 먼저예요
17:24	2020-05-29 13:17:54	진짜 개같이 힘드네 진짜 미안해 아냐 미안할 거 없어 이거 진짜 빠지는 거 되는 것이고 이렇게 해서 이런식으로 넘어지고 몇 번 넘어져야 돼 3번정도
14:23	2020-05-29 13:14:53	{"text":"스타트 나우 맵 오디오 레코더이랑 스타2 스타2랑 스타 블 나 오게 만들면 되는 거지 근데 스타 풀 거리는 지금 기간이 어떻게 되나요 지금
18:25	2020-05-29 13:18:55	{"text":"노래 연기가 부족한 거 같긴한데 너는 왜 이렇게 어려운 거 알지 그러니까 이 씨방"}
15:34	2020-05-29 13:16:04	{"text":"갈음 하겠다라고 하시며 네 그러면은 그거 일 세부 전공에서 그 속살을 넣었을 경우에는 독일의 대표로서 자격이 이런 곳을 밟아야지 조건이
18:55	2020-05-29 13:19:25	{"text":"잘해야 되는데 헤헤 헤헤 헤헤 헤헤 헤헤 공부는 그렇게 재미있냐 제일 힘들어 지금 삶이 힘들다 삶이 힘들다 삶이 힘들어 그럼 이것도 오디오
16:04	2020-05-29 13:16:34	{"text":"조롱으로 쓴 거예요 기간이 거의 졸업 하 셔야 할수가 없어요 나머지 뇌가 발열 버선 발은 그냥 법학은 아니지만 미디어 렙 13 이런 이런
19:56	2020-05-29 13:20:26	{"text":"너한테 가족은 데이터가 여자친구가 생겼어요 그래서 힘들어 그래서 연기 안해도 되는 데이터 타입과 많이 넣어 좋은것도 간다라는 거지 녹음"
19:26	2020-05-29 13:19:56	{"text":"진짜 요즘 지금 기분이 안 좋은 게 내 친구가 죽었어 어떻게 진짜로 몰라서 그래서 국민 장례식장에 가 봐야 되나요 그렇게 좋지 않아 그렇게
20:56	2020-05-29 13:21:26	상관 없지? 응 그냥 오빠 그 시간을 뭘 하는 것을 시트에다가 적고 조금 이따가 또 보자 너무 힘든게 아냐 2시간씩 20분 1시간뒤 또 보면 되겠네 내가 또
18:35	2020-05-29 13:19:05	{"text":"그래서 저희가 건장 드리는 건 인정 합의 끝내 끝내주는 데 b2까지 끝내고 독일의 꽃 하트 포즈 미스터 라이프 락페도 이렇게 꾸며 보는 과정이

Figure 7.1: STT transcriptions

In the proposed pipeline we employed the NAVER's Speech Recognition API which claims to have the highest speech recognition rate for the Korean language, however, many words or spoken parts could not be grasped by the API and erroneous data still exists in the generated transcription. Therefore, it is still required to review this transcription manually before feeding those data into the sentiment analysis component. Additionally, the API cannot distinguish between questions, answers, commands, and statements. Since punctuation also affects the overall prediction result of the sentiment analysis, it also needs to be inserted manually.

We discovered that the sentiment analysis prediction does not label the expressed sentences correctly at times. The reason lies in the fact that the KOSAC corpus is based on phrases extracted from newspapers. A conceivable approach to gain a better prediction is to extend the original corpus with pronouns from our daily conversations. A possible listing of pronouns is presented in Figure 7.2. Also, future work should consider to segment the involved speakers in the audio data, since multiple speakers make it difficult for the sentiment algorithm to compute the correct sentiment label. In this case, it is conceivable to use algorithms to predict the punctuation marks of the expressed phrase.

Battery depletion may constitute another limitation. Especially, if the electrical heart sensor of the Apple Watch remains on, the battery may deplete

	종류
1인칭	나, 저, 우리, 저희
2인칭	너, 너희, 당신, 그대
3인칭	이 분, 이 아이
	그 분, 그 아이
	저 분, 저 아이
	누구,어느분, 아무,아무분
	자기, 저희, 당신
	얘, 걔

Figure 7.2: Possible list of pronouns

even faster. Therefore, it is essential to identify the time when biometric data collection is not necessary so that the Apple Watch can be turned off. Hence, further studies should attempt to identify these time frames through tailored interviews with the students.

