Emotional Keyboard: To Provide Adaptive Functionalities Based on the Current User Emotion and the Context

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Abstract. Improving the User Experience (UX) of mobile devices is of vital importance due to the advent of emerging technologies and the prevalence of using mobile devices. This research aims to develop a model for a mobile device that can suggest adaptive functionalities, based on the current user emotion and the context by changing the user's negative emotions (sadness and anger) into positive ones. As a proof of concept, a keyboard named "Emotional Keyboard" was developed through five prototypes iteratively using Evolutionary Prototyping. Action Research was adopted as the methodology along with User-Centered Design (UCD) which further included two user surveys. The first three prototypes were implemented to decide the most optimal perception from facial expressions and text analytics. Subsequent prototypes provided affective functions to the user such as listening to music, playing a game, chat with friends, based on the detected negative emotion and the context. The evaluation of each of the prototypes was performed iteratively with user participation. The final (fifth) prototype evaluation was done in two phases, an individual analysis (to measure the performance of each user separately), and an overall analysis (a general analysis that averaged all the results from individual analysis and measured the performance of the overall model). Results of both analyses showed that eventually the Emotional Keyboard was able to predict the adaptive functions correctly to the user and it did not terminate its learning process where the users' feedback was continuously used to improve its performance. In conclusion, an "Adaptive System with User Control" was developed thus improving the acceptability and usability of a mobile device which aligns with the research aim.

Keywords: Human-Computer Interaction, Adaptive System, Emotion Detection, Facial Expressions, Text Analytics, Prototyping, User-Centered Design, Affective Computing, Mobile Computing

1 Introduction

The term "User Experience (UX)" describes the satisfaction that a user acquires when using a particular system or a product while performing their day-to-day needs [1]. According to [2], improving the UX of computer systems is important and popular in the field of Human-Computer Interaction (HCI) since it provides users with a positive and comfortable experience. Improving UX leads to the concept of "Affective Computing" which provides a system that can adapt to the users' needs by considering user emotions and the emotional communication between the user and the system [3].

As explained in "Affective Computing" [3], emotions can be considered a factor to be used when designing a usable system [4]. The intelligence from emotions was used when designing intelligent robots [5], user interfaces [6], and appliances for households [7]. In addition to the emotions, more complex and affective system functionalities such as changing the colour, font size, and device widgets have been considered in previous research work by identifying the user's context and the environment as discussed by [8] and [9]. Context can be subdivided into categories based on the user, platform, or environmental aspects [10]. User aspects such as user profiles, cognition, user activities, and environmental aspects such as location, time, and weather were commonly considered when developing adaptive systems [8–10]. It was proven that multimodal information such as emotions and context parameters can be perceived using multiple sensors to accomplish human-like decisions making and analysis of these inputs leads to a context-dependent model [11].

Due to the convenience of smart technologies, the incorporation of functionalities to enhance the affective UX of mobile devices [12, 13] is more popular rather than desktop systems [14], especially due to the ability to integrate mobile multimodal interactions [15]. Many applications were developed by taking user emotions and the context into account to produce effective and affective usable systems through personalization and customization. To facilitate further improvement, models could be created to gather user data and emotions which could then be stored in a profile. It can later be used to predict the most affective action to be performed by the system based on the context data and also to provide affective feedback [4]. Furthermore, when analysing the HCI research that has been carried out over the past 60 years [16], it can be seen that developing context-aware systems has become a trend since it is highly needful.

Considering the above, there is a need to introduce a system that can provide more affective functionalities to improve the UX of a mobile device while considering user emotions based on the context in real-time. To the best of our knowledge, there are no systems that use emotions and context to provide adaptive functionalities rather than only providing adaptive interfaces, to enhance the acceptability and usability of the system. Besides, detecting emotions through both facial expressions and text analytics has not been carried out for mobile devices and most of the researchers have used user emotions or context alone to provide adaptive user interfaces.

The rest of the paper is organized as follows. Section 2 introduces the background to the research and discusses the related work, followed by Section 3 which will discuss the research methodology and design. Then the implementation, evaluation, and results for each prototype will be discussed in an iterative manner in Section 4. Section 5 will discuss the conclusion of the research questions by highlighting the research contribution. Finally, Section 6 will discuss the limitations and implications for further research.

2 Background and Related Work

2.1 Emotions

User emotions can be defined either using Emotional Categories or Emotional Dimensions [17]. Most of the researchers have used Emotional Categories where emotion will only have one discrete label which will represent only one value. Ekman's model [18] which constitutes six discrete emotions such as "anger", "disgust", "fear", "happiness", "sadness", and "surprise" is widely used among Emotional Categories in many types of research. Plutchik's wheel of emotions is another example that considers the emotions as four couples – joy-sadness, anger-fear, trust-disgust, and anticipation-surprise [19]. To limit the scope of this research, the most popular Ekman's was considered when detecting emotions from facial expressions and text analytics.

2.2 Emotion Detection

Several methods can be used to detect user emotions that can be divided into two categories which are, verbal and non-verbal [20]. Verbal communication through conversational devices is more popular among the elderly population [21–23]. However, this research considered a young target audience who are in between 18 - 24 years. Hence, this research considered only the non-verbal emotion detection techniques to restrict the scope.

For instance, non-verbal techniques such as facial expressions [24], text analytics and typing pattern analysis [25], body gestures [26], gaze direction [27] and brain signals [28] can be used individually, but more accurate and improved results can be obtained when two or more of the above methods are combined thus leading to multi-modal emotion detection [29]. However, this research used only facial expressions and text analytics. Justifications for not utilising other techniques are mentioned in Table 1.

Even though there are minor practical limitations such as endurance from face oval slanted cover, problems that occurred due to the location of the camera, problems with lighting, and uneven illumination [26] when using facial expressions to detect emotions, it has been proven that detecting emotions through facial expressions is more accurate [24, 25] than other methods that are mentioned in Table 1.

Apart from facial expressions, text analytics also plays a major role when detecting emotions [17, 27, 28]. Usually, a person interacts with a mobile device by typing using the keyboard. Although text analytics suffers from minor limitations such as ambiguity of words, lack of ability to recognize sentences without keywords, the need for phonetic data, and trouble in deciding emotion markers [29], it is meaningful to analyse the text content that the user is typing rather than analysing the behavioural factors such as typing pattern as justified in Table 1. Hence, this research decided to evaluate the practical applicability of text analytics together with facial expressions to recognise emotions.

Table 1. Methods to detect user emotions and their suitability.

Method	Justification
Typing pattern	Typing pattern depends on the text familiarity, gender, and the age of the user, but not only on the emotional state of the user [32, 33].
Gaze Direction	Since gaze direction is a subpart of detecting emotions through facial expressions [34], [24], considering this individual will not have a significant impact.
Gestures	It is difficult to capture head gestures (head position), hand gestures (shape and motion), and body motion (spinal column, DOF body, body centre mass, joints) [35] through a mobile device.
Brain Signals	It is not practical to measure brain signals using a mobile device and it requires to take scalp EEG signals to be taken using special equipment [36].

