Laughter as a Controller in a Stress Buster Game

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ABSTRACT

Laughter has been known to have therapeutic benefits ranging from reducing stress and inflammation in the short term to lowering cholesterol and blood pressure in the longer term. Studies have also shown that even faked laughter could provide some of these benefits. In this paper, we present the design and validation of a game, "Laugh Out Loud", in which laughter acts as the controller of the game mechanics. The goal of the game is to bloom a wilted flower by laughing. The primary components of this system are a laughter detector and a game interface. The laughter detector is a machine learning algorithm that analyses signals recorded by the microphone in real time and measures the intensity and duration of laughter. The game interface displays a wilted flower that starts blooming step by step as the player laughs, with a fully bloomed flower at the final level. Each level has an increasing level of difficulty, which means that the player has to laugh louder and longer for crossing the higher levels. The game interface is implemented as an Android app, with the intention of making the well-being intervention available anytime, anywhere. To validate the game, we conducted a study in which 48 participants were asked to play the game, one at a time, while seated alone in a closed room. 76.6 % participants reported that they experienced reduced stress after playing the game. We present findings of this study and observations that could lead to some design improvements.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing systems and tools**.

KEYWORDS

laughter, game design, positive psychology, machine learning, stress-relief, digital psychology, digital health, mHealth

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1 INTRODUCTION

Well-being refers to the presence of positive emotions and moods such as happiness, contentment and self-confidence, absence of negative conditions like stress, anxiety, and depression as well as aspects such as life fulfilment, life satisfaction and the resilience to deal with and recover from setbacks. An important aspect of our daily experience is stress and it has a significant influence on our well-being. Stress is the body's reaction to a threat and is usually a short-term experience. If the stress motivates us to act on the threat, it is positive. However, when it results in insomnia, poor concentration, and impaired ability to do the things we can normally do, it is negative. Stress has even more implications in the context of the workplace. A report from the National Institute for Occupational Safety and Health [10] indicates that 40 percent of workers reported their job was very or extremely stressful. It also indicates that job stress is more strongly associated with health complaints than financial or family problems. In the past 20 years, many studies have looked at the relationship between job stress and a variety of ailments. Mood and sleep disturbances, upset stomach and headache, and disturbed relationships with family and friends are examples of stress-related problems that are quick to develop and are commonly seen in these studies [10].

Humor and laughter can be effective self-care tools to cope with stress. Laughter provides a physical release for accumulated tension and stress [19]. Laughter has been known to have therapeutic benefits ranging from reducing stress and inflammation in the short term to lowering cholesterol and blood pressure in the longer term. Current literature broadly distinguishes between 'simulated' versus 'spontaneous' laughter [17]. Spontaneous laughter is laughter triggered by a stimulus, such as a joke. Simulated laughter is voluntarily and consciously triggered by oneself (self-induced, a 'fake' laugh, or non-humorous laughter) , and is not caused by humor or other stimuli [29]. Despite the limited number of publications, there is some evidence to suggest that simulated laughter has also some effects on certain aspects of health [17]. The systematic review and meta-analysis presented in [29] suggests that (1) 'simulated' (non-humorous) laughter is more effective than 'spontaneous' (humorous) laughter, and (2) laughter-inducing therapies can improve depression.

In this paper, we present the design and validation of a mobile game, "Laugh Out Loud", that aims at inducing a simulated laughter. This is achieved by a design, in which laughter is the controller of the game mechanics. This means that the input signal to the game is provided through the sound of laughter, and the actions in the game are performed when laughter is detected by the microphone. The goal of the game is to bloom a wilted flower by laughing at a certain intensity. The primary components of this system are a laughter detector and a game interface.

The key contribution of this paper is a novel concept of a laughter-controlled purposeful game, where-in, the game progress is achieved by performing laughter, which in itself is a well-being intervention. This serves the dual purpose of delivering an intervention while also motivating the user to execute the intervention in a repeated manner. The concept is validated through an implementation and a study, the results of which make us believe that such a game-design can be used to deliver well-being interventions.

The following sections of the paper discuss the training and testing of a machine learning classifier that detects laughter in audio signals captured by the microphone, the design of the "Laugh out loud" game, and a study conducted to evaluate the game and the effects of its usage. While the concept of laughter as a controller in a game is novel and not commonly found, there are a few laughter detection apps and stress buster apps that we compare and contrast with in the Related work section. We conclude the paper with a discussion on future work.

