SensAI+Expanse
Adaptation on Human Behaviour Towards Emotional Valence Prediction

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***Abstract*—An agent, artificial or human, must be continuously adjusting its behaviour in order to thrive in a more or less demanding environment. An artificial agent with the ability to predict human emotional valence in a geospatial and temporal context requires proper adaptation to its mobile device environment with resource consumption strict restrictions (e.g., power from battery). The developed distributed system includes a mobile device embodied agent (SensAI) plus Cloud-expanded (Expanse) cognition and memory resources. The system is designed with several adaptive mechanisms in the best effort for the agent to cope with its interacting humans and to be resilient on collecting data for machine learning towards prediction. These mechanisms encompass homeostatic-like adjustments, such as auto recovering from an unexpected failure in the mobile device, forgetting repeated data to save local memory, adjusting actions to a proper moment (e.g., notify only when human is interacting), and the Expanse complementary learning algorithms' parameters with auto adjustments. Regarding emotional valence prediction performance, results from a comparison study between state-of-the-art algorithms revealed Extreme Gradient Boosting on average the best model for prediction with efficient energy use, and explainable using feature importance inspection. Therefore, this work contributes with a smartphone sensing-based system, distributed in the Cloud, robust to unexpected behaviours from humans and the environment, able to predict emotional valence states with very good performance.**

Keywords*—*emotional valence prediction; context adaptation; memory; human-agent interaction.

I. INTRODUCTION

The scientific evidence of epigenetics reveal on/off mechanisms inside chromosomes of human agents and reinforces the importance of any entity continuous adaptation to its environment. Additionally, some natural entities such as human individuals with self-consciousness and emotion-driven cognition developed a bond between the evolutionary way of emotions and their supporting physical structure as proposed by Damásio [1]. In a sense, it is clear that an agent's behaviour will not develop independently of the environment and that its affective states are paramount in the adjustment. Further, a developed behaviour may be the result of an ongoing, bidirectional interchange between inherited traits (e.g., parameter initial value) and the environment (e.g., data collected from an interacting human). Therefore, it may be envisioned an artificial agent adjusting empathetically towards the interacting human current behaviour and affective state [2][3]. The concept of empathy [4] may be used as a starting point for social glue bringing better interaction, communication and mutual helping. Human-Agent Interaction (HAI) should be based on the way each entity perceives contact, together with the perception of human's affective states in a multimodal approach [5][6]. Hence, the affect sensing using wearable or mobile devices, such as a smartphone seems appropriate. The American College of Medical Informatics (ACMI) has already envisaged this path. In the 1998 Scientific Symposium, one of the informatics challenges for the next 10 years was "Monitor the developments in emerging wearable computers and sensors — possibly even implantable ones — for their potential contribution to a personal health record and status monitoring" [7]. Twenty years have passed since this awakening for the mobile device as a sensing tool. Smartphone sensing for behavioural research is thriving with active discussions [8][9] including exploration on correlates between sensors' data and depressive symptom severity [10].

This paper describes the SensAI+Expanse system and its adaptive mechanisms towards emotional valence prediction ability on humans. The individuals may be diverse in behaviour, age, gender and place of origin. Accordingly, the developed system encompass a mobile device embodied agent SensAI and its Cloud-expanded (Expanse) cognition and memory resources. SensAI collects data from several sources including (a) device sensors, such as Global Positioning System (GPS) and accelerometer; (b) current timestamp in user calendar; and (c) available text writings from in-application diary and social network posts (Twitter status). These written texts in (c) will be subjected to sentiment analysis [11] in order to collect emotional valence from this modality source. The ground truth is obtained from the user when reporting about current sentiment (positive, neutral, negative). On the other hand, the artificial agent will be subjected to a simple adaptive process by means of interaction with humans. An empathy score value is presented during this interaction. The score