In spite of the fact that the above two methods have a few limitations, both these methods have state-of-the-art APIs and SDKs which can easily be used when detecting emotions [30, 31]. The first half of this research was focused on finding a method to combine these two techniques and to assess the practical applicability and appropriateness of these methods when detecting emotions while using mobile devices, but not to improve the accuracy of emotion detection.

2.3 Context

The term "Context" has a broad meaning. In popular concepts such as Spatiotemporal Structure Learning [9] and Situated Computing [14], context is defined using physical location, time, weather, and user activities. Furthermore, some recommender systems have kept track of time, recorded recently used and frequently used menu items, and recommended menus automatically when using mobile devices [37].

2.4 Different Techniques to Design an Adaptive Systems

A system that can adjust and blend its actions or configurations to assist different user requirements according to the status of the user, the status of the system and the current context in real time can be defined as an adaptive system [38, 39]. Several techniques [40] have been proposed to do the adaptation of user interfaces as follows.

- **Adaptable or Manual System:** A system where the user can change the settings manually.
- **Adaptable with system support or User selection:** A system that supports the user to do the adaptation process.
- **Adaptive with user control or User approval:** The system controls the adaptation process with the direction of the user and gives freedom to the user to choose alternative actions if necessary.

- **Fully adaptive:** The entire management process is done by the system which does predictions without disturbing the user by considering the user profile and other variables.

The focus of this research is to introduce a model which is "Adaptive with User Control".

2.5 Applications

Significant researches have been performed on conversational devices that evaluated verbal communication (voice) when interacting with different types of users [21–23, 44, 45]. These focused on audiences who had speaking disabilities to produce Alternative and Augmentative Communication (AAC) [45] and to assist elderly people [44], [23] (or old people with low technical knowledge [21]). However, since the target audience of this research is youngsters (who are in between 18 – 24 years) and to restrict the scope, the focus here is on applications that do not use voice as input but use other techniques such as recognizing emotions using facial expressions and text analytics. Evaluation of verbal communication techniques with a wider audience can be done as future research.

EmotionPush [12] is an Android application that could detect user emotions from the text message content in Facebook Messenger and send notifications to the user. That study aimed to observe the users' behavioural patterns when a negative or a positive emotion was identified. However, no action was taken to change the mood of the user. Situation Dependent Browser [8] is another type of a system, that utilised users' context (location, time, user activities and circumstances) to search and filter out resources of a user's computer. This concept gave a vast meaning to the "user context" by allowing other researchers to think about it.

AUBUE (Adaptive User-Interface Based on User's Emotion) [6] is an adaptive interface that changed the colour of the user interface considering the user's emotion by analysing the typing pattern and the recently/frequently used keyboard keys (For example, how many times the backspace was used). While AUBUE was using emotions and recently/frequently used functions, another research named Spatiotemporal Structure Learning with Samsung Galaxy S [9] used emotions and context to recommend mobile applications to the user by changing the user interface. Moreover, another adaptive interface was developed to customise the menu of a mobile device by keeping track of the frequently and recently used activities when using the mobile device [37].

Among the aforementioned applications that have been developed as affective and usable systems, Table 2 summarizes the features, where "Yes" depicts that a particular application has a particular feature corresponding to the column name, while "No" depicts that a particular feature is not available. None of the applications has all the mentioned features which are what this research focuses on.

Table 2. Summary of features in the applications.

Application	Adaptive Interface	Adaptive Functions	Detect Emotions	Detect Context	Recently and Frequently Used Functions
EmotionPush [12]	No	No	Yes	No	No
Situation Dependent Browser [8]	No	No	No	Yes	No
AUBUE (Adaptive User-Interface Based on User's Emotion) [6]	Yes	No	Yes	No	Yes
Spatiotemporal Structure Learning with Samsung Galaxy S [9]	Yes	No	Yes	Yes	No
Automatic Mobile Menu Customization System [37]	Yes	No	No	No	Yes

In conclusion, emotion detection using the methods stated in Table 1 has several limitations when compared to facial expressions and text analytics which have state-of-the-art APIs to identify emotions. Hence, combining these two techniques and checking the practical applicability and appropriateness of these methods using mobile devices will be evaluated in the first part of this research. Moreover, according to the best of our knowledge, no application addresses all the features stated in Table 2. Nevertheless, each has its benefits as reviewed in [4]. Incorporating all of these features paved the path to finding a way to build an optimal model for decision-making to perform affective interactions by considering user emotions based on the context.

3 Research Methodology and Design

3.1 Research Questions

Two research questions will be addressed through this research where the latter is prominent.

1 How to aggregate different emotion detection techniques to decide the most meaningful emotion?
2 How a new model can be developed to do optimal decision-making in order to perform affective interactions by considering user emotions based on the context?

3.2 Research Methodology

The research methodology used here is Action Research [41] with User-Centered Design (UCD) [42] where every step from requirement gathering to evaluation was performed with user participation in an iterative manner. User participation will happen through prototype evaluation with Evolutionary Prototyping [43] and the usage of two survey questionnaires.

Action Research contains five stages. The first phase of Action Research is *Diagnosing,* where in this research, the basic resolutions were decided from the literature by analysing the concerns and complexities in existing approaches. The next step is *Action Planning* where the research design was planned and participant selection was done based on the decisions taken in the previous phase. Participants were selected using non-probability sampling methods such as convenient sampling and expert sampling [41]. The UCD was incorporated during the next stage, which is *Action Taking*. The development of Questionnaires and Interviews was conducted to decide users' prerequisites while securing the options to be considered during this research. Furthermore, prototypes were implemented to eliminate the mismatch between the user's mental model and the designer's mental model which paved the way to develop a more usable system. Otherwise, a system that was designed only considering the designer's mental model may not be usable because the user's mental model and the designer's mental model may not always match [42]. In the next step, *Evaluating*, the designed user surveys and prototypes have been assessed with the user participation. The speciality of this research is, from the first iteration until the last, in each stage, the evaluation was performed rather than doing it at the end of the research. In the last step, which is *Learning*, the analysis was done by considering both quantitative and quantitative data. The output and learnings from this stage were provided as input to the *Diagnosing* stage (the first stage again) to begin the next iteration.

The subsections named *Evaluation and Results* of each prototype in *Sections 4.2 and 4.4*. will elaborate more on user participation during the UCD process.

3.3 Research Design

The research design consists of seven steps as follows where the Prototype Evaluation (the 3rd step) was carried out iteratively as shown in Figure 1 due to the iterative structure of the research methodology.

1. Conducting User Survey 1
2. Prototype Evaluation (for the 1st Research Question)
3. Conducting User Survey 2
4. Prototype Evaluation (for the 2nd Research Question)
5. Final Evaluation
6. Final Results

According to Figure 1, in the first step, a questionnaire was carried out as the user survey 1. Based on the analysis of that, prototype evaluation was started by developing three prototypes respective to the first research question to find a way to aggregate emotions from the facial expressions and text analytics to decide the most meaningful emotion. Then, another questionnaire was designed and carried out to collect the data required to proceed with the next prototype evaluations. Thereafter, another two prototypes were developed and evaluated. The final evaluation was carried out in the next step based on the final prototypes and finally, the results were presented as an Individual Analysis and an Overall Analysis.