2 LAUGHTER DETECTION MODEL

The laughter detection model is a machine learning classifier that detects laughter in the input audio signal. Apart from laughter, the other input that participants may provide while playing is speech. Hence, it is important that the laughter detector accurately distinguishes between these two signals. The model is trained using speech and laughter data collected of 30 participants. After the model got trained and tested with the data, it is ported on android mobile for getting real-time responses during game execution.

2.1 Laughter Data

The laughter and speech data for building the laughter-speech classifier is collected in office premises in an open workplace atmosphere and not in a closed room. This is to capture the noise of the environment as well. This helped us in getting the data in the real-time context rather than a lab setting. The speech and laughter data was captured at the participants' desk using smartphone mic. The audio data is captured at 16 kHz sampling rate, using single channel, and defining 16 bit sample size. 15 male and 15 female associates, from the age group of 22-40 participated. The data collection was carried out in below steps:

- Participants were explained about the objective (develop a laughter detection machine learning model) of data collection and the protocol that they need to follow to provide their speech and laughter data. As per the protocol, they had to converse initially, and then laugh in-front of the smartphone mic.
- The participants' consent was taken before proceeding with the further steps.
- Followed by their positive consent, the speech response was captured during a general conversation.
- They were asked to laugh intentionally and again their laughter was recorded. This is to capture, the speech and artificial laughter both for each participant. Almost 74 % of the participants started laughing naturally followed by their artificial laughter session towards the end. Hence, the natural laughter was also captured in the same setup. Only the audible part of the natural laughter was included in our training set.
- The data was anonymously stored by using the participant ID given to each participant.

Table 1: Utterance count for each class

Data-set	Speech	Laughter
LocalDB-Train	86	86
LocalDB-Test	56	56
ESC-50	55	55
SSPNet	72	72

This gave 136 utterances collected for each (laughter and speech) class. Henceforth, this data-set is referred to as LocalDB. The train and test class distribution is as shown in the Table 1. Other data-sets used for testing the accuracy and comparing with state of the art results are the ESC-50 data-set [22] and the SSPNet Vocalisation Corpus [27]. The utterance count of both these data-sets are also described in Table 1. As seen in the Table, the data-set is balanced with an equal number of train and test set utterances. The balanced data-set helps in avoiding biases in the prediction outcome. The overall accuracy calculation of the classifier is done as weighted average recall (WAR).

2.2 Features and Machine Learning Model

Below steps are taken on the captured audio data:

- Pre-processing
- Feature extraction
- Building the machine learning model

The audio data is pre-processed by converting it to 8 kHz sampling rate for further processing. The data is manually segmented to retain the audible laughter sections using the Audacity tool [28]. The laughter sections are further automatically segmented into shorter frames. Since an audio signal is highly random in nature, the features are extracted for every 20 msec of audio frame for which the audio signal is assumed to be stationary. Hence, each

Table 2: Accuracy (in %) Comparison using different machine learning algorithms

Algorithm	Overall Acc
Random Forest	84.6
SVM	58.7
Decision Tree	68.5
kNN	63.9
DNN	68.3

processing frame has a size as shown in Equation 1.

$$\begin{aligned} frame\_size &= sampling\_rate * frame\_duration \\ frame\_size &= 160\ samples \end{aligned} \tag{1}$$

Both time and frequency domain features are used for training the machine learning model. The time domain features work on the time domain acoustics. However, frequency domain features work on the spectrogram of the audio data. For the collected speech and laughter utterances, the time-domain features extracted are, Root Mean Square (RMS), time-domain auto-correlation, and Zero Crossing Rate (ZCR). The frequency domain features are 13 Mel Frequency Cepstral Coefficients (MFCCs). This forms a feature vector of dimension 16. RMS is a good indicator of loudness, and hence is used for detecting the intensity of laughter. Also, it is a significant factor in detecting the presence/absence of audio. Time domain auto correlation represents the pitch contour which again varies significantly between speech and laughter. The selection of features is based on the low level descriptor (LLD) groups described in [2]. The authors of [2] also mention spectral energy. However, it is not used as a feature for this task, as it did not add value to the accuracy to our model. These features are extracted for every 20 msec (160 samples) frame of the audio data, giving a feature vector of dimension 50x16 for each second of audio signal.