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decays over time, it also changes with some factors, such as the frequency of human reporting. This visual adaptive metric should be perceived by the human as current human-agent empathetic score. The Expanse complementary resources comprise several heuristics and algorithms, such as unsupervised location clustering parameters auto discovery and supervised learning hyperparameters auto tuning. These are continuously adapting to the data set of each human entity. Further, preliminary results from a running study with the agent in the wild, publicly available for installation, are presented. This methodology contributes to avoid a well-known Western, Educated, Industrialized, Rich, and Democratic (WEIRD) society bias in research studies involving human subjects exclusively from academia. Moreover, performance results of a comparison study between state-of-the-art machine learning algorithms are presented and a model is elected as the best for future studies.

The first section introduced the purpose of this investigation and the work done so far. Next, Section II will describe the mechanisms in place for the developed mobile agent system adaptive capabilities. Section III describes the research study including the followed method and the achieved results. Finally, Section IV summarises the outcomes and presents a future perspective.

II. SensAI+Expanse Adaptive Mechanisms

This section describes the adaptive mechanisms in place for the developed SensAI+Expanse as a distributed, fault-tolerant, mobile, and Cloud-based system from scratch. The platform is used as a research tool for continuously, online, gather and process sensory data. Figure 1 depicts the general data flow between the SensAI agent and its expanded resources. The collected data from mobile sensors and HAI is processed and stored locally. Additionally, data is periodically synced in order to feed the learning process and prediction service.

The general HAI is initially restricted by its parameter values which drives SensAI. This behaviour may be influenced by the agent's context along the interaction timeline and changes may emerge as adjustment details. Complementary, SensAI Expanse contains a myriad of adaptive mechanisms regarding collected data from human behaviour. These actions work towards Automated Machine Learning (AutoML) and efficient prediction. The emotional valence ground truth values used for prediction performance measurement are reported by humans. The main interface includes three emoticons as depicted in Figure 2. Moreover, this mechanism is robust to interaction bias, such as high-frequency repeated button (emoticon) clicks. Also, on cases of mistaken valence promptly corrected by an additional hit on a different emoticon. It includes a simple yet effective heuristic of accounting only for the last hit during a defined time interval. All these actions are contextualised, i.e., the location and timestamp of the event are collected.

SensAI has two ways of collecting data by doing it (a) passively using several sensors, such as accelerometer and GPS; and (b) actively by interacting with the human using

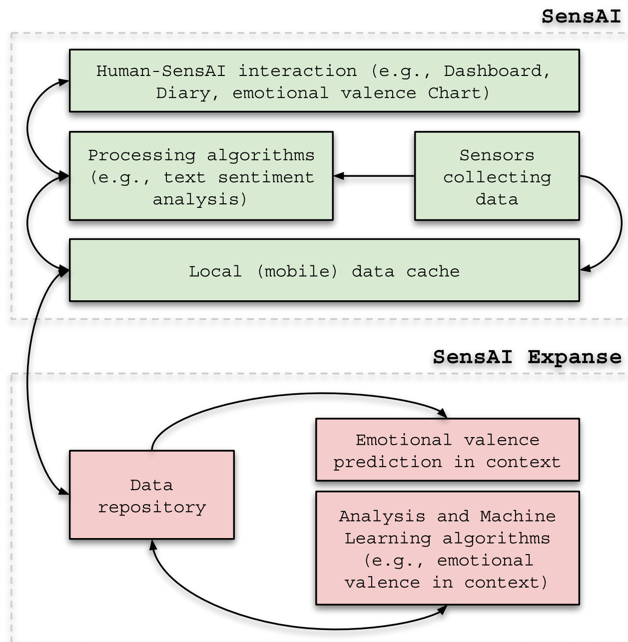

Figure 1. SensAI+Expanse general data flow.