Predominantly, in this study, we gathered the views and opinions of the teachers regarding their experienced challenges in noticing bullying situations/tendencies and their overall opinion towards school violence detection and intervention systems. The answers of the teachers were indeed insightful for this research and the design of the prototype. However, it is still essential to listen to the views of the students and parents and have their input. Since the system revolves primarily around the students' data, it is essential to know whether the students would give their approval to use this system and in what way their opinions diverge from the teachers' views. The user interviews with the students (primary, middle, and high school students) were already approved by the Institutional Review Board (IRB) of Seoul National University. However, the COVID-19 pandemic made it difficult to conduct user interviews with the students.

Lastly, some of the teachers pointed out that obtaining a warning notification about a bullying situation is indeed beneficial, and yet it should not just end there. Future research should also take into account the reaction to a bullying event. As the teachers are able to enter their conducted bullying remediation through the provided editable table in the monitoring dashboard, all these measures are added to the system and could be brought in relation to the other data. Hence, it would be feasible for the system to give feedback on the long-term usefulness of the conducted measures. The feedback could be accomplished either with the use of machine learning, through A/B testing or through conducting survival analysis.

However, in the scope of this work, it is more important to build a basis and a functional vertical prototype for a bullying detection and reporting system. We hope that with our work, we inspire and initiate a further inquiry in this research direction.

Chapter 8

Conclusion

In this work, we conducted a user interview with thirty-five teachers with the purpose of following a user-centered design and design thinking-based approach. Through this interview, we were able to figure out the teachers' problems and obstacles regarding bullying, learn about their intervention techniques, and indicators for detecting bullying cases. We were also able to gather their opinions and suggestions revolving around the adoption of a wearable-based system to address bullying. Subsequently, we could derive several design guidelines that we applied to our system and suggested a monitoring dashboard.

We proposed a system pipeline that comprises of the following components: wearable data collection component, manual reporting component, internal sentiment analysis component carried out by fastText (consisting of speech-to-text service to create the transcriptions) trained on the KOSAC corpus, bullying recognition component using classification algorithm random forest, monitoring dashboard, and feedback loop. This pipeline can be used to lay out the foundation to make inferences about school violence cases based on the captured data of the students (heart rate (as bpm), outdoor location data (longitude and latitude), audio data (expressed sentences), and movement data (gravity, acceleration, rotation, and attitude)). Due to the fact that there is no training data set labeled by domain experts (teachers), the current research does not aim at improving the accuracy (precision) of the bullying prediction. It was expected to have a rather dismal result in terms of the prediction of bullying cases, however, the recall aspect, especially of the sentiment analysis component, shows a decent performance. This aspect should be further enhanced in future research. And, as pointed out in the limitations and future work section, since the KOSAC corpus consists of phrases from newspapers and are consequently expressed in the third-person-perspective, a feasible approach would be to extend the corpus with pronouns from our daily conversations to achieve a better sentiment prediction. Furthermore, we noticed that audio data itself is a rich data source that holds many indicators capable of detecting bullying incidents. In this sense, it may be worthwhile to identify the different speakers, the sighs, and intonation in the voice.

Even though there is no available labeled data set yet, we do believe that with this presented solid pipeline it would be possible to conduct a passive data collection and reach high-quality data over time with the integrated feedback loop. In addition, we have come to realize that wearable devices indeed do have the capability to gather high-quality data. To our surprise, especially, the retrieved audio data showed rather good quality and the participants do not need to be close to the device while talking. The participants knew that their data was captured continuously, meaning that they knew they were monitored. And yet, most of the participants showed no inhibitions in terms of their activities and expressed conversations as if they were not monitored. For this reason, we think collecting student data is feasible and valuable data can be collected. We suppose that even though the students might be inhibited in the beginning they will not show inhibitions regarding the actions and revealed conversations once they got used to the device. However, this aspect needs to be verified more in-depth.

This research presents an approach to make the issue of bullying measurable and therefore gives the opportunity to handle it more effectively. This provides assistance to the teachers to detect bullying incidents and tendencies in the class. It is not intended to replace the judgment of the teacher with the results of the system. Instead, the traditional approach (just relying on the teachers' decision-making) should be amplified by taking advantage of the advanced machine learning techniques and capabilities of wearable devices. This research can be considered as the beginning to disrupt the typical approach of teachers towards cases of school violence.