The balanced training data-set is used for training a Random Forest Classifier. Random Forest is an ensemble algorithm that makes use of multiple decision tree classifiers on various sub-samples of the data-set. We used scikit-learn [21] library's Random Forest algorithm and configured it to use 100 decision trees. Before using the Random Forest algorithm, the model's accuracy was tested with other machine learning algorithms from scikit-learn such as Support Vector Machine (SVM), k-Nearest Neighbour (kNN), Decision tree, and a Deep Neural Network (DNN) from tensorflow. The DNN architecture comprises of 2-hidden dense layers with a ReLu activation function and one dropout layer with a dropout factor of 0.95. A low weight DNN has been selected for building the model with minimal resources. As the final intention is to import the model on an android smartphone, it should be consuming optimised resources. The accuracy obtained for every 20 msec frame is as reported in Table 2.

From Table 2, Random Forest gives the highest accuracy on our data set, hence, it was selected.

2.3 Testing the Laughter Detection Model

The laughter detection model is trained and tested with the data collected at the workplace environment. We have tested this model also on other data-sets collected for other contexts and demographics such as the ESC-50 and the SSPNet vocalisation corpora. Our model outperforms the state of the art results on the given data sets. The accuracy of our model is as shown in Table 3.

Table 3: Model accuracy (in %) on different data-sets

Data-set	Speech Acc	Laughter Acc	Overall Acc
LocalDB-Test	96.6	80.6	88.6
ESC-50	84.2	93.2	88.7
SSPNet	81.4	92.3	86.8

As seen in Table 3, the model accuracy of both the classes exceeds 80 %. We have further compared these accuracies with an open source toolkit in Section 5.1.

As we process every 20 msec frame at a time, we get predictions for every such frame, where we get a mix of predictions of both the classes. To derive a prediction for an utterance from the frame-level predictions, every 500 msec of the utterance is processed. 500 msec duration is often preferred for calculating high level descriptors in audio processing. A majority rule was applied to classify a 500 msec chunk as laughter. Once, the prediction for every 500 msec is obtained, the utterance level prediction for laughter is achieved by again applying the majority rule on these batches of an utterance.

2.4 Calibrating Laughter Levels

In order to configure the laughter detector as the controller for the game, it is necessary to label different thresholds of laughter parameters at different levels. This is achieved by labelling each level in terms of corresponding threshold values of the selected laughter parameters: energy and laughter duration.

The energy of a laughter is calculated using the RMS value. As mentioned before, we process every 20 msec of an audio frame, hence, the RMS value for every 20 msec of a frame is calculated. Laughter is not a continuous signal, hence, duration of laughter refers to the number of predictions obtained in every 500 msec (half a second) of audio. Accordingly, in every 500 msec, we would get 25 predictions of laughter and an equal number of RMS values.

We analysed the laughter clips of the training data collected (as explained in Section 2.1) for deriving the threshold values for the energy and laughter duration parameters. From the data, the RMS and duration values of those artificial laughter clips were studied, after which the participants started natural laughter. That is, on the verge of artificial and natural laughter. It was seen that an average RMS value of 30 and laughter prediction count of 14 in every 500 msec of such an audio clip is obtained.

3 GAME DESIGN OF LAUGH OUT LOUD

Our primary objective behind Laugh Out Loud (LOL) is designing a laughter controlled game. Laughter therapy is a much recognised intervention for stress management and is commonly practiced in large groups and gatherings. Implementation of a therapeutic intervention like laughter therapy in games to relieve stress qualifies it as a "serious game". A serious game is a game designed for a purpose, other than pure entertainment. We use the Serious Game Design Assessment (SGDA) framework [13], to formally conceptualise the

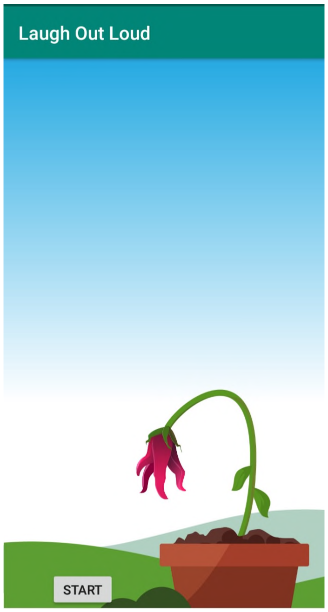

Figure 1: First screen of the Laugh out Loud Game
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game and describe it in terms of the framework parameters. An empirical evaluation of the game with a group of human subjects was performed. We conducted two design and evaluation iterations, because a need to re-calibrate some game elements was envisaged during the empirical evaluation. Another set of subjects evaluated the re-calibrated game. A description of the game design elements follows:

3.1 Purpose

The main purpose of a serious game is to impact the player in a specific way. [13]. Our primary objective behind designing Laugh Out Loud (LOL) is to induce simulated laughter, so players derive the psycho-physiological benefits of it. Specifically, LOL will be offered as a stress buster, i. .e., a game that helps players experience relief from stress.

