different number of epochs, that is, when the database will be fully used. The maximum number of epochs/rounds used for training is 50. Note that when comparing DLmodels and FL models, we treat one epoch (DL) andone round (FL) as equivalent. Here, we aim to understand the impact of individual FL parameters on the overall FL performance. To this end, we chose to observe the changes in performance produced by varying the number of epochs/rounds and the percentage of clients used for training during each round of the FL model trained when using the full dataset. We will include a metric called F-score, with which we will present the behavior of the model itself in relation to the number of clients per round, i.e. not only does it change the number of users who have access to each page, we also change the percentage of clients that are used for training in each round. The model fitted to this experiment is characteristic of 50 rounds.

6 RESULTS AND DISCUSSION

In this section, we present the results obtained from the various experiments regarding the behavior between the FL and DL models. FL is an online learning strategy and transfers the model weights to the FL centralized server in each round of operation, FL- based macro F-score curves are presented as continuous with respect to the data transfer volume. In contrast, since DL is an offline strategy and the data needs to be fully transferred to the centralized server to perform the model training. DL and FL strategies, multiple runs were conducted to calculate 95% confidence intervals for the macro F-score. We will look at the result for the macro F-score when using the full dataset (Figure 2). It is noteworthy that even in the case where the full dataset is used, the FL model slightly approaches the DL model in the case of 35 epochs, this is a result because the DL model has a fairly relative growth since the beginning compared to the FL model. The performance degradation of FL relative to macro F may come as a result of the small number of epochs used to train the local FL models. A slight degradation in terms of the performance itself is observed with the DL strategy, in the situation of the full feature dataset. We conclude that by increasing the number of local epochs in the FL strategy, it approaches the DL strategy, which shows the benefit of FL implementation.

Figure 3 shows a heatmap that presents the achieved macro F-score of the FL model when varying the percentage of clients used for training in one round and the total number of rounds used for training. More specifically, on the horizontal axis, Figure 2 show the percentage of clients used for training in each epoch and on the vertical axis, it shows the maximum number of rounds. After roughly 20 rounds of training, the performance of the FL model plateaus and the achieved performance varies by at most two percentage points. Furthermore, Figure 3 also suggests that using a larger percentage of clients, i.e., above 50%, for training during one round produces better results. In our case, the best results seem to be produced by an FL model that uses 80% of all clients to update the centralized model in each training round.

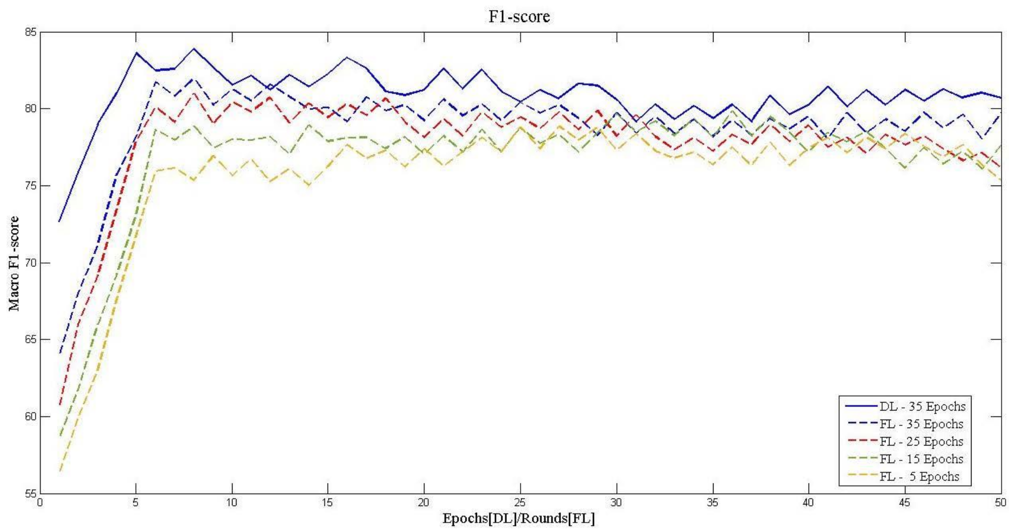

Figure 2: A comparison between FL and DL in terms of Full-featured dataset.