The above process is explained in detail in the next section, Implementation, Evaluation and Results.

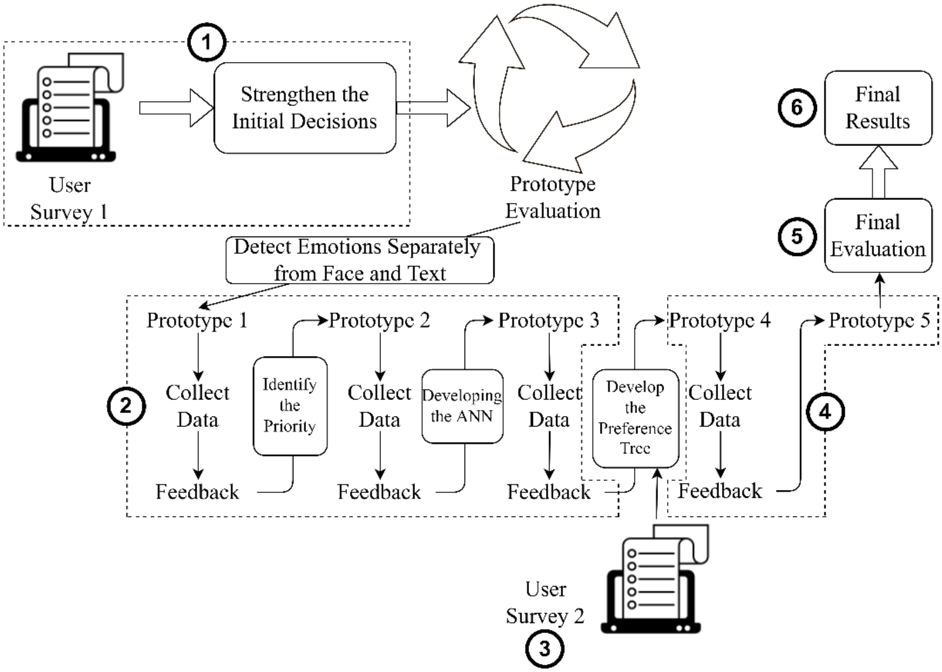

Fig. 1. Steps of the research design.

4 Implementation, Evaluation and Results

4.1 Conducting User Survey 1

As shown in Figure 1, the first step of the research design was to conduct User Survey 1. A questionnaire entitled *"Improving User Experience based on User Emotions when using Mobile Devices"* was created where the main aim was to strengthen the initial decisions before starting the research. This questionnaire consisted of seven questions, out of them, questions 1 to 3 were about the demographic data of the participant such as age (divided into age groups), gender (male/female) and occupation (student/working). Questions 4 to 7 were the prominent ones which are listed in Table

3. A pilot study was carried out with 10 participants, and then the questionnaire was improved and distributed as a Google Form to the general public (using snowball sampling [41]) and 310 responses were obtained. Overall, the highest number of responses were from students who were between the age of 18-24 which was the intended target group of this research.

As shown in Table 3, the initial decisions were taken for each prominent question. Upon considering these decisions, prototype development and designing of User Survey 2 were initiated.

Table 3. Questions and initial decisions from User Survey 1.

Question	Decision
Q4. Which emotions need to be tracked especially to provide adaptive functions?	Most voted emotions were "joy" (61.6%), "sadness" (48.1%), and "anger" (47.7%). Since "joy" is a positive emotion there was no need to change that emotional state. Therefore, it was decided that the "sadness" and "anger" were focused to convert into a positive state.
Q5. Which functionalities should be considered?	Most voted functionalities were to Listen to Music (69.4%), Use Social Media (50.6%), Chat with Friends (42.9%), Play a Game (35.8%), Browse the Gallery (28.4%) and Browse the Internet (22.6%). Hence, it was decided that the adaptive system should prompt these functions as the affective action to change the mood of the user.
Q6. Do those functionalities depend on the time of the day?	67.1% voted Yes. Hence, the decision was taken to incorporate the time factor when deciding the affective action.
Q7. Do those functionalities depend on the location?	82.9% voted Yes. Hence, the decision was taken to incorporate the location when deciding the affective action.

4.2 Prototype Evaluation (for the 1st Research Question)

The research design consists of two phases for Prototype Evaluation (Steps 3 and 5). By the end of each prototype evaluation, the data was recorded and decisions were taken to improve the prototype using the Evolutionary Prototyping approach [43]. This section will discuss the implementation, evaluation and results for prototypes 1, 2 and 3 which will cover the first research question.

Prototype 1

Implementation. The main reason for developing Prototype 1 was to get an insight into how emotions can be detected separately from facial expressions and text data and to identify the practical limitations through user evaluations. A keyboard named

"Emotional Keyboard" (compatible with Android devices) was developed with the ability to track emotions from facial expressions and text separately and send notifications to the user as shown in Figure 2.

A freely available version of IBM Watson Tone Analyzer API [30] (which is used by both commercially and non-commercially funded research [44]) was used to detect emotions from the text where seven emotions such as "joy", "fear", "sadness", "anger", "analytical", "confident", and "tentative" have been identified. A notification stating the maximum emotion was sent to the user after each tracking interval of 60 seconds.

Similarly, this application captured image frames every 60 seconds, from the front camera and processed them using Affectiva SDK [31] (one of the best facial recognition software [45] that has a freely available version) which outputs emotion percentages for emotions such as "joy", "fear", "sadness", "anger", "surprise", and "disgust" according to Ekman's Model [18] and the notification was sent to the user.

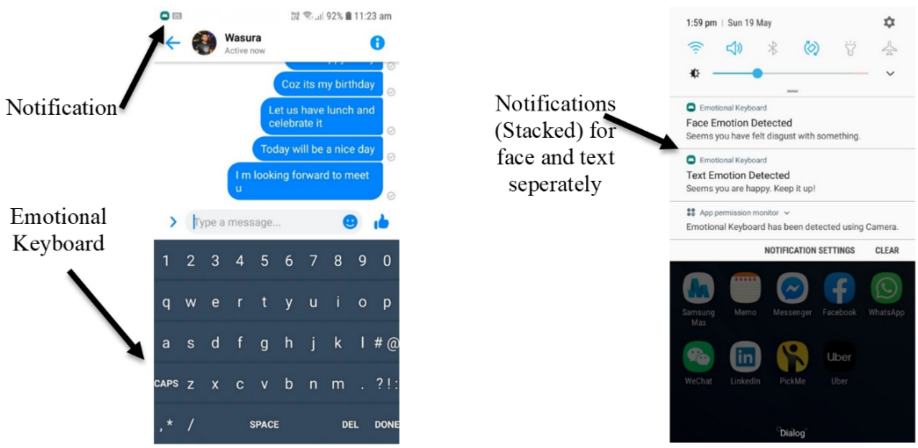

Fig. 2. Prototype 1 - Demonstration and stacked notifications.