3.2 Content and Information

The element content and information refers to the information, facts and data offered and used in the game [13]. When the player opens the game, we show the picture of the game object, a message on the screen that says "Laugh Out Loud" and a "Start" button. The game object is initially shown in an undesirable state, which invokes the feeling to do something about changing its state. The three game objects considered in our design are a wilted flower, a table fan that is not moving, and a dark alley. The player's goal would be to fully bloom the wilted flower, get the fan to rotate at full speed and brighten the dark alley, respectively. In this paper, we have conducted an empirical evaluation using the wilted flower as the game object. Figure 1 shows the initial state of the wilted flower that is shown to the players.

3.3 Game Mechanics

The game mechanics are the methods which are invoked by suited agents for interacting with the game world. The SGDA framework also asks for the pivotal in-game goal of the game, the operation of the reward system, the main playful obstacles/challenges, the difficulty balancing, and the win condition [13]. The game play is to revive the game object from an undesirable state to a desirable state and the core game mechanic uses laughter as the controller/input. The message "Laugh Out Loud" prompts the player to start laughing. As the laughter detector recognises laughter through the microphone, the flower is gradually revived to a healthier state. This feedback motivates the player to laugh more and cause further progress in the state of the flower. The player would be required to keep laughing till the flower is fully bloomed and erect, which is the end goal. The controls available to the player are intensity of the laughter and duration of the laughter. The player can vary these two and observe the effect on the flower. If the player is tired of laughing or does not find motivation to laugh more, he may stop the game by clicking the "Done" button at any time during the game. Once the goal state is reached, the game is complete and the "Done" button on the screen changes to the "Restart" button, and a message saying "Great! You have done it" is shown to the player (cf. Figure 2). The aimed at satisfying feeling of seeing the fully bloomed flower and the stress relief experienced after laughing both serve as the reward mechanism in the game. We expect players to come back / want to play again to experience this feeling. The revival of the flower on the screen was divided into six levels with equal difficulty. Difficulty is a combination of laughter parameters, intensity, and duration of laughter. Since this is a highly subjective matter, we chose to begin with an initial difficulty level and refine it based on the feedback received during the evaluation. As explained in Section 2.4, the average energy threshold was configured with an RMS value of 30 and the duration was configured with 14 Laughter counts in every half a second.

3.4 Fiction and Narrative

While the content holds the provided information and the mechanic impacts the game-play possibilities, the dimension of fiction and narrative introduces a context that is relevant to the game purpose [13]. The LOL game offers a simple narrative that the flower is being shown in an undesirable state and there is an action possible to revive it. This is analogous to the game purpose, where the player is feeling stressed (undesirable) and needs an action to relieve the stress (desirable). The act of the simulated laughter, aims to revive not only the flower on the screen, but also the player in his real life.

3.5 Aesthetics and Graphics

This component of the SGDA Framework refers to the audiovisual language (aesthetic, characteristics, imagery, style preferences, artistic media, and the computer graphic techniques) conceptualised, chosen and used by the designers for the visualisation, and the display of the elements involved in the game. [13]. A flower was chosen as a game object as studies have shown better mental health outcomes in visuals with green imagery [24]. We also chose flower as a game object as its real-world characteristics like smell, colour, texture etc. are generally found appealing and relaxing. As a game

Figure 2: Goal state on achieving the final level
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object, the visuals of the flower from the wilted to the revival stage are designed to induce a feeling of happiness and achievement.