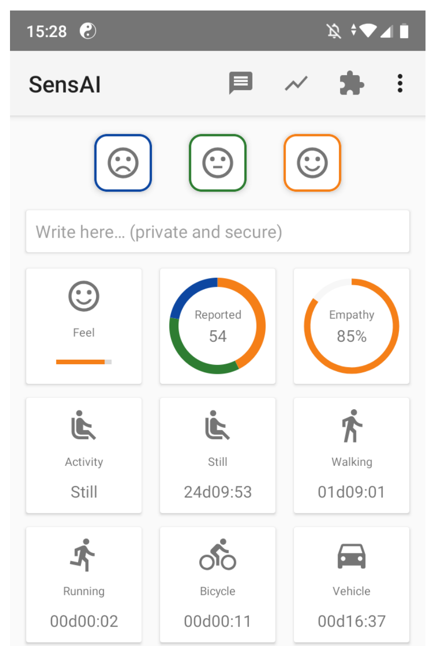

Figure 2. SensAI main user interface and system notification bar.

display notifications and buttons for emotional valence reporting. Moreover, SensAI displays information about the human physical activity aggregated time by each recognisable type (e.g., running), current emotional valence status, self-report statistics, and agent empathy score as depicted in Figure 2. Additional displays are available with (a) sentiment chart with the chronology of reporting and messaging emotional valence values; (b) private diary for writing messages to self where text is subjected to sentiment analysis [11], including

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a SensAI report of current averaged emotional valence status and physical activity every three or so hours; and (c) several statistics about sensors event count, last Expanse data sync, and data collecting uptime.

A. SensAI

The mobile device embodied agent has several mechanisms in place for specific adjustments. These workings are included in different modules. Each one of those is autonomously managed although orchestrated by `Homeostasis` module with periodic health checks. `SenseiStartStop` is a fail-safe last resort to deal with device start/stop and also unexpected SensAI failures such as asynchronous illegal states causing the application to crash, i.e., be removed from running state. Activity, service and special modules are instantiated objects from code developed classes. Some run on demand, others periodically, as services and activities on dedicated threads or the main user interface thread. The relevant activities and services for SensAI embodiment are described below.

`Homeostasis` is paramount to guarantee some tolerance to failures and keep the agent in a good health, it is a scheduled, service designed to regulate the embodiment. Every run checks for critical aspects, such as database health and data feed. It takes proper actions to solve some common failures, such as sensor data `Feed` not running. Moreover, adapt itself to the interaction state, i.e., if at rest then database optimisations and fix actions may run, conversely, updating notifications, such as empathy level only happen when the human user is paying attention. This mechanism prevents potentially disturbing events, such as too frequent device's screen awaking just for an empathy value adjustment. The homeostasis-like solution for the SensAI application is complemented with `SenseiStartStop` required to protect and guarantee `Homeostasis` service to run as expected.

`SenseiStartStop` is a system event receiver to assure persistence and robustness against the device failures and reboots. It does a system registration at SensAI first start to be called on device boot and on application upgrade dealing with those special states. This registration also signals Android operating system to revive SensAI in case of unexpected crash and removal from running state.

`Feed` is a started service running autonomously in the background. Several other services run on demand in an adaptation to save mobile device resources consumption, such as battery. This module encompasses and manages all data collecting from sensors, such as Android-device hardware types (e.g., accelerometer). Moreover, a balanced data acquisition rhythm, such as $active = 2s$, $inactive = 8s$, $f = 1/5Hz$, and $D = 20\%$ is devised and in place for relevant data to be acquired without draining too much power. This rhythm as well as other thresholds may be subjected to automatic adaptation in the future. Furthermore, Figure 3 depicts a persistent notification message which includes empathy level adjustment in a progress bar triggered by emotional valence reports (using emoticon buttons). Also, a dashboard is available with relevant information including empathy level. An active SensAI main user interface dashboard was already depicted in Figure 2.

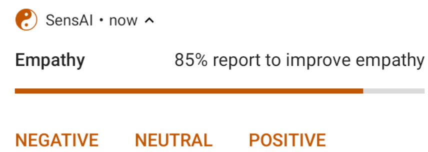

Figure 3. Empathy notification including valence report buttons.

