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Enhancing stress detection in wearable IoT devices using federated learning and LSTM based hybrid model

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ABSTRACT

In the domain of smart health devices, the accurate detection of physical indicators levels plays a crucial role in enhancing safety and well-being. This paper introduces a cross device federated learning framework using hybrid deep learning model. Specifically, the paper presents a comprehensive comparison of different combination of long short-term memory (LSTM), gated recurrent unit (GRU), convolutional neural network (CNN), random forest (RF), and extreme gradient boosting (XGBoost), in order to forecast stress levels by utilizing time series information derived from wearable smart gadgets. The LSTM-RF model demonstrated the highest level of accuracy, achieving 93.53% for user 1, 99.40% for user 2, and 97.88% for user 3. Similarly, the LSTM-XGBoost model yielded favorable outcomes, with accuracy rates of 85.88%, 98.55%, and 92.02% for users 1, 2, and 3, respectively, out of 23 users studied. These findings highlight the efficacy of federated learning and the utilization of hybrid models in stress detection. Unlike traditional centralized learning paradigms, the presented federated approach ensures privacy preservation and reduces data transmission requirements by processing data locally on Edge devices.

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1. INTRODUCTION

In recent years, the proliferation of wearable internet of things (IoT) devices has significantly transformed the landscape of personal healthcare monitoring, as shown in [1]-[5]. Stress, a prevalent health issue associated with various physical and mental ailments, can currently be better monitored by incorporating wearable sensors and IoT technologies. Accurate detection of stress levels using wearable devices can result in timely interventions, thereby leading to notable enhancements in health outcomes.

Despite advancements in wearable technology, several challenges persist in the accurate and efficient detection of stress. Traditional centralized models for stress detection raise significant privacy and security concerns as they require data to be transmitted to central servers for processing. Additionally, these models often fail to achieve high accuracy and robustness across diverse user datasets due to their inability to effectively capture temporal dependencies in physiological data.

Previous research has explored various methods for stress detection using IoT devices. Major contributors in this field have utilized single neural network architectures or traditional machine learning models. Can *et al.* [6] utilized convolutional neural networks (CNNs) for stress detection but faced limitations in capturing long-term dependencies in the data. Patel *et al.* [7] implemented random forest (RF) models, which provided robust classification but lacked the ability to handle sequential data effectively. Chen *et al.* [8] employed long short-term memory (LSTM) networks, achieving better performance with time-series data but encountering computational inefficiencies on resource-constrained devices.

The existing literature highlights several unresolved problems, including data privacy and security issues, model accuracy and robustness, and the effective handling of sequential data. High computational requirements of deep learning models limit their practical application on wearable devices, and there is variability in model performance across different users due to individual physiological differences. Furthermore, delays in data processing hinder real-time detection capabilities, and limited evaluation metrics do not provide a full assessment of model performance. To address these gaps, our study introduces a federated learning [9] framework combined with a hybrid deep learning model for stress detection using data provided from wearable IoT devices. The federated learning approach enhances privacy and security, addressing significant privacy concerns in centralized data collection methods. Furthermore, the evaluated hybrid models, such as the combinations LSTM-RF and LSTM-XGBoost, are presenting the highest accuracy for almost all the involved users. These models are optimized for computational efficiency, making them suitable for implementation on resource-constrained devices using TinyML techniques. On the other hand, the federated learning approach ensures that the studied models generalize well across different users by training on diverse local datasets, mitigating variability in individual physiological responses. Moreover, our evaluated models support real-time stress detection, enabling timely interventions and improving overall health outcomes.

The following sections of this manuscript will demonstrate the relevance and impact of our work, section 1 provides the introduction and background. Section 2 describes the methodology and experimental setup. Section 3 presents the results and their implications. Section 4 discusses the findings and compares them with existing works, and section 5 concludes with future work directions.

2. MOTIVATION AND RELATED WORKS

Recent advancements in stress detection using wearable IoT devices have highlighted the potential of federated learning and hybrid models to address key challenges in the field. Alahmadi *et al.* [10] provided a comprehensive overview of a privacy-preserved IoT-based mental stress detection framework using federated learning, emphasizing the importance of decentralized learning models in preserving data privacy while enabling effective model training across distributed devices. Similarly, Jiang *et al.* [11] explored privacy-preserving techniques in federated learning, focusing on their integration within IoT frameworks to ensure secure data handling and processing. These studies underscore the potential of federated learning to address privacy concerns, which is a critical aspect of our research.