3.6 Framing

Besides the design elements listed above, framing of these elements in terms of the target group, their play literacy is an essential element of the game design [13]. Our target users are the working population in the age group of 25 to 60 years. While we believe that the game mechanics are suitable for most people in this demographic group, it is possible that people suffer from lung related disorders such as asthma, or such experiencing throat infections may have trouble playing the game as it may aggravate their conditions. We did not choose such participants in the evaluation. We plan to add suitable disclaimers in the initial screen of the game. Different people have different capacities and intensities of laughing and it is expected that some players may not be able to laugh beyond a certain intensity and would find it potentially difficult to progress in the game. At this point, the design does not cater for such individual differences. The possibility of addressing this is discussed in the future work section.

3.7 Coherence and cohesiveness

The last and perhaps most important aspect of the design is how all the design elements described above holistically relate to each other and to the game's purpose. The core game mechanic of using laughter as a controller bridges the gap between the game world and the real world seamlessly. When the player laughs, it is not only affecting the game world (revival of the flower), but also the real world (stress relief). Further, seeing a flower bloom is a pleasing visual and is likely to help a stressed person calm down to an extent. Reviving something from an undesirable state to a desirable state is likely to generate a feeling of achievement and happiness, which again supports the game purpose in a significant way. All the game elements of content, mechanics, aesthetics, and narrative are thus in good alignment with the overall purpose of relieving players from stress.

4 EMPIRICAL EVALUATION OF LAUGH OUT LOUD

The objective of this study is to evaluate the Laugh Out Loud game with a group of human subjects to gauge if the game meets the intended purpose. The following sub sections describes the study setup, execution, and results.

4.1 Study Setup

The participants for the study were recruited through volunteering. We explained the purpose of the study and those who volunteered were selected. We had a total of 48 participants from the age group of 21 - 50 years, including 27 male and 21 female subjects, working in a multinational company. The study was conducted in a corporate office premise in a sound proof meeting room where the participants could laugh out loudly and freely. We designed a one pager brief which was to be given to the participant to explain the purpose of the study and request consent for recording their conversations before, after, and during the game. These conversations were recorded for performing qualitative analysis on the participants' feedback. The LOL game was installed on an android smartphone that was placed on the table along with the brief.

4.2 Study Execution and Data Collection

During the study execution, each participant went in the sound proof room, alone. The participant read the brief and provided their consent and then went on to respond to a pre-game-play survey. This records a subjective rating of the participant's current stress level. The moderator did not interact much with the participants, as this would have interfered with the recorded stress level. Also, the information about the laughter parameters that are configured for crossing the game levels was not informed.

The participant then plays the game. This is followed by a post-game-play survey in which the subjective rating of stress-levels after the game-play is recorded. After having played the game, the participant calls the moderator, who has a conversation with the participant and collects qualitative feedback about the experience. The following data was captured from each participant:

- Subjective rating of stress levels before playing the game
- Demographic information, age
- Audio recording of participants laughter during the game play
- Number of levels completed
- Number of attempts
- Subjective rating of stress levels after playing the game
- Audio recording of the semi-structured interview conducted by the moderator, that contains qualitative feedback
- Duration spent by the participant with the game. This is calculated as the time duration between the 'start' and 'done' instances.

The study execution was conducted in two phases. This was done because many participants found difficulty in crossing the initial level itself. The first phase of study execution was conducted with 14 participants. Based on their feedback the game difficulty levels were re-calibrated and the second phase of execution with the remaining 34 participants was conducted.

4.3 Analysis and Results

The data collected in the study execution was converted to a tabular form for ease of analysis. Analysis on various aspects of the game and participant experience was performed. A description of our findings follows:

