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Corrigendum: Real-time affect detection in virtual reality: A technique based on a three-dimensional model of affect and EEG signals

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A Corrigendum on
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by Pinilla A, Voigt- Antons J-N, Garcia J, Raffe W and Moller S (2023). Front. Virtual Real. 3:964754.
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In the published article, an author name was incorrectly written as **Sebastian Moller**. The correct spelling is **Sebastian Möller**.

In the published article, there was an error in the presentation of supervised learning. It was mentioned that supervised learning tends to be less computationally expensive than deep learning. However, this statement is incorrect because it implies that deep learning belongs to a different category than supervised learning. In fact, it is possible to build a supervised deep learning model.

A correction has been made to **Introduction**, Paragraphs 8 and 9. These paragraphs previously stated:

"At the same time, deep learning methods tend to require more computational power than supervised learning methods. Partly, because deep learning tends to require larger datasets and involves more parameters than supervised learning methods (Val-Calvo et al., 2019). Therefore, an emotion recognition system based on deep learning might not be affordable for most users.

Consequently, the technique proposed in this manuscript is based on a supervised learning approach, similar to Val-Calvo et al. (2019). One of the key steps when building a supervised learning model is identifying the most relevant features for the construct of interest. This process is known as feature selection. A common method for feature selection is Recursive Feature Elimination (RFE), which has been used previously in the field of affect detection (Val-Calvo et al., 2019). This method requires defining a fixed number of features to select. The classification model is fit multiple times, and in each iteration, the less relevant features are removed until reaching the number of features that have been previously defined."

The corrected paragraphs appear below:

"At the same time, neural networks tend to require more computing power than some traditional machine learning algorithms, such as Random Forest. Partly, because neural networks usually require larger datasets during the training phase to achieve similar accuracy. Additionally, real-time analysis of EEG signals is particularly demanding in terms of computing power because the data must be processed at the same speed that it is recorded.

Computing power is not a limitation when a High-Performance Computing (HPC) system is available. However, most users do not have access to an HPC center. It is possible to overcome this challenge by training a neural network at an HPC center and deploying the trained model (e.g., Singh and Tao, 2020). However, this approach is not optimal for building user-dependent models in real-time, because it would require 1) capturing enough data from each user to train user-dependent neural networks, 2) transferring the data from each user to an HPC center, 3) training at least one neural network per user, 4) transferring the trained models back to the device of each user, and 5) completing the entire process at a speed that does not disrupt the experience of the user.

In contrast, a Random Forest classification model usually can be trained using consumer-grade hardware. Therefore, this algorithm could be used to train affect detection models on the user's device. This approach is consistent with edge computing (Cao et al., 2020), an emerging paradigm that supports the benefits of processing the data on the user's device. Some of those benefits are 1) minimizing the amount of data that is transferred over the network, reducing bandwidth consumption and avoiding potential pitfalls caused by network disruptions, 2) strengthening security and privacy, because most of the user's data remain on their device, and 3) reducing the operational costs. Thus, Random Forest might be more suitable than neural networks for building user-dependent affect detection models in real-time.

One of the key steps when building a Random Forest classification model is identifying the most relevant features for the construct of interest. This process is known as feature selection. A common method for feature selection is Recursive Feature Elimination (RFE), which has been used previously in the field of affect detection (Val-Calvo et al., 2019). This method requires defining a fixed number of features to select. The classification model is fit multiple times, and in each iteration, the less relevant features are removed until reaching the number of features that have been previously defined."

Another correction has been made to **Discussion**, Paragraph 3. The final sentence previously stated "However, those studies used deep learning methods, while the technique proposed in this manuscript used supervised learning methods." but should be "However, those studies used neural networks, while the technique proposed in this manuscript used Random Forest". The corrected paragraph appears below:

"A two-way repeated measures ANOVA was conducted to compare the mean accuracy of the classification models obtained with each feature selection method (LME vs. RFECV). No statistically significant differences were found. Yet, LME led to classification models slightly more accurate than their RFECV counterparts. The mean accuracy obtained with both feature selection methods was between 87% and 93%, suggesting that the proposed technique leads to reliable results, regardless of the feature selection method used (see Figure 4). These results are consistent with previous studies in affect recognition using EEG signals, where classification models with an accuracy of 90.77% (Xu and

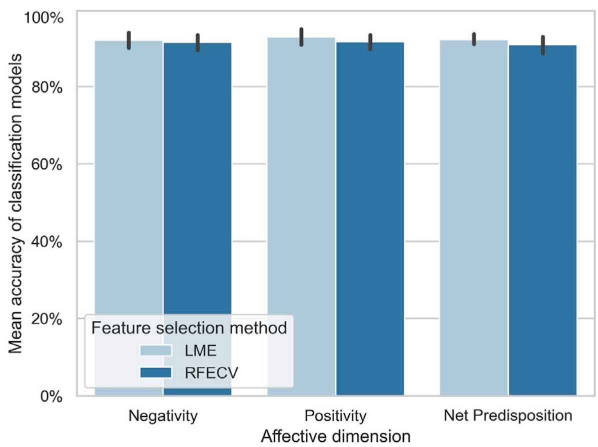

FIGURE 4
Mean accuracy of the classification models for each affective dimension of the ESM (Cacioppo et al., 1997). The accuracy of the classification models trained with features selected using LME was not statistically significantly different than the accuracy of the models trained with features selected using RFECV. The accuracy of the classification models was similar across affective dimensions. Error bars depict CI, 95%.

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Plataniotis, 2012) and 90.4% (Song et al., 2018) were reported. However, those studies used neural networks, while the technique proposed in this manuscript used Random Forest."

Finally, the following two references have been added to the Reference list.

The authors apologize for these errors and state that this does not change the scientific conclusions of the article in any way. The original article has been updated.

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