Several studies have investigated the use of hybrid models to improve diagnostic accuracy in IoT devices. Yaqoob *et al.* [12] examined the integration of various machine learning models, demonstrating how hybrid approaches can significantly enhance diagnostic accuracy in wearable devices. Almadhor *et al.* [13] presented a detailed analysis of wrist-based electrodermal activity monitoring for stress detection using federated learning, emphasizing the potential of hybrid models in this domain. Yaqoob *et al.* [14] leveraged hybrid models to achieve enhanced diagnostic accuracy, particularly in the context of skin lesion diagnosis. Khan *et al.* [15] proposed an asynchronous federated learning approach for improved cardiovascular disease prediction, highlighting the practical implications of timely health monitoring. Junior and Kamienski [16] expanded on this by developing hybrid models that combine multiple neural network architectures to improve the accuracy and responsiveness of performance behavior detection in fog-IoT systems.

Despite these advancements, traditional centralized models still pose privacy and security risks, and existing models often fail to achieve high accuracy across diverse datasets due to limitations in capturing temporal dependencies in physiological data. High computational requirements also limit the practical application of deep learning models on resource-constrained wearable devices. Nandi and Xhafa [17] focused on optimizing hybrid models for real-time emotion state classification, offering insights into the performance enhancements achievable through model integration and optimization techniques. Tripathy *et al.* [18] addressed the scalability of federated learning in IoT environments, discussing how scalable solutions can be implemented to handle growing data volumes and device counts in IoT networks.

Our study represents a significant advancement over existing work by taking into account enhancing not only the accuracy and robustness of stress detection but also ensures efficient and secure data handling through federated learning and edge computing. By addressing the heterogeneity of datasets and the challenge of imbalanced data, our approach provides a scalable and practical solution for real-time stress monitoring in wearable IoT devices. The key to the success of a federated learning solution using a cross-device architecture lies in proposing an efficient and effective solution. This solution, must take into account the limited computational resources of edge devices and the unique data of each user in measuring stress levels. This can be done by combining LSTM and RF or XGBoost as we will discover in the next section.

3. METHOD

Our paper addresses the challenge of accurately detecting stress levels using data from wearable IoT devices while preserving user privacy. Traditional centralized models for stress detection raise privacy concerns and often fail to achieve high accuracy across diverse user datasets. We introduce in this section, a cross-device federated learning framework using hybrid deep learning models. This approach aims to improve stress detection accuracy while maintaining data privacy by processing data locally on edge devices. In a federated learning context, datasets from users are not merged due to privacy concerns and to the distributed nature of the problem. Instead, some computations are done locally on each user's data and then aggregate the result. Figure 1 describes the adopted workflow for our study.