4.3.1 Difficulty of Game levels and its re-calibration. As outlined above, the original version of the game consisted of 6 levels for the wilted flower to achieve full bloomed state. Each level was designed of equal difficulty. The condition to bloom the flower and pass it on to next stage is to laugh with an energy measured by an average RMS value of 30 and for the duration of 14 laughter counts. Only when the participants laughed out with the required effort, the flower bloomed from one stage to another. Participants showed low motivation as all levels were equally calibrated and it required them a lot of effort to overcome the first few levels of the game itself. Hence, The game was re-calibrated for 12 levels. The first four levels were set to have low difficulty, the next four levels had medium difficulty and the last four were set to the highest difficulty level. It was important to set difficulty levels in the game in order to increase the player engagement and the repeat play value. Since the design is a game and not a one time experiment, it was essential that we incorporate a challenge in the form of difficulty levels that would enable players to revisit the game. Level segregation was hence essential to engage players and give them a reason to achieve something greater every visit to the game. Therefore, we wanted the game to have at least three difficulty levels, again, the laughter training data was analysed for getting corresponding threshold values of the laughter parameters. The levels were adjusted with reference to the participant feedback as received earlier. We are aware that game challenges are followed by game motivations like power ups, scores and collectibles, but for this version of the game, we tested the basic setup and hence did not include extensive incentives. In the original version, we had analysed the laughter instances on the verge of artificial and natural laughter. These values were configured for the highest difficulty level in the re-calibrated version. Now, we analysed the laughter instances towards the start and middle of the complete laughter session. We could form two clusters of the training laughter data with respect to laughter parameters, RMS and laughter prediction count. These threshold values are as described in Table 4. After the re-calibration, the study participants were able to make better progress. Most participants were able to cross initial levels and that provided the motivation to play the game to higher levels. It was observed that the maximum time a participant could spend on the original version was up-to 4 minutes which increased to more than 7 minutes with the re-calibrated version. The maximum level that the participants could reach to was 4 in the original version, however, with the later version, 50 % of the participants could target the high difficulty levels 8 and beyond. These results were achieved on multiple trials by the participants. The multiple attempts were voluntarily made by the participants. Some of them even stated that they would have continued attempts if they had the game on their personal handheld mobile devices.

Table 4: Energy and duration threshold for three difficulty levels

Difficulty Level	Energy Threshold	Duration Threshold
Low	15	8
Medium	20	10
High	30	14

Table 5: Table showing difference in the stress level of participants in version 1 and version 2 of the game. Stress values in percentages

Game Version	SR Positive	SR Neutral	SR Negative
Version 1	43	50	7
Version 2	60	23	17

4.3.2 Impact on Stress levels. 76.6 % of the participants reported that they experienced stress relief during the qualitative feedback conversation. We used the pre and post stress levels to compute Stress Reduction (SR), as (SR = pre-stress - post-stress). SR positive indicates that stress levels have been reduced, SR negative indicates that stress levels have gone up, and SR neutral indicates that stress levels remained unchanged. In Table 5, we present the stress reduction data for both original and re-calibrated versions. 60 % of the participants experienced a positive stress reduction. We also observe that the percentage of participants showing neutral stress reduction was very high in the original version. This could be attributed to the fact that many people could not reach the higher levels and gave up very early, as a consequence reporting that they did not experience any difference. In contrast to this, in the re-calibrated version of the game, 50 % of those who experienced high level of stress reduction had reached up to the medium difficulty level. These achievers are equally distributed among male and female categories. From the qualitative analysis of the semi-structured interviews that the moderator had with the participants, it was observed that 50 % of the participants who reported neutral stress reduction in the pre and post survey felt better and enjoyed the activity.

4.3.3 Game Play: Attempts, Levels, Duration. The analysis for these game play related aspects was conducted on the phase 2 data that had 34 participants. The study received 100 % participation. All the associates who read the initial study brief participated till the end. The reduction in the stress level of the participants can be attributed to various factors in the activity like the game level achieved, the number of game trials, as well as the time spent playing the game. Below are some of the prominent observations:

- The maximum number of trials in males were made by participants of the age group 26 - 30 years and that of females

Table 6: Average game levels achieved by male and female participants per age group in years.

Age Group	Male	Female
21-25	6.57	6.60
26-30	3.67	2.50
31-35	3.00	5.67
36-40	2.00	-
41-50	8.40	4.00

in the age group 31 - 35 years, cf. Table 7. It is also observed that with every trial they have tried improving on either energy, or duration or both of the laughter. As mentioned before in section 4.2, the participants were not informed about the parameters that they need to control in the game. This validates the choice of laughter parameters selected in the game.

- The maximum average level of laughter achieved by males was in the age group 41-50 and that of females was in the age group 21-25 as seen in Table 6. Looking at further intricacies, 30 % of the male participants from the age group 21 - 25 years could achieve levels as low as 2 or 3, however, the other 70 % achieved higher difficulty levels of above 7. All these were having a pre-stress level of 3 on a scale of 1 to 5, where 1 is no-stress and 5 is high stress. Also, the qualitative analysis of the recorded laughter shows that the quality of their laughter was really loud and audacious. This indicates us to focus on the mentioned age groups for our further studies in order to derive significant conclusions.
- Table 6 also shows that the highest levels were achieved by male participants in the age group 41 - 50 years. However, the sample size for this demographic was comparatively small (n=5). The age group 21 - 25 years has the second best average levels reached, for both male and female participants. This might indicate that the laughter levels are better calibrated for a certain age group, or that the design elements have a better appeal with this demographic group.
- An analysis of the duration of the game play and the levels achieved in the game is plotted in Figure 3, and we observed that there was a very weak correlation between the duration of the game and the game levels achieved (cf. Table 6). As it was configured, the energy and duration of laughter was directly proportional to the number of levels achieved by the participants. This is so because, apart from laughter, the game duration (the complete duration participants spent with the app) also comprises of pauses that the participants take between the laughter instances.