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APPENDIX A

교사 인터뷰용 설문지

1. 선생님께서는 학교에 얼마동안 근무를 하셨나요?
2. 학교에서의 일과를 대략적으로 설명해주세요.
3. 학생들과 하루에 어느정도 시간을 같이 보내시나요?
4. 퇴근 시간은 어떻게 되시나요?
5. 퇴근 이후에도 학교와 지속적으로 연락을 취하시나요?
6. 다문화 가정의 자녀 또는 학기 도중 전학을 오는 학생들의 비율은 어느정도 입니까?
7. 이러한 학생들이 학우들과 잘 어울리는 편인가요?
8. 학생이 이상징후나 평소와 다른 행동을 보이는 것을 관찰하신 적이 있으십니까?
9. 학생이 감정적으로 문제가 있을 때 알아채실 수 있으신가요?
   - (예) 어떻게 알아채실 수 있으신가요?
10. 선생님이 생각하시는 따돌림, 괴롭힘의 징후에는 무엇이 있나요?

11. 선생님께서는 따돌림, 괴롭힘이 의심될 때 어떤 조치를 취하시나요?
12. 선생님께서는 따돌림, 괴롭힘을 확신하실 때 어떤 조치를 취하시나요?
13. 선생님께서는 학급에 따돌림 혹은 괴롭힘이 있다는 것을 어떻게 확신하실 수 있으십니까?
14. 선생님께서는 따돌림이나 괴롭힘이 주로 어디서 발생한다고 생각하십니까?
15. 학생이 따돌림이나 괴롭힘을 당할 경우 학생에게 무슨 위험과 문제가 생길 것이라고 생각하십니까?
16. 따돌림 혹은 괴롭힘을 당하는 학생이 주변에 이를 말하지 못하는 이유는 무엇이라고 생각하십니까?
17. 매년 교육자들을 대상으로 하는 학교폭력에 대한 다양한 프로그램이 있는 것으로 알고 있습니다. 이러한 교육의 한계점에 대해 설명해주세요.
    - 저희 프로젝트의 아이디어는 다음과 같습니다.
    - 웨어러블 디바이스 (웨어러블 디바이스가 무엇인지, 스마트워치를 예시로 설명할 것)를 사용하여 학생의 심박수, 현재 위치, 주변의 오디오, 행동정보와 같은 생체데이터를 수집하여 서버에 저장합니다.
    - 수집된 데이터를 통해 학생의 행동정보와 감정상태(부정적, 긍정적)를 추정하고 이상징후가 있다고 판단될 경우 보호자 (부모님, 선생님)에게 자동으로 경고를 보냅니다.
18. 선생님께서는 저희 프로젝트에서 웨어러블 디바이스를 활용하는 것에 대해 어떻게 생각하십니까?
    - 되물으셨을 경우, 장단점을 설명해달라고 이야기

19. 선생님께서는 저희 프로젝트에서 괴롭힘, 따돌림 감지를 위해 학생의 생체 정보를 활용하는 것에 대해 어떻게 생각하십니까?

    - 되물으셨을 경우, 프라이버시 이슈를 설명

20. 선생님께서는 학생들의 감정상태에 대한 이해가 따돌림이나 괴롭힘의 징후를 파악하는데 도움이 되신다고 생각하십니까?

21. 선생님께서는 이 시스템이 있다고 가정하였을 때, 이 시스템을 어떻게 활용하시겠습니까?

22. 선생님께서는 시스템에서 자동으로 경고를 보내는 방식이 학생 혹은 주변인이 수동으로 신고하는 방식에 비해 어떤 이점이 있다고 생각하시나요?

23. 선생님께서는 이 시스템에서 경고신호를 보낼 때 누구에게 보내야 한다고 생각하십니까?

24. 선생님께서는 이 시스템으로부터 경고신호가 왔을 때 어떤 행동을 취하시겠습니까?

25. 만약 선생님이 퇴근하신 후에 이러한 경고 신호를 받으신다면 어떤 행동을 취하시겠습니까?

26. 선생님께서는 이 시스템의 경고 신호를 휴대폰이나 컴퓨터 중 어떤 것으로 받으시는 것이 더 낫습니까?

27. 이러한 경고 신호들을 (몇개의 알림을 포함) 얼마나 자주 받기를 원하십니까?

28. 선생님께서 컴퓨터의 경고 신호 데이터를 시각적으로 보여준다면 상황의 도움이 된다고 생각하십니까

29. 경고 신호에는 어떤 정보가 포함되면 좋을까요?

30. 오늘 저희가 질문하지 않았던 내용 중 저희에게 추가적으로 의미가 있을만 한 의견이나 질문이 있으십니까?