`Sentiment` analysis utility including integration with language detection, translation and more is provided by specific libraries and services included in SensAI. All contributing for the best effort to get the sentiment value along with the language. A heuristic is in place to adapt the analysis to human idiosyncratic aspects, such as mixed languages (English and Portuguese supported) and emoticons amongst other abbreviations when writing short messages. To deal with this rich and sometimes creative written content the best effort approach is depicted in Figure 4.

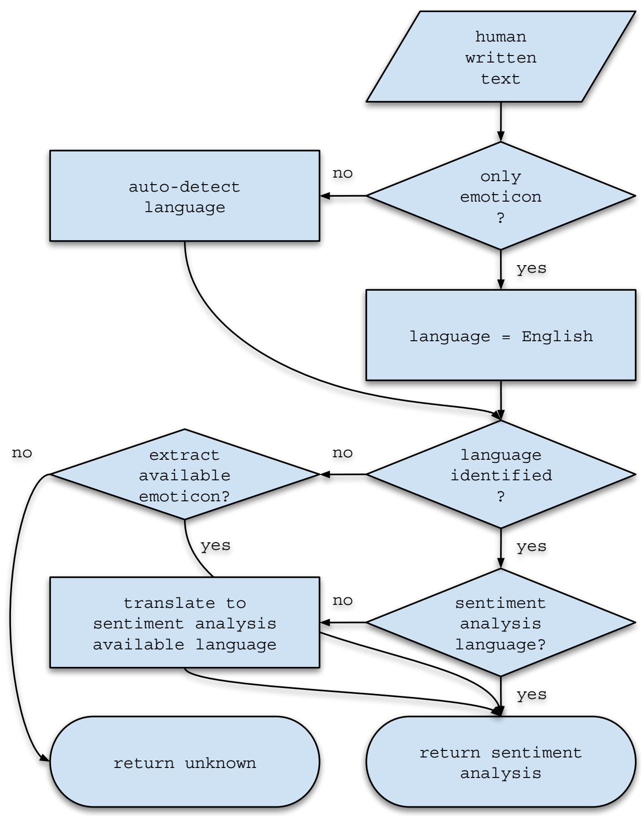

Figure 4. Sentiment analysis heuristic.

`Expanse` is a periodic and scheduled service for data syncing with a memory aggregator in the Cloud — SensAI Expanse. It is robust to failures using a mechanism similar to a transaction, i.e., only successfully transferred data is marked as such (able to be deleted after cache persistence time limit). Moreover, on lack of a suitable data connection available it will adapt by increasing verification frequency for later try to sync. This mechanism of local cache and Cloud sync is paramount to restrict memory resources consumption and guarantee proper data collection.

B. SensAI Expanse

The agent Cloud-expanded resources — Expanse — are the augmentation spread of the SensAI limited smartphone resources (e.g., data persistence, processing and power). Expanse stores data from all SensAI agents anonymously to guarantee that the human's privacy is kept when the data flows to analysis. It includes a repository with historical data, processing algorithms, services of machine learning towards prediction of emotional valence in context, i.e., SensAI augmented memory and cognition. Moreover, processing all eligible data through available algorithms towards AutoML requires (a) adaptation to the diverse human behaviours reflected in the data set; and (b) Bayesian efficient auto discovery on parameters. Software architecture modules and services are depicted in Figure 5.

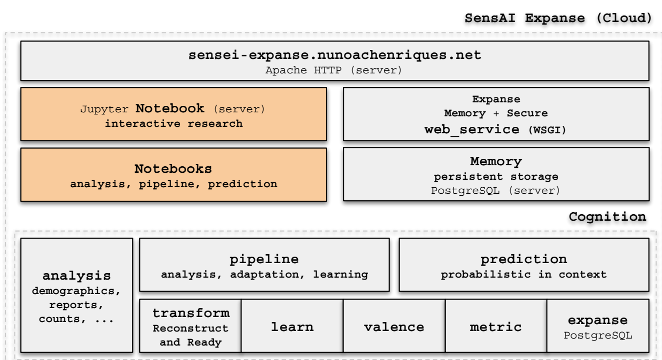

Figure 5. Expanse software architecture modules and services.