Evaluation and Results. A focus group of 40 participants was selected using convenient sampling and expert sampling [41] with informed consent. Three rooms with adequate lighting and a mobile phone with a 5-megapixel front camera were used. The evaluation was mainly performed using two techniques which were by showing videos to participants and chatting using Google Hangouts. During the activity, users were asked to provide feedback related to the pop-up notifications that stated the user's emotion. When the user taps on a notification, an Alert Dialog was shown asking if the user is satisfied with the emotion or not. If the user presses YES, the data was recorded instantly, but if the user presses NO, another screen was shown requesting a manual selection of the actually felt emotion which was recorded in a Firebase Real-time Database separately for emotions from text analytics and facial expressions. (Further, the respective emotion object with percentages was recorded apropos each notification and that data was used to train an Artificial Neural Network (ANN) when developing Prototype 3 later)

During the evaluations, 492 emotions (records) were captured and recorded, where 100 were from facial expressions and 392 from text analytics. When considering the emotions from facial expressions, almost all the emotions were predicted in the wrong manner and only "joy" was detected correctly. However, when considering the emotions from the text, almost all the emotions were predicted correctly. Several observations were made while evaluating facial expressions; the rotated camera failed to detect emotions, incorrect emotions were detected with participants wearing spectacles, "joy" was easily captured through smiles, and "surprise" was captured through raised eyebrows or opened mouth which is 76.5% wrong. It has been decided that emotions from the text were more suitable in this scenario and developed Prototype 2 to give the priority to the emotions from the text which will be discussed in the next section.

Prototype 2

Implementation. The 2nd iteration of the research design started with the implementation of Prototype 2. Since the results from facial expressions were not accurate, the evaluations of Prototype 1 proved that the practical usage of detecting emotions through the face has limitations. Hence, the same prototype was changed to improve the identified limitations as follows.

- If emotions from both face and text were available, a decision was taken to consider the emotion only from the text.
- If the emotions were available only from the face, then checked the confidence of the emotion is greater than a predefined threshold (50% - which was decided through trial and error during the Prototype 1 evaluations).

Evaluation and Results. The same notification process, feedback, and evaluation procedures have been carried out with the same 40 participants. 502 emotions (records) were retrieved where 59 were from facial expressions and 443 from text analytics. The number of emotions detected from facial expressions was reduced from 100 to 59, which proves that the priority given to the emotions from the facial expressions was reduced. When considering the emotions from the text almost all the emotions have been detected correctly.

Comparing Prototypes 1 and 2 using Precision. During the prototype 1 and 2 evaluations, the precision for each emotion was calculated with the YES and NO counts as shown in Table 4 and Table 5 by assuming the detected emotion belongs to the positive class. Therefore, the YES count corresponds to the True Positives and the NO count corresponds to the False Positives. The results in Table 4 and Table 5 show that the Precision value for all the emotions in Prototype 2 is higher than in Prototype 1, except for "disgust". Thus, can be proven that Prototype 2 has performed better than Prototype 1.

Table 4. Prototype 1 - Precision values.

Emotion Type	Emotion	YES count	NO count	Precision (%)
Face	anger	0	1	0
	disgust	21	21	50
	fear	0	3	0
	joy	25	10	71.43
	sadness	1	1	50
	surprise	4	13	23.53
Text	analytical	76	12	86.36
	anger	7	2	77.78
	confident	29	9	76.32
	fear	3	3	50
	joy	66	37	64.08
	sadness	28	11	71.79
	tentative	81	28	74.31

Table 5. Prototype 2 - Precision values.

Emotion Type	Emotion	YES count	NO count	Precision (%)
Face	anger	0	0	0
	disgust	10	22	31.25
	fear	0	0	0
	joy	14	2	87.5
	sadness	0	0	0
	surprise	3	8	27.27
Text	analytical	89	6	93.68
	anger	9	1	90
	confident	45	7	86.54
	fear	10	6	62.5
	joy	97	17	85.09
	sadness	28	8	77.78
	tentative	91	29	75.83

Prototype 3

Implementation. Using the data collected during the previous prototype evaluations in the 3rd iteration (as shown in Table 6) an ANN was trained and embedded in Prototype 3. The aim of this was to propose a more practical system since the data that have been used consist of the behavioural factors and the compatibility of the context.

The ANN was converted into a TensorFlow Lite model and embedded in the Android app. Six and seven emotions were detected from facial expressions and text analytics accordingly using the same APIs and SDKs and fed to the model (6 + 7 = 13) as input where the model outputs nine emotion classes where the maximum of them is the optimal emotion.

Table 6. Prototype 3 – ANN configuration.

Layer	Description
1st Layer - Dense	13 input nodes to perceive 13 values corresponding to emotions from face and text. Rectified Linear Unit (relu) was used as the activation function.
2nd Layer - Dropout	A fraction rate of 0.5 was used.
3rd Layer - Dense	With 9 output nodes corresponding to 9 emotion classes which are **"analytical", "anger", "confident", "disgust", "fear", "joy", "sadness", "surprise",** and "**tentative".** The softmax function was used as the activation function.

Evaluation and Results. The model was trained with a batch size of 10 and 200 epochs and an Adam optimizer with a learning rate of 0.001. Categorical cross-entropy was used as the loss function and 70% of the data was used to train the model while 30% was used to do the validation. As shown in Figure 3, the training accuracy has converged to 75.04% while validation accuracy has converged to 78.17%. As shown in Figure 4, the training loss has converged to 0.89 while the validation loss has converged to 0.7658. Since training and validation accuracies and each of the losses are similar, it can be seen that the model has not been overfitted.

The user evaluation was done using the same procedure with the same set of participants, and the data was recorded to create a multiclass confusion matrix as shown in Figure 5. "surprise" was not detected and the users have not selected "surprise" when a wrong prediction was done by the model. This means, that "surprise" is not an emotion to be considered when using mobile phones since "surprise" was a part of "joy", which can be proven by a large number of predictions of "joy" which was correctly predicted.

The testing accuracy was calculated which is 83.57% along with the other performance measures. Table 7 contains a summary that consists of only three emotions ("joy", "sadness", and "anger") which were selected from User Survey 1. The limitation of this model was the low values for Recall and F-score for "sadness". These values can be increased if the model can be further trained using more data or by implementing the use of Active Learning [46] to dynamically train the model which paves the way for future research. Except for Recall and F-score, other values show that this model is practically applicable to combining emotions which confirms the first research question (*"How to aggregate different emotion detection techniques to decide the most meaningful emotion?"*). Further prototypes will focus on the second research question.