4.4 User experience

Some participants were initially curious about the techniques involved and wanted to test the same. They not only laughed but also tried to speak to the flower to see if it blooms. During the initial conversations, they wanted to know if their facial expressions can also

Table 7: Average number of game trials for male and female participants per age group in years.

Age Group	Male	Female
21-25	2.00	1.50
26-30	2.33	1.17
31-35	1.00	2.00
36-40	2.00	-
41-50	1.60	1.50

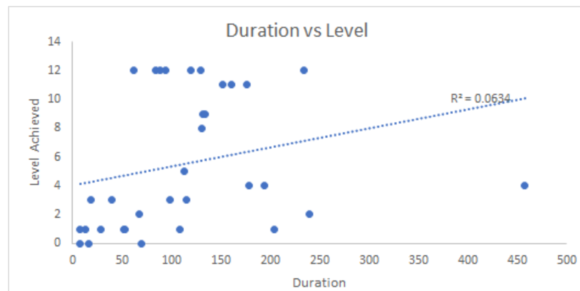

Figure 3: Game Levels Achieved Vs Game Duration

be useful in this activity. This indicates us towards the participants' interest in using different modalities available with smartphones. They also tried to check if different pitch levels of laughter can help them in climbing up the levels fast. After performing the activity, we asked them about their overall experience where they mentioned that they would like to have this app with them and would like to try laughing multiple times in a day. Many reported that they enjoyed the activity and hence are feeling relaxed.

The qualitative analysis of the semi-structured interview gave us some significant keyword clusters such as enjoyment, focus, motivation, and difficulty. Almost 85 % of the participants enjoyed the activity of which more than 50 % showed a pre-stress level of more than 3, on a scale of 1 to 5, with 1 being no-stress and 5 being high-stress. 3 out of 48 said that they focused only on laughter and kept their eyes closed while laughing. They felt relaxed and could also reach up-to higher levels, but did not enjoy the activity much. 38 % of the participating subjects reported that they need some motivation to laugh, such as a video or a joke. They also wanted to use the app with their friends and family where laughing would be effortless. As mentioned before, participants found the original version very difficult. In the re-calibrated version, many reached up-to level 8, which corresponds to a medium difficulty level. They stated that they were trying hard to further bloom the flower. However, they could not cross the highest difficulty level. They reported that beyond this level (level 8), the game becomes very difficult.

5 RELATED WORK

In this section, we compare and contrast our work with similar efforts made in the past. Both the primary components regarding laughter detection and the game design are discussed.

5.1 Laughter Detection

Looking at the benefits laughter at-large can have on an individual's health and life, it is imperative to monitor and capture the laughter events in real time. With this thought on mind, several smartphone and wearable based applications that recognise laughter from speech are developed. One of them is presented in [12], where the machine learning model is using an LSTM RNN technique. They have a very high accuracy reported on the SVC vocalisation corpus, however, it should be noted that the training data also comprises of data from the same context and we have reported cross corpus accuracy in Table 8. Also, we wanted to go for low resource measures which would enable the users to play the application multiple times without being concerned about the battery usage of a smartphone.

BodyBeat [25] and BodyScope [30] are other applications using the speech signal for the detection of laughter events. The mobile system of BodyBeat has a specially designed microphone attached to a neckpiece, whereas that of BodyScope has a wearable acoustic sensor embedded into a headset. Both of these systems need the sensors to be mounted on the neck of the user, and are highly intrusive.

Similarly, [1] and [6] are wearable based sensing systems which capture and recognise non-speech body sounds including laughter. However, they make use of physiological signals and body movement for detection of laughter events.