Adaptive actions start, amongst other things, with `analysis` on gathering data aggregations and filtering eligible human entities. This eligibility selection has more steps through the `pipeline` process until reaching the final data samples for machine learning. Before the final step, `transform` acts on cleaning, reconstructing and fixing collected data such as upsampling data within proper boundaries related to collecting parameters previously used to save resources in SensAI. The Expanse developed custom `pipeline` for SensAI learning uses a myriad of heuristics and other algorithms. These include a data class (negative, neutral, positive) imbalance (reports count) degree from [12]. Also, a custom valence class count check and restrict in order to adapt the learning process in cases such as emotional valence reported for only two (or even one) classes. The final eligible entities are achieved after these valence class count and imbalance degree processing.

The `learn` module integrates several state-of-the-art algorithms from two main categories of (a) unsupervised ones, such as HDBSCAN for clustering location coordinates and accurately drop outliers; and (b) supervised for multi-class classification, such as Extreme Gradient Boosting by XGBoost and a custom multilayer Perceptron using Keras in TensorFlow.

Additional steps are in place towards AutoML by making use of (a) the learn process calling a function for running HDBSCAN clustering algorithm on the different `min_samples` provided in order to find the best `min_cluster_size` parameter; and before each call to one of the classification algorithms learning process (b) an auto search is in place for the best cross validation N splits regarding the algorithm minimum number of accepted classes. Next, a hyperparameter auto tuning with cross validation for each specific model uses Bayesian optimisation. Finally, the model with parameters fit for each human current data is achieved and performance metrics such as F1 score are computed. The current knowledge from the learning process is stored using the `expanse` module and the `Memory` component. The `prediction` module is serving answers from Web service requests in the Cloud. These responses are for contextualised (location and moment) emotional valence prediction requests for the requiring human, as depicted in Figure 6.

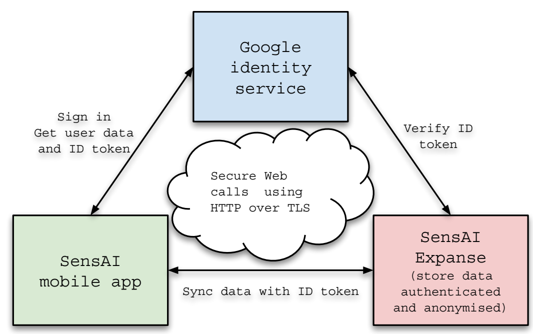

Figure 6. End-to-end secure communication.

All communications are end-to-end secured and digitally signed, restricted to the owner available data, i.e., a human A cannot obtain the prediction for a human B.

III. STUDY

In this section, it will be described the applied method and the outcomes of a research study comprising a population of human individuals interacting with SensAI in the wild.

A. Method

The participants are gathered from all kinds and creeds, i.e., avoiding the laboratory usual limitations, such as sampling only from WEIRD societies known as a frequent bias [13]. This goal is accomplished by choosing to collect data using smartphone sensing [14] by means of an Android application. SensAI has already been installed by users from ten different countries and four continents (Africa, America, Asia, Europe). A total of 57 participants installed SensAI, eight were discarded for not sharing demographic data thus 49 (18 female, 31 male) remained eligible. The pipeline process

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further reduces the population to 31 eligible individuals after valence class imbalance restrictions are applied. Moreover, demographic data comprises birthdate and gender at this stage, extending the collection to other aspects such as income and education level is foreseen as of interest for future studies.