Figure 1. Federated learning workflow for our study

In order to train and evaluate our proposed hybrid models, we used the PRIDE dataset introduced by [19]. It offers an extensive array of characteristics that encompass the physiological and behavioral dimensions of the individuals participating in the study. After the data preprocessing phase, where we did incorporate the "stressed" variable, which will be predicted by our model after training, feature encoding, data integration and normalization, a feature importance analysis was made using RF classifier to prepare the dataset for the federated learning model. The dataset contains time series data collected from wearable devices over one week, 24 hours per day, for 23 test subjects. They are aged between 21 and 52 years old. Data logs include data from 00:00 to 23:59 each day, and Gaps of at least 40 minutes three times a day for battery recharging. The dataset contains timeseries data from 23 subjects, organized for each subject as described in Figure 2. Figures 3 and 4 present an example of the heart rate and the skin temperature over time for a random user.

```
RangeIndex: 466945 entries, 0 to 466944
Data columns (total 28 columns):
 #   Column                     Non-Null Count   Dtype
---  ------                     --------------   -----
 0   USERID                     466945 non-null  int64
 1   MeanXGyroAccelo            466945 non-null  float64
 2   StdrdevXGyrosAccelo        466945 non-null  float64
 3   MeanYGyroAccelo            466945 non-null  float64
 4   StdrdevYGyrosAccelo        466945 non-null  float64
 5   MeanZGyroAccelo            466945 non-null  float64
 6   StdrdevZGyrosAccelo        466945 non-null  float64
 7   MeanXGyroAngV              466945 non-null  float64
 8   StdrdevXGyrosAngV          466945 non-null  float64
 9   MeanYGyroAngV              466945 non-null  float64
 10  StdrdevYGyrosAngV          466945 non-null  float64
 11  MeanZGyroAngV              466945 non-null  float64
 12  StdrdevZGyrosAngV          466945 non-null  float64
 13  MeanofXaxisAccelerometer   466945 non-null  float64
 14  StdrdevXAccelr             466945 non-null  float64
 15  MeanofYAccel               466945 non-null  float64
 16  StdrddevYAccel             466945 non-null  float64
 17  MeanofZaxisAccelerometer   466945 non-null  float64
 18  StandarddeviationofZ       466945 non-null  float64
 19  HeartRate                  466945 non-null  int64
 20  SkinTemperature            466945 non-null  float64
 21  Pedometer                  466945 non-null  float64
 22  Distance                   466945 non-null  float64
 23  Speed                      466945 non-null  float64
 24  Pace                       466945 non-null  float64
 25  calories                   466945 non-null  float64
 26  UV                         466945 non-null  int64
 27  Stressed                   466945 non-null  int64
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Figure 2. Dataset column description

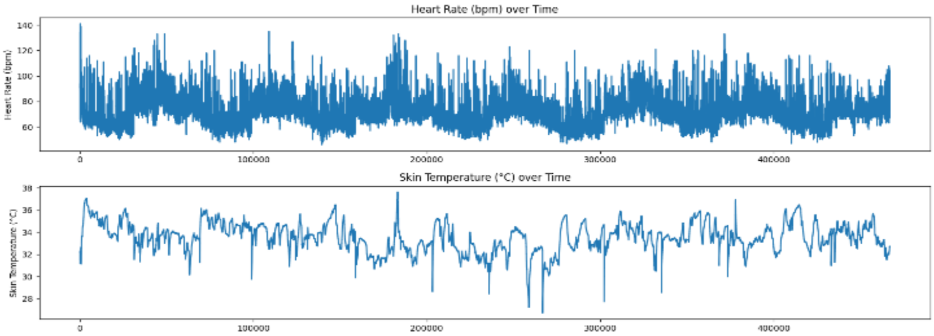

Figure 3. Heart rate and skin temperature over time for user 1

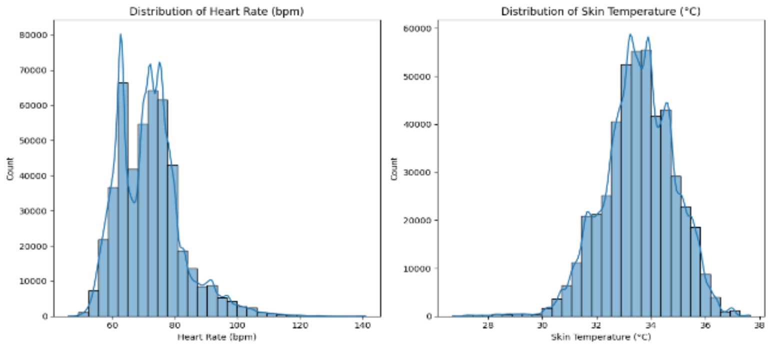

Figure 4. Distribution plots for heart rate and skin temperature

The data belonging to individual users is uploaded onto the respective local device. In order to preserve privacy and respect the federated learning approach. The PRIDE dataset contains data from 23 users separated on two files for each user (all the files have the same columns). The first file presents data in normal conditions, the second contains data when the user is under stressful conditions. We first cleaned data, add headers and coded Stressed column values (binary variable 0='normal' and 1='stressed'). At the end of this step, we prepared one merged file for every user which will be used in the next step to select important features that influence the target "stressed".

In order to reduce the number of features on the dataset, we used a RF classifier to detect the most important features for our study. We first calculate feature importance locally for every user, then aggregate the result to have the above classification as on the Figure 5. Then the top 10 features with the highest importance score are used since they are the features that contribute the most to the model's prediction.

