Hybrid Federated Learning for Stream Classification with Concept Drift*

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Abstract

Federated learning aims to decentralize the learning process of a machine learning technique using many edge devices [5]. In this mechanism, the classifier is built based on the local data then it will be sent to a master node where the aggregation will be performed [1, 2]. The local data will not be sent, only the model; this provides more privacy-preserving and reduces communication traffic. Most medical data classification tasks require a patient privacy-preserving and fast response [4]; Federated learning can provide both. The research aims to design and implement an efficient adaptive classification model that works in the Federated Learning environment while maintaining accuracy and patient privacy. This can help patients with critical medical conditions (such as a patient with epilepsy or heart problems), the medical staff, and relatives to take the necessary procedures to avoid any repercussions or serious injuries that may lead to death or disability. Wearable devices that contain sensors for EEG signals or vital signals provide a source of data required for the classification model, and the ease of availability of smart devices currently, such as mobile and smartwatches, and their connection to the Internet contributes to the implementation of the proposed system and its use anywhere outside or inside health institutions [3]. The diversity of data sources leads to different features in each patient's data stream (Edge device). And since horizontal federated learning requires similar features between Edge devices, it is

^{*}This research was supported by the $\acute{\rm U}$ NKP-22-3 New National Excellence Program of the Ministry for Culture and Innovation from the source of the National Research, Development and Innovation Fund.

possible to hybridize the model with vertical learning, in which each Edge node contains two classifiers, as shown in Figure 1, one for similar features and the other for different features. In the master node, a Boosting principle can combine models of the first type, while Bagging can be used to aggregate models of the second type. The work also studies the effect of concept drift in the data stream on the performance of the local and aggregated classifier and how to deal with delayed labeling. Depending on the ability of adaptive machine learning algorithms, it is expected to obtain a fast and accurate response from the classifiers in the edge devices close to the patient.



Figure 1. Diagram of Hybrid Federated Learning

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