Regarding the system prediction performance, a comparison study assessing a few state-of-the-art algorithms and two metrics was in place. The set of estimators comprises linear (Logistic Regression), non-linear (Extreme Gradient Boosting), and connectionist (TensorFlow Keras MLP) distinct approaches. Also, one more estimator is used as baseline (Dummy) generating predictions by respecting the training set's class distribution (option `strategy=stratified`). The two metrics studied were F1 score (option `average=weighted`) and Matthews Correlation Coefficient (MCC) prepared for multi-class ($n = 3$) case from `scikit-learn` package. Both metrics are very popular and with good software support for machine learning.

B. Results

The preliminary results were achieved by first using the MCC metric on four estimators. The performance statistics depicted in Figure 7 revealed unexpected overly high values (e.g., baseline median near 0.8) raising red flags about possible issues, such as estimators overfitting.

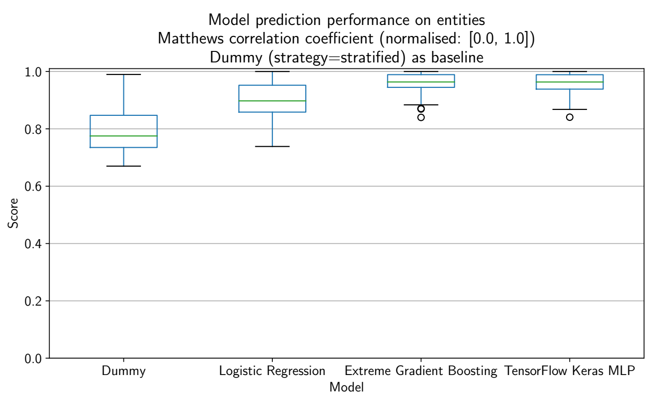

Figure 7. Model prediction performance statistics using MCC.

In order to verify the overfitting issue possibility on the first results (after several runs to sustain the achieved values) a different score metric is used. F1 score is selected for performance evaluation within the same experimental conditions. The results are depicted in Figure 8.

There is evidence of measurement discrepancies between F1 versus MCC over the population datasets, as depicted in Figure 9. In order to assess the significance of these differences, a Mann-Whitney U test is applied on F1 versus MCC and the results presented in Table I show that the null hypothesis (H_0: two sets of measurements are drawn from the same distribution) can be rejected, i.e., evidence of significant differences on F1 versus MCC results.

As a result, F1 measurements seem reasonably nearer to the expected baseline statistics than MCC. Further inspection

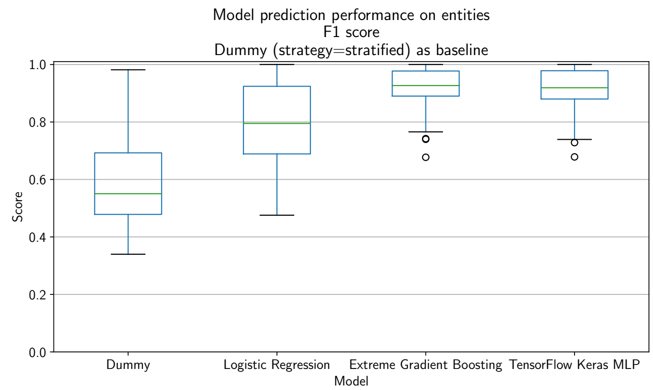

Figure 8. Model prediction performance statistics using F1 score.