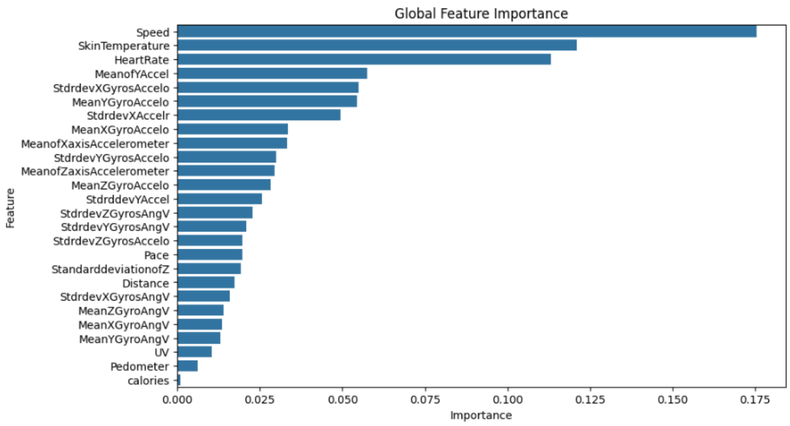

Figure 5. Feature importance

After data analysis, we found that the two classes for target "stressed" are not balanced, which will cause certainly a model overfitting. That's why, we used SMOTE technic to balance data for each user. When utilizing algorithms such as XGBoost or other models that offer functionality for incorporating class weights, it is possible to assign weights explicitly to use class weighting technic. The next step consists on training models locally using each user's dataset, the result weights were loaded after that and then aggregated to update the global model. The model result will be discussed in the "result and discussion section". The data that was gathered then analyzed utilizing Python and TensorFlow libraries, and the key measures utilized for the evaluation of the stress detection model included accuracy, precision, recall, and F1-score.

In this study, multiple neural network architectures were applied to measure their efficiency in stress detection within the federated learning context. The utilization of the LSTM network in combination with gated recurrent units (GRU), RF, and XGBoost allowed for the exploitation of LSTM's capacity to capture prolonged dependencies in sequential data. GRU, which is a simplified iteration of LSTM, offers computational efficiency while upholding performance standards [20]. RF, as an ensemble technique comprised of decision trees, bolsters predictive precision and mitigates overfitting, whereas XGBoost, an optimized gradient boosting algorithm, enhances speed and performance by means of sequential tree construction. Moreover, the integration of residual networks (ResNet) with LSTM and CNN [21] was carried out to leverage ResNet's skip connections for the training of deep networks, LSTM's capability in recognizing sequential patterns, and CNN's proficiency in extracting spatial hierarchies. These specific architectures were chosen due to their complementary strengths in addressing diverse data characteristics, such as temporal dependencies and spatial hierarchies, with the aim of optimizing the predictive capabilities of the study.

Aiming to evaluate the effectiveness of our federated learning model, a stratified approach was utilized to divide the dataset into training and testing sets. This stratification technique guarantees that the distribution of classes remains uniform across both sets, thereby enhancing the credibility of the model's performance. Initially, data preprocessing was conducted individually for each user's dataset. The preprocessing procedure involved standardizing the features to achieve a mean of zero and a variance of one, followed by reshaping the data to conform to the input specifications of the hybrid models. More specifically, the StandardScaler tool from the scikit-learn library was utilized to standardize each user's data, while the target variable was reshaped to match the expected input format. Subsequently, the dataset underwent an 80-20 split to create training and testing subsets. This allocation involved utilizing 80% of each user's data for model training purposes, with the remaining 20% designated for performance evaluation. The division was executed through the implementation of the train_test_split function from scikit-learn, which ensured a random division by establishing a fixed random state. This partitioning was essential to maintain uniformity and avoid possible bias in the model's performance metrics caused by data leakage between the training and testing phases. To enhance the generalization capability of our hybrid LSTM models and to avoid overfitting, dropout layers were incorporated into the proposed architectures. Dropout serves as a regularization method where, in each training iteration, a portion of neurons is randomly chosen to be disregarded. This action prevents an excessive dependency on specific neurons within the network and fosters the formation of more resilient features that exhibit reduced sensitivity to noise and variability present in the input data. A dropout rate of 0.5 was employed, indicating that 50% of neurons were randomly excluded during every training cycle. This particular rate was selected based on empirical findings and prior research [21]-[26], showcasing its efficacy in diminishing overfitting within analogous neural network structures. A comparison was conducted between multiple federated learning architectures using different hybrid models to evaluate the efficiency of the federated methodology.