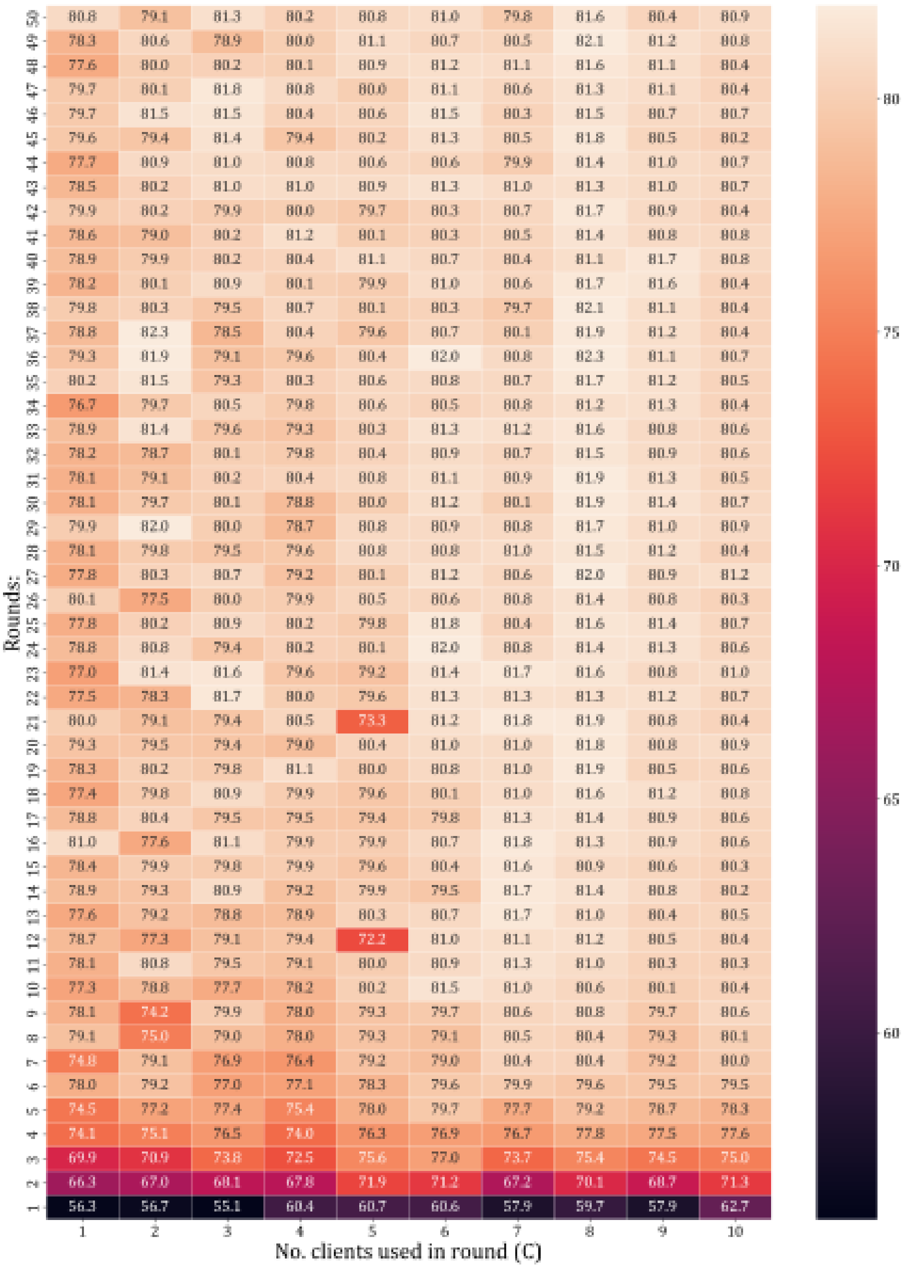

Figure 3: Macro F-scores achieved by an FL model when varying the number of clients used for training in each round and the total number of rounds used for training.

7 CONCLUSIONS

This paper presents the advantage that the FL strategy has in terms of IoT implementation, as well as the advantages that can be seen in terms of eHealth. The FL strategy is presented as a distributed collaborative approach to Artificial Intelligence - AI that is able to offer all of this to distributed IoT devices without the need for data sharing. The emphasis here is on the use of FL in scenarios used for HAR. What can be concluded is that the importance of the number of clients and local epochs for FL model training are key parameters in this experiment. The correct selection of the parameters, i.e. the optimal ones, leads to the fact that the performance of the FL strategy is quite close to that of the already existing DL strategies, which justifies the implementation of FL.

The future direction of research will continue to deepen the benefits and advantages that the FL strategy offers us, in terms of creating different models that will have different demands and testing their behavior in relation to DL.

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