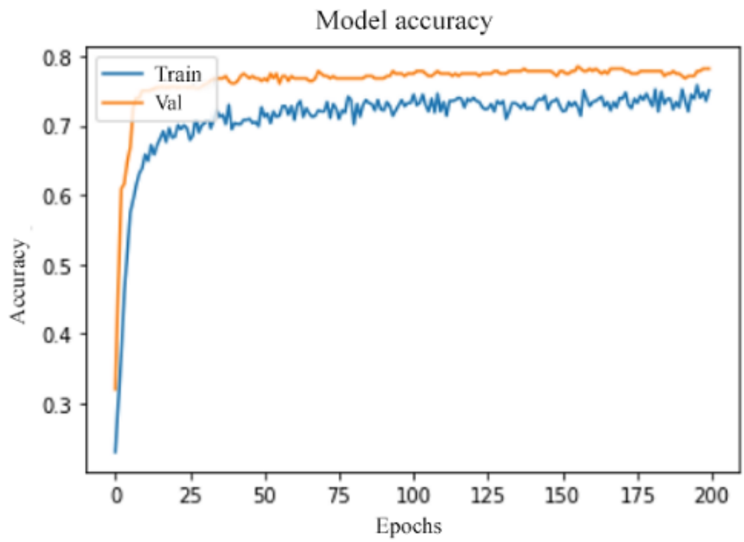

Fig. 3. Training accuracy vs. Validation accuracy.

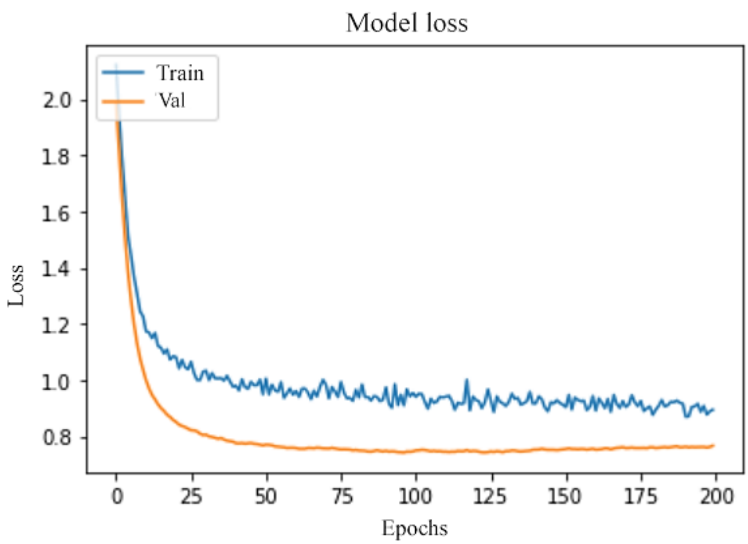

Fig. 4. Training loss vs. Validation loss.

KNOWN CLASS	PREDICTED CLASS: analytical	anger	confident	disgust	fear	joy	sadness	surprise	tentative
analytical	139	0	0	3	0	0	0	0	0
anger	2	8	0	0	0	0	0	0	1
confident	1	0	27	0	0	0	0	0	0
disgust	0	0	0	9	0	1	0	0	0
fear	0	0	0	0	2	0	0	0	0
joy	2	1	0	1	0	61	0	0	2
sadness	14	0	1	7	0	1	18	0	3
surprise	0	0	0	0	0	0	0	0	0
tentative	14	0	0	1	0	1	3	0	36

Fig. 5. Confusion matrix for Prototype 3 evaluation.

Table 7. Prototype 3 - Performance measures for “joy”, “sadness” and “anger”.

Emotion	Accuracy (General)	Precision	Recall	Specificity	F-Score
joy		95.31%	91.04%	98.97%	93.13%
sadness	83.57%	85.71%	40.91%	99.05%	55.38%
anger		88.89%	72.73%	99.71%	80%

4.3 Conducting User Survey 2

After analyzing the results of User Survey 1 and the evaluation of prototypes 1, 2 and 3, another questionnaire, titled *“Collecting Data to Improve User Experience based on User Emotions when using Mobile Devices”* was designed to capture data to develop Prototype 4 that has the ability to suggest the most adaptive function for the user based on his/her emotion and the context. A similar process to User Survey 1 was carried out with 10 participants using the same sampling techniques and then distributed the questionnaire as a Google Form where the target audience was the students and employed people who are in between 18 – 24 years. 209 responses were obtained.

The collected data from this survey was used to build a tree named “Preference Tree”, which was used later in Prototypes 4 and 5 to decide the most affective function based on the highest probability.

4.4 Prototype Evaluation (for the 2nd Research Question)

This section will discuss the implementation, evaluation and results of Prototype 4 and the implementation of Prototype 5. Since Prototype 5 is the final prototype, the evaluation and the results will be discussed in sections *4.5 Final Evaluation* and *4.6 Final Results*.

Prototype 4

Implementation. The UI of the keyboard is similar to the previous prototypes but this can suggest adaptive functions such as *Browse Internet, Browse the Gallery, Chat with Friends, Listen to Music, Play a Game* and *Use Social Media* by considering the user's emotion based on the context using a Preference Tree (named as "adaptiveFunctions" as shown in Figure 6) that consists of the probabilities that a particular user performs a function. The development of the Preference Tree was done using the data from User Survey 2. When a particular user installs the app, the user must register by creating an account where a profile for that particular user was created by recording his/her Preference Tree in the Firebase Real-time Database (The probabilities were updated in the user profile based on his/her personal choices using the feedback during the evaluations later).

After the registration, the context parameters such as location, user activity, and time were perceived as follows. Before the first use, the user must log in to his/her account and set the location of Home and Workplace manually. The current location was retrieved using Google Play Services where a 20-meter radius was considered when deciding whether the user is at Home, Work, or Outside. Current user activity was detected using the Activity Recognition Client in Android based on Accelerometer data and three groups of activities were detected such as whether the user is "In a vehicle", "Walking", or "Still (Standing)". Time was taken from the system. If the current time is between 5.00 am and 1.00 pm, then decided that it was morning, otherwise evening. The time range was decided by considering the practical usage of this app during the prototype evaluations.

The emotion was detected using the ANN introduced in Prototype 3. "sadness" and "anger" were tracked since User Survey 1 concluded that "sadness" and "anger" are vital in providing a positive experience to the user.

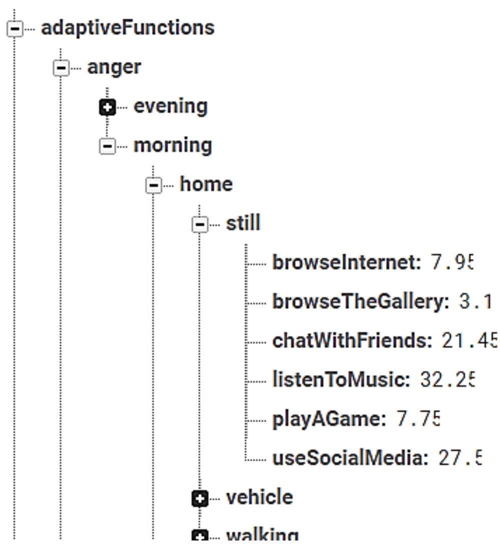

Fig. 6. Prototype 4 – Traversed branch.