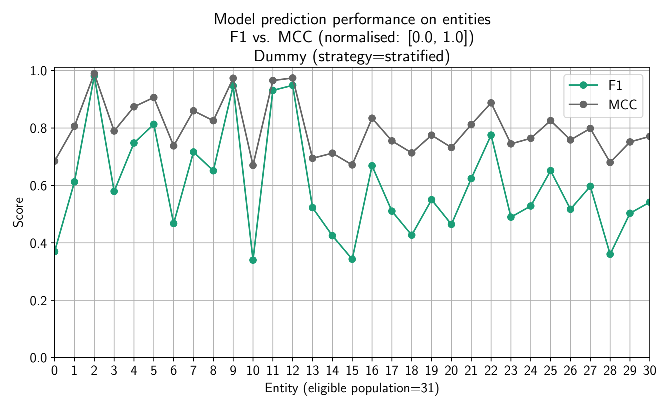

Figure 9. Model prediction performance on entities: F1 vs. MCC.

using the confusion matrix for some cases from the $26/31$ (83%) with more than 10 percentage points difference uphold F1 score as more accurate than MCC. Moreover, making use of the classification report no pattern was identified correlating the inspected cases, i.e., all distributions have distinct data shapes. Although the MCC is considered to have advantages over the F1 score, specifically in the binary classification case, such claim [15] was not evidenced in this research with the current eligible population and datasets. The results of this study using F1 score for each model are summarised in Table II and depicted in Figure 8.

The Extreme Gradient Boosting model is elected as best

TABLE I. F1 VS. MCC (FIGURE 9): MANN-WHITNEY U TEST RESULTS

Metrics	p value	Meaning ($\alpha = 0.05$)
F1 vs. MCC	2.237×10^{-2}	H_0 can be rejected ($p < \alpha$)

TABLE II. ALL FOUR ESTIMATORS AVERAGE F1 SCORE AND TOTAL DURATION

Model	F1 average	Duration
Dummy	0.600	00:00:46
Logistic Regression	0.795	01:46:22
Extreme Gradient Boosting	**0.910**	**01:54:34**
TensorFlow Keras MLP	0.907	24:35:11

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option amongst the other two additional models plus baseline also available. The choice for this model is further supported by an interest towards (a) Explainable Artificial Intelligence (XAI) predictions; and (b) efficient energy use besides overall score achievement. Regarding (a) the Extreme Gradient Boosting includes feature importance scores for each entity model thus proper explainable context (e.g., the specific location feature with the highest score). As for (b) evidence already presented in Table II show Extreme Gradient Boosting as the best performer although marginally to the second yet for less than a tenth of the processing duration. Therefore, Extreme Gradient Boosting is simultaneously on average the best model for prediction with efficient energy use and also easy explainable by feature importance inspection.

IV. Conclusion and Future Work

This paper has described the SensAI+Expanse smartphone sensing-based system, distributed in the Cloud, robust to unexpected behaviours from humans and the mobile demanding environment, able to predict emotional valence states with very good performance. The SensAI agent adapts to the restricted resources and volatile environment of a mobile device where an operating system dictates behaviour rules. Any ill-behaved application is automatically stopped by the system and may even be excluded from restarting. These cases where processing takes too long usually result in the application being stopped and declared Application Not Responding (ANR). There is no evidence of any ANR in the Google Play Console used to monitor all events from SensAI. Conversely, there is evidence of a few "Illegal State" crashes from which the agent recovered and continued to interact after a maximum of fifteen-minute delay (interval for periodic scheduled checks). Furthermore, battery consumption is kept at one digit percentage (e.g., 1%) for a day-long use in several devices laboratory and regular testing. The outcomes presented show evidence, restricted to population and data samples in this research, of SensAI+Expanse ability to adapt and learn to predict emotional valence states with a high score of $F1 = 0.910$ on average (Table II and Figure 8). Therefore, SensAI+Expanse contributes as a novel platform for studies about human emotional valence changes in context of location and moment. Moreover, it reinforces smartphone sensing contribution as a tool for continuous, passive, and personalised health check, such as emotional disturbances, in spatial and temporal context. Furthermore, all the source code is published as free software under the Apache License 2.0. Future work should investigate emotional valence report discrepancies amongst population demographics, such as age and gender. Furthermore, an assessment over the agent robustness to those differences would be of interest. Thus, studies about the agent's neutrality to distinct age ranges and gender combinations should be in place by means of the elected Extreme Gradient Boosting model with F1 score.

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