In the domain of signal processing and affective computing, laughter sound is closely associated with speech signals as they occur mostly together. In our context of the experiment as well, we wanted to avoid interference of speech in the laughter-detection based game. The laughter classifiers developed in [23], [18], [9], and [26] have classified laughter from speech. The authors of [11] have classified different types of laughter such as, single laughter, overlapping laughter, laughed speech, laughter in some other speaker's speech, and mixed of all are detected. The authors have used the laughter detectors in applications such as speech recognition [8], in emotion detection [14], in humor and sarcasm detection [3], [23], and for depression detection [18]. We compared the accuracy of [26], which is an open source tool-kit for laughter detection, with our algorithm and have presented a detailed comparison in Table 8. As seen in the Table, the accuracies are reported on LocalDB, ESC-50 and SSPNet vocalisation corpus. The authors of [26] have used MFCC and delta-MFCC features to train a 3-layer feed-forward neural network. They have used 'Switchboard-1 Release-2' corpus, which contains approximately 260 hours of speech from about 2400 telephone conversations between 543 speakers for training and testing the model.

Other work published are using their own data-sets and hence a direct comparison of the accuracy cannot be established. Our algorithm exceeds the state of the art accuracy in detecting laughter from speech. Also, we are detecting different levels of laughter to improve engagement in our game. This model is ported on a smartphone device and is invoked from the game interface.

Table 8: Comparing accuracy with open source toolkits

Dataset	Our Model	Open Source Toolkit
LocalDB	88.6	64.3
ESC-50	88.7	61.4
SSPNet	86.8	66.5

5.2 Game/App Designs for stress relief

Several solutions have been designed for effective stress relief and most of them are based on digital apps [5]. Some of these smartphone applications are BrainHQ (https://www.brainhq.com/) which focuses on brain exercise to help the users reduce depression risks, Headspace (https://www.headspace.com/) for mindful meditation, Cognifit (https://www.cognifit.com/) to provide neuro conginitive assessment tools and SuperBetter (https://www.super betteratwork.com/) to help in defining and achieving tasks and goals. One of the application to provide evidence-based interventions in the fields of positive psychology, mindfulness, and cognitive behavioural therapy is happify (https://www.happify.com/).

However, studies have shown that digital games were shown to be better stress relievers than mindfulness apps in relieving post work stress [4]. Another study has shown that game based biofeedback techniques are better than non-game based biofeedback techniques when it comes to stress management [20]. Biofeedback games refers to systems which takes inputs from a player's physiology and provide game outputs accordingly [16]. [15] is an example of a social computer game which motivates people to increase physical activity by using a game mechanism. Further studies have also shown the effectiveness of biofeedback-based games over puzzle-based games in combating issues of stress management [7]. This helped us establish that in the domain of stress management, biofeedback games are showing immense potential in providing a deep personal and effective experience. The game Laugh Out Loud has been designed with a similar approach, with a unique feature of laughter being used as a controller to influence objects in the game. Further, the cohesion of the game elements and their strong alignment with the game purpose are strengths of the LOL game.

6 CONCLUSION AND FUTURE WORK

In this paper, we presented a serious game – "Laugh Out Loud" – that is aimed at inducing laughter in the players, so that players derive the psycho-physiological benefits of laughing, particularly, stress relief. We presented a design of the game and its elements using the Serious Games Design Assessment (SGDA) framework [13]. An empirical evaluation of the game, conducted with 48 subjects, showed that 76 % of the participants experienced stress relief after playing the game. Analysis of the game play showed that participants in the age group of 21 - 25 years show very good achievements in terms of levels reached, indicating that the game also serves the purpose of entertainment well. We received qualitative feedback that is encouraging, for example, "felt good", "it was good", "it has made me calm", while also suggesting that there is room for improvement, for example, "it was very difficult to laugh without any stimuli", or "generally, I don't laugh loud", "meanwhile I was getting to cough, so I was unable to bloom", or "no motivation".

These statements indicate opportunities for future work. There is a need to cater to individual differences in styles and patterns of laughter. This may be achieved by training or adapting the laughter model with individual data. Going ahead, we would like to implement and use an optimised LSTM RNN technique. This is to further enhance the accuracy measure and more accurately detect the laughter instances.

We also have the opportunity to serve all personas and demographics better, by allowing players to choose game objects and narratives of their choice. We could incorporate design elements such as funny characters, voice mimicry, humorous content, that may serve as additional stimuli for laughter.

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