The system decides the adaptive function by first detecting the emotion, then the time, then the location, and then the user activity. This means a branch from the Preference Tree will be traversed from top to bottom. In the example shown in Figure 7, the branch which should be traversed in the Preference Tree is “anger -> morning -> home -> still”. The leaf node of this particular branch consists of the functionalities to be suggested with the probabilities based on User Survey 2 as shown in Figure 6. The system will suggest the function which has the highest probability, which is “Listen to Music” in this case.

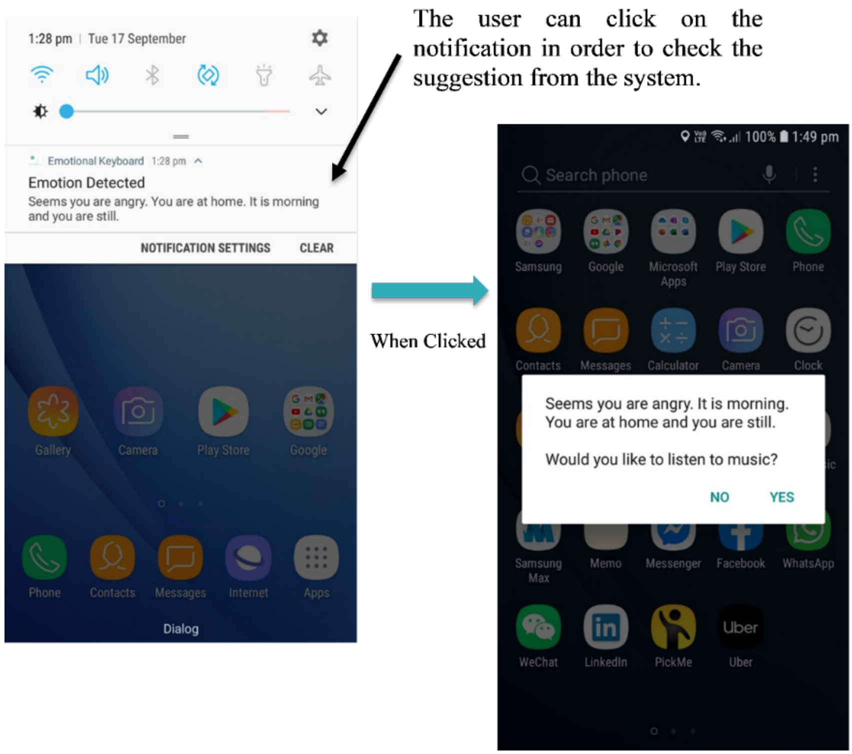

Fig. 7. Prototype 4 – Suggesting functions.

If the user presses “YES”, the probability of the suggested function was increased in that particular traversed branch using (1) where P_{inc} is the increased probability of the chosen function and $P_{current\_chosen}$ is the current probability of the chosen function.

$$P_{inc} = \{(P_{current\_chosen} + 1) / 101\} \times 100\%. \quad \mathbf{(1)}$$

Further, the probabilities of other functions were decreased in that particular branch using (2) where P_{dec} is the decreased probability of other functions and $P_{current\_other}$ is the current probability of the other function.

$$P_{decr} = \{P_{current\_other} / 101\} \text{ x } 100\%. \qquad \mathbf{(2)}$$

If the user presses "NO", then he/she was asked what he/she wanted to do at that moment, and similarly, the probability of the chosen function was increased and the probabilities of other functions were decreased using (1) and (2) accordingly. Finally, the branch in the database was updated for the particular user.

Evaluation and Results. Out of the 40 participants, 9 males and 9 females were selected using convenient sampling [41]. The users were asked to install the app on their mobile devices, and register and use it as much as possible daily, for 30-45 days. The feedback was recorded in the Firebase Real-time Database.

After the user evaluations, the YES count (which depicts that the model has suggested a correct function) and the NO count (which depicts that the model has suggested a wrong function), were plotted with the time instance as shown in Figure 8. The Time Instance axis starts from 0 and keeps increasing. When a particular user has responded to a notification for the first time, it will be the time instance 1. Then, again when he/she responds, it will be the time instance 2. Similarly, this will keep on increasing one unit at a time for each response from the user. For different users, the total number of time instances will differ based on the usage of the application.

Figure 8 shows the plot for User 1, which depicts that with time the YES count increased but it could not exceed the NO count. This means the model may take more time to suggest the functions correctly. This analysis depicts that this model takes more time to produce the correct suggestions which are not practical to evaluate. Due to this limitation, another approach was required which can manipulate this time constraint and it was developed as Prototype 5 which will be discussed in the next section.

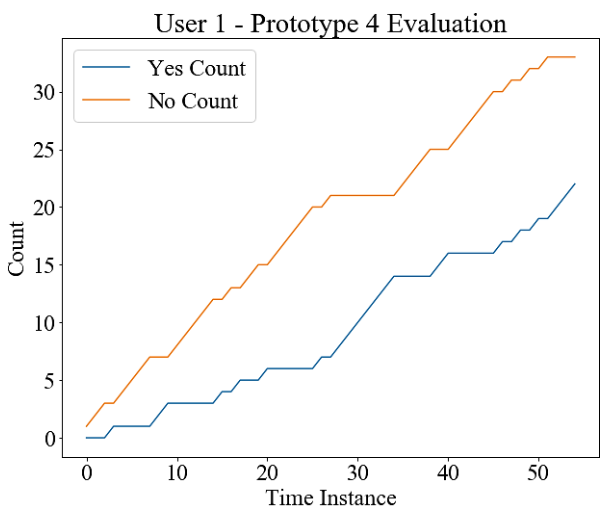

Fig. 8. Prototype 4 – User 1 evaluation.

Prototype 5

Implementation. The functionality of this prototype was similar to Prototype 4 but the implementation differs a bit by keeping track of frequently used functions [37].

When the user is registering for the first time, a new field named "frequentFunctions" was added to the database as shown in Figure 9. When the user was providing feedback each time, the count of the particular function in the field "frequentFunctions" was incremented. Using this new field, a new probability value named "Frequent Probability" was calculated for each function using (3) where $P_{frequent}$ is the frequent probability of the chosen function, Count(chosen_func) is the count of the particular chosen function in "frequentFunctions", and Count(all) is the total count in "frequentFunctions" field.

$$P_{frequent} = \{Count(chosen\_func)/Count\ (all)\} \text{ x } 100\%. \quad \textbf{(3)}$$

After calculating the Frequent Probabilities for each function, those were added to the corresponding Preference Tree probabilities and were averaged using (4) where P_{new} is the new probability of the chosen function, $P_{frequent}$ is the frequent probability of the chosen function calculated using (3) and $P_{current\_chosen}$ is the current probability of the chosen function from the Preference Tree.

$$P_{new} = \{(P_{frequent} + P_{current\_chosen})/2\} \text{ x } 100\%. \quad \textbf{(4)}$$

These new probabilities were compared with each other and the adaptive function which had the maximum new probability was suggested to the user. When the user has given feedback, the same procedure was used to update the Preference Tree and the count of the chosen function was increased in the "frequentFunctions" field in the database.