4. RESULTS AND DISCUSSION

In this section, we are going to present the main finding of our study. Table 1 and Figure 6 summarize the results of each evaluated hybrid model over a sample of 3 users from a list of 23 to simplify the results presentation. We noticed that the combinations LSTM-RF and LSTM-XGBoost are presenting the highest accuracy for almost all users. Those results were obtained by simulating the federated learning context using Google Colab with the configuration described on Table 2.

However, the varying performance observed across users overall signifies that the model's efficacy may vary depending on the unique data characteristics of individual users. While maintaining consistently high precision, endeavors to improve recall for specific users could potentially boost the overall performance and applicability of the model. This variability in model performance across different users, can be attributed to individual differences in physiological responses to stress. This highlights the need for more personalized models in future research. That's why we intend to explore, in future work, Individual-based learning that involves tailoring stress detection models to specific individuals by leveraging personalized data from wearable devices. The combination of this approach in a federated learning context may allow for the fine-tuning of algorithms to the unique physiological and behavioral patterns of each person, enhancing the accuracy of stress detection.

Table 1. Comparison of the used model's efficiency

		Precision	Recall	F1-score	Accuracy
LSTM-CNN	User1	91.10%	55.91%	69.29%	75.17%
	User2	66.10%	68.15%	67.11%	66.50%
	User3	90.50%	74.23%	81.16%	83.14%
LSTM-GRU	User1	96.31%	48%	64.06%	73.01%
	User2	95.85%	57.82%	72.13%	77.59%
	User3	96.33%	97.73%	97.02%	96.99%
LSTM-RF	User1	96.44%	90.41%	93.33%	93.52%
	User2	99%	99.80%	99.39%	99.39%
	User3	97.32%	98.48%	97.90%	97.88%
LSTM-XGBoost	User1	87.64%	83.61%	85.58%	85.87%
	User2	97.77%	99.37%	98.56%	98.55%
	User3	92.42%	91.62%	92.02%	92.02%

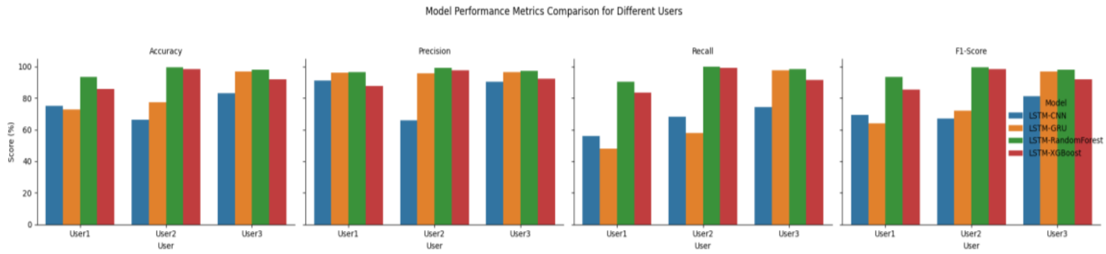

Figure 6. Model performance metrics comparison for 3 users as an example

Table 2. Computing experimental details

Specification	Details
Connection	Backend Google compute engine
Language	Python 3 (GPU)
Total RAM	12.67 GB
GPU	NVIDIA T4
Programming platform	Python 3.8 with TensorFlow 2.4
Number of client nodes	23
Learning rate	0.001 (Adam)
Batch size	32
Epochs	Average of 20 (using early stopping technic to ovoid overfitting)

5. CONCLUSION

In conclusion, our study demonstrates that integration of the LSTM with RF or XGBoost within a federated learning context improves stress detection accuracy while preserving user privacy. However, we noticed a significant difference in the improvement of accuracy from one user to another. For instance, the LSTM-XGBoost combination demonstrated notable efficacy, especially for user 2. This observation leads us to explore other technologies that could help enhance our model while preserving user data privacy and considering the limited computational resources of edge devices. Finally, future research should focus on individual-based learning within federated frameworks to personalize stress detection models, improving real-time monitoring and intervention capabilities. This research provides a robust foundation for privacy-preserved, IoT-based health monitoring systems, with applications extending beyond stress detection to various health-related domains.

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