국문 초록

사이버 폭력을 포함한 학교 폭력은 그 특유의 복잡성으로 인해 매우 다루기 힘든 양상을 나타낸다. 이에 학교폭력이 학생들에게 끼치는 단기적, 장기적 부정적 영향을 방지하고 아이의 건강한 발전을 보장할 수 있도록 효과적으로 문제들을 모니터링할 수 있는 시스템을 개발하고 대처방법을 개선할 필요가 있다. 기존의 학교폭력 관련 연구에서는 전통적인 학교폭력 탐지 및 대처 방법을 사용하였으나 이러한 방법으로는 학교폭력을 탐지하는데 큰 한계점이 있는 것으로 나타났다. 학교폭력 모니터링 능력을 향상시키고 효과적인 대처를 가능하게 할 수 있도록 우리는 웨어러블 기술과 기계학습 방법 (감성분석과 랜덤 포레스트 분류 알고리즘)을 활용하는 시스템 파이프라인을 개발했다. 또한, 교육 분야의 전문지식을 시스템 디자인에 적용하고 점진적으로 수집되는 데이터의 질을 향상할 수 있는 가능성을 열어두기 위해 설계한 시스템에 피드백 채널을 제공한다. 추가적으로, 선생님과 진행한 사용자 인터뷰에서 추출된 디자인 가이드라인을 고려한 모니터링 대시보드의 초기 시각 설계를 제안한다. 본 연구는 학교 폭력이 유발하는 사회적 문제를 측정가능하게 만들뿐만 아니라 기존의 고전적인 학교 폭력 대처 및 접근법을 혁신하는 시작점을 제안한다.

주요어: 의사 결정 지원 시스템; 웨어러블 컴퓨팅; 기계학습; 사용자 중심의 설계; 교육

학번: 2017-22345

감사의 글

낯선 한국에서 가족없이 대학원 생활을 하면서 어려움을 많이 겪었고 힘든 시간이 많았습니다. 그동안 수많은 사람들의 도움을 받았습니다. 그리고 이 분들이 없었다면 지금의 저 또한 없다는 것을 자신있게 말할 수 있습니다. 이 자리에서 그 분들께 감사의 인사를 드리고자 합니다. 먼저 교수님께서 저를 받아들여주신 것에 대해 감사드리고 싶습니다. 애초에 저는 지식이 많지 않았기 때문에 어려움을 많이 느꼈지만 교수님께서 아낌없이 지도해주시고 격려의 말씀을 해주셔서 제가 많은 도전을 이루고 현명한 사람으로 성장하게 될 수 있었습니다. 이에 진심으로 감사드립니다.

또한, 저는 다음과 같은 분들께 감사의 말을 전하고 싶습니다. 먼저 신유정 님께 감사드리고 싶습니다. 신유정은 저를 항상 격려해주었고 저보다 제가 갖고 있는 실력들을 믿어주었습니다. 신유정은 저에게 매우 중요한 사람이 되었기에 진심으로 유정에게 감사합니다. 유타 하슬러께도 큰 고마움을 전하고 싶습니다. 유타는 항상 제게 힘을 주었고 응원해줬습니다. 유타가 없었더라면 제가 오래전부터 포기했을 것입니다. 그리고 제가 김기주님께도 감사하다는 말을 전하고 싶습니다. 저의 실력과 할 수 있는 것을 믿어줬고 저를 많이 도움을 줬습니다. 특히 한국에서 제가 아는 사람이 없었을 때 큰 감동을 받았습니다.

또, 이세희 오빠께도 감사한다는 말씀을 드리고 싶습니다. 처음 연구실에서 연구를 시작했을 때, 저 때문에 아마 힘드신 시간을 겪으셨습니다. 바쁘셨더라도 항상 저를 위해서 시간을 내주셨고 저에게 좋은 조언을 주셨습니다. 이세희 오빠는저에게 아주 좋은 멘토입니다.

마지막으로, 김재영께 감사의 말을 전하고 싶습니다. 특히, 외국인 학생으로서 연구실에서 많이 외로울 수 있는데 김재영은 저와 거리를 두지 않았으며, 저를 외국인으로 대하지 않았습니다. 아마 귀찮을때가 분명히 있기는 하지만 제가 하고

싶은 말을 항상 끝까지 들어주었습니다. 제게 항상 가치 있는 조언을 줘서 정말 감사합니다.

이렇게 많은 분들의 도움을 받은민큼 모든 분들을 실망시키지 않고 앞으로도 저의 최선을 하겠습니다.

2020년 06월 02일

호탄융 올림