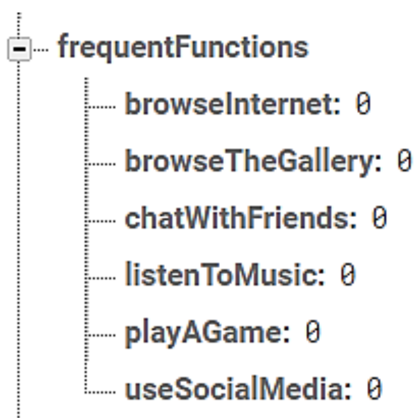

Fig. 9. Prototype 5 – "frequentFunctions" field.

Evaluation and Results. The evaluation and the results of this prototype will be discussed in the next two sections (*Sections 4.5 and 4.6*) since this is the final prototype.

4.5 Final Evaluation

This is the last evaluation step with the final evaluation that was performed for the final prototype (Prototype 5) with user participation by giving the application to the users to use while performing their day-to-day activities.

The same evaluation procedure was carried out with the same 18 participants. They were asked to use the prototype for 30-45 days and the data was recorded. Similarly, as done in Prototype 4, for each participant, the analysis was done by plotting the YES count and the NO count with time.

4.6 Final Results

Two analyses have been performed namely, an Individual Analysis and an Overall Analysis. The individual analysis can be divided into three categories as shown in Table 8.

18 individual graphs were plotted for the 18 users and the intersection points of each graph depict the overrun of YES count by NO count for a user. It was observed that for any user there were one or more situations where the YES count overrun the NO count. Table 9 interprets the graphs of three users who belong to the three categories mentioned in Table 8.

Table 8. Three categories of Individual Analysis.

Category	User
(1) Plots with one intersection point in between	Users 1, 3, 13, 14, 17 and 18
(2) Plots with more than one intersection point in between	Users 2, 4, 6, 7, 8, 9, 10, 11, 12, 15 and 16
(3) Plots without an intersection point in between (The intersection point is at the end of the plot)	User 5

Table 9. Interpretation of graphs in Individual Analysis.

User	Interpretation
User 13	Figure 10 consists of only one intersection point, which depicts that the YES count has overrun the NO count and was increased until the end.
User 16	As shown in Figure 11, the reason for more than one intersection point is the continuous increment of YES and NO counts in nearby time instances. This depicts the dynamic behaviour of the model which was trying to do the predictions correctly as much as possible.

User 5	As shown in Figure 12, until the end, the YES count was not able to overrun the NO count. But, it has a high rate for the increment of the YES count than the NO count which means after the intersection point there is a high probability that the YES count may overrun the NO count at some time instance in the future.

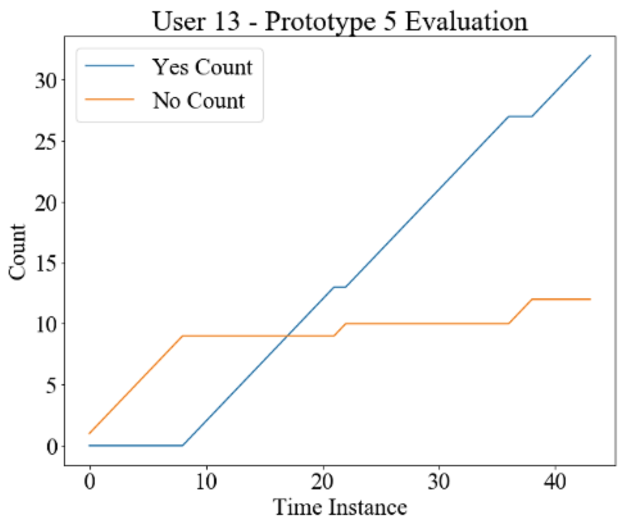

Fig. 10. Prototype 5 – User 13 evaluation.

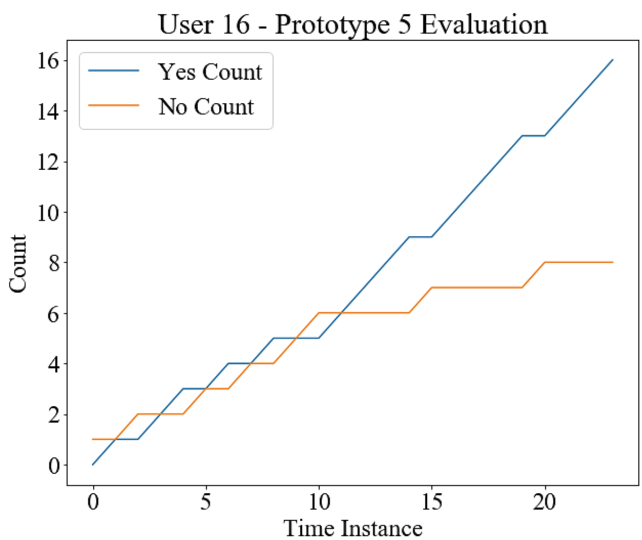

Fig. 11. Prototype 5 – User 16 evaluation.

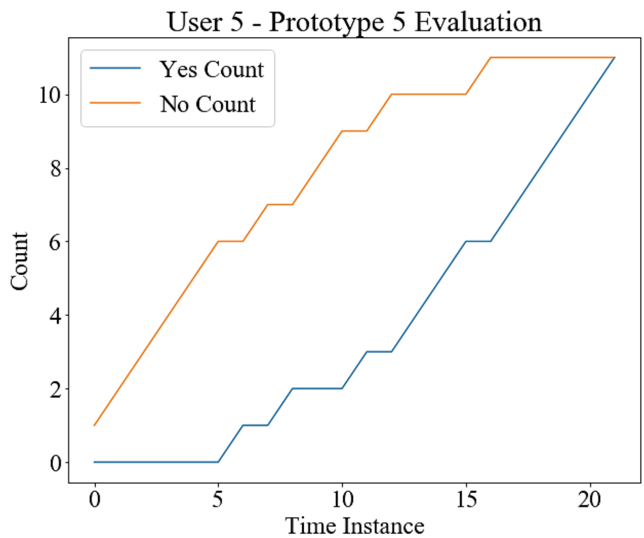

Fig. 12. Prototype 5 – User 5 evaluation.

Since this dynamic behaviour of the model is difficult to interpret, the overall analysis has been performed. For all the users, the total YES count was averaged for each time instance using (5) where $Avg_{t,YES}$ is the average YES count for time instance t, $\sum Count_{t,YES}$ is the total YES count for all the users in the time instance t and $Total\_Users_t$ is the total number of users available in time instance t.

$$Avg_{t,YES} = (\sum Count_{t,YES} / Total\_Users_t). \quad \textbf{(5)}$$

Similarly, the total NO count was averaged for each time instance using (6) where $Avg_{t,NO}$ is the average NO count for time instance t, $\sum Count_{t,NO}$ is the total NO count for all the users in the time instance t and $Total\_Users_t$ is the total number of users available in time instance t.

$$Avg_{t,NO} = (\sum Count_{t,NO} / Total\_Users_t). \quad \textbf{(6)}$$

To visually illustrate the overall analysis, the total YES count and the NO count for all the users were plotted as shown in Figure 13. Two intersection points have been identified between the time instances 10 and 20. These points depict how much time the average YES count has generally taken to overrun the average NO count. It means out of the total 40-time instances (since the maximum of the x-axis is 40), the model has started to do the predictions correctly in a reasonable amount of time (that is between the time instances 10 and 20).

Until the time instance range between 10 and 20, the average YES count and average NO count have increased at a similar rate, which means the model has done the correct predictions as well as the incorrect predictions at a similar rate. Moreover, in that range, the average NO count is greater than the average YES count. Thus, it can be proven that, between the time instances 10 and 20, the average YES count has overrun the average NO count and the rate of the average YES count was increased more than the average NO count in consequent time instances until the end of the evaluation. It generally gives the inference that the model has started working properly for any user.

As explained under the individual and overall analysis phases, it has been proven that the model can dynamically predict the functions without halting the learning process. This leads to the concept named "An Adaptive System with User Control" [40] where the user can correct the wrongs that the model has been doing since the user has control over it.

Since the final prototype incorporated the neural network of Prototype 3 (which is the successful prototype that satisfied the first research question: "*How to aggregate different emotion detection techniques to decide the most meaningful emotion*") to decide the most meaningful emotion, and with the overall analysis the suggestion of the most affective function was done correctly for any user (with time) based on both the emotion and the context, it confirms the second research question (*"How a new model can be developed to do optimal decision making in order to perform affective interactions by considering user emotions based on the context?"*).

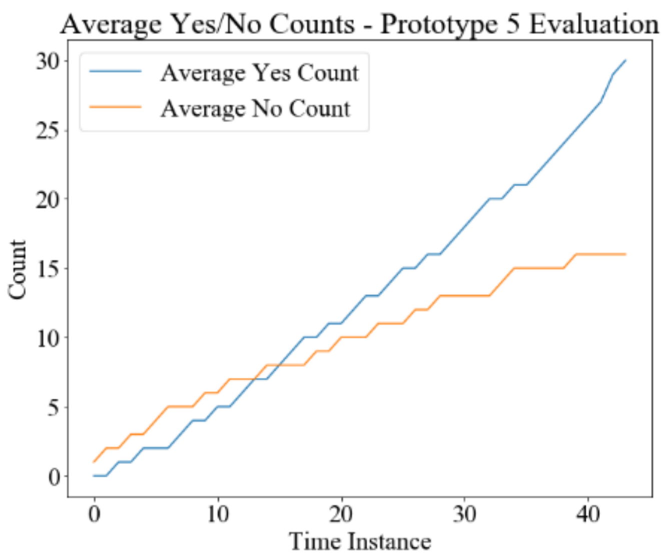

Fig. 13. Prototype 5 - Overall Analysis.

5 Conclusion

Due to the popularity of smart technologies, mobile phones have become a part of our day-to-day lives. Therefore, improving the UX of mobile devices is vitally important.

The main aim of this research was to develop a model for a mobile device that will provide the ability to make optimal decisions about the functionalities by considering real-time user emotions based on the current context, which increases the acceptability and usability of that system. Two research questions have been identified, two user surveys have been carried out and five prototypes have been developed with UCD using Evolutionary Prototyping.

A user survey and three prototypes were developed to confirm the first research question; *"How to aggregate different emotion detection techniques to decide the most meaningful emotion?"*. First, User Survey 1 was carried out which strengthened the initial decisions before implementing the prototypes. The base of the prototypes was a keyboard named "Emotional Keyboard" compatible with Android devices, which can track emotions from facial expressions and text. Prototype 1 was implemented by detecting emotions from facial expressions using Affectiva SDK [31] and detecting emotions from text using IBM Watson Tone Analyzer API [30] separately. Drawbacks of detecting emotions through facial expressions were identified during user evaluations due to issues in camera orientation, uneven illumination, and misjudged emotions. This was solved in Prototype 2 using threshold values to focus on textual expressions. At this point, the solution to the first research question was already attained, but an ANN was developed using Keras (with TensorFlow) and embedded into Prototype 3 using where the ANN was trained using practically collected data during the evaluations of Prototypes 1 and 2. It has given 75.04% training accuracy and 78.17% validation accuracy. From the data collected during the user evaluations of this prototype, a multiclass confusion matrix was designed and calculated the Accuracy, Precision, Recall, Specificity and F-Score values for each emotion. The calculated testing accuracy was 83.57%, which implies the practical usage of this model is better when compared with training and validation accuracies, thus leading to the completion of the first research question.

Finding the answer to the second research question; *"How a new model can be developed to do optimal decision making in order to perform affective interactions by considering user emotions based on the context?"*, was started by conducting User Survey 2. A Preference Tree was created using the data from User Survey 2 which consists of the probabilities that a particular user performs a function based on his/her current emotion and the context. A Preference Tree was created separately for each user for his/her profile and the functions were suggested by traversing the branches of the tree based on the user's emotion and the context. The user evaluations of Prototype 4 were such that the user can respond to the suggested activity by choosing whether he/she likes or not to use that. But this model was not practical to use in day-to-day life since it took more time to produce the correct suggestions. As an improvement, Prototype 5 was developed by keep tracking of frequently used functions [37]. The user evaluations were carried out and the user feedback was recorded. With time, the model was able to correctly suggest the user activities which can be proved by the increment of the number of "YES"s (User agreed to use the activity) when considering the analysis for each user and generally, the conclusion is, that this model is acceptable as an adaptive system with user control [40] which can suggest functions based on the user emotion and the context.

6 Limitations and the Future Work

Since this research was conducted by introducing a keyboard as a proof of concept, the main focus was on enhancing UX. Thus, the performance of the hardware device was not considered. The pace of the device battery drain is considerably fast since this prototype uses several background processes and sensors to perceive multi-dimensional factors. Therefore, it needs to be investigated before introducing a final product. In addition, the used keyboard layout is deprecated from Android API level 29 (Pie) because the Android Open Source Project (AOSP) insists the developers use their widget instead of using their inbuilt one to be more convenient.

This research focused only on two of the non-verbal emotion detection techniques which are facial expressions and text analytics. Recognising emotions using voice (verbal) was completely opted out to restrict the scope of this research. Hence, future research can be performed to evaluate such methods with a wide target audience that can include the elderly population [44], [23].

When providing adaptive functions this research only considered the user emotions and the context parameters such as location, time, and user activity. However, further research can be conducted to test how the physical characteristics of the user, sensory abilities, cognition and non-functional characteristics (such as accessibility, privacy, security, and safety) [47] can be considered in the context to make a more personalized profile for the user that can be used to suggest functions based on those.

Further, this research only considered suggesting functions for a particular emotion (along with the context) that the user will agree to perform, but it was not measured whether the negative emotion has changed to a positive one or not after performing that function. Further research can be carried out to discover this level of satisfaction with a more structured user evaluation process.

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