DOI: ***

ORIGINAL ARTICLE

Smart Work Package Learning for Decentralized Facial Fatigue Monitoring

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ABSTRACT

Agile and accurate detection of construction equipment operators (CEOs) with severe fatigue is critical for preventing accidents and ensuring precision construction occupational health and safety (COHS). Monitoring CEOs' fatigue status has become a critical component of the smart work package (SWP) system for heavy equipment operation. CEOs with drowsiness can be identified using deep learning based on their non-invasive facial videos or invasive biosignals. However, the dilemma between technology achievements and data privacy is widening. Thus, to help monitor facial fatigue data from CEOs on worldwide construction sites without privacy exposure risks, this study introduces the Smart Work Package Learning (SWPL), a decentralized deep learning approach that improves the previously proposed federated transfer learning-based smart work package framework by involving a consortium blockchain network without a centralized model parameters aggregator. To illustrate the feasibility of SWPL for developing fatigue classifiers, this study research on non-invasive facial fatigue monitoring and SWPL merges the model updates from distributed SWPs. These updates are validated by the SWPs in the blockchain network and are then stored on the blockchain. More than 351 videos were derived from 119 operators. The results show that SWPL outperforms individual SWP. Moreover, SWPL achieves data privacy-preserving and security by the design of the blockchain network. The SWPL proposed in this study will significantly open up the advanced development of precision COHS.

1 INTRODUCTION

With increasing advancements and adoptions of intelligent construction equipment systems (ICES), construction equipment operators' (CEOs) operation information in each cockpit can be gathered distributedly by smart work package (SWP) module (Li, 2019), which can provide real-time CEOs fatigue analytics to monitor fatigue states using real-time data sensed from various sources, e.g, heart rate, camera, electroencephalogram. (Li et al., 2020). As an essential component of ICES, the SWP can help monitor each CEO's fatigue status, alert to CEO and site superintendents when the fatigue level exceeds the given threshold, and improve shift or break mechanism, ultimately guaranteeing the on-site construction occupational health and safety (COHS).

Monitoring the facial fatigue of CEOs, e.g., eye state, yawning, nodding, compared with measuring physiological signals, is a non-invasive, fast-speed, and cost-effective way for the precision COHS (Li et al., 2019; Liu et al., 2020). Currently, deep learning techniques demonstrate the efficient performance for facial fatigue prediction through learning facial expression features and improving prediction performance (Yu et al., 2018; Dua et al., 2021). It will use massive spatial-temporal facial image data for training purposes. As SWP is inherently decentral in distributed construction equipment, the size of local data is always inadequate to train reliable classifiers or predictors. Consequently, aggregating data into central is a way that has been widely applied to address the local insufficiency.

While centralized solutions are more technology achievable, they have built-in drawbacks, such as traffic for boosted data and increased issues with ownership, privacy, security of information, and the formation of data monopolies (e.g., big data discriminatory pricing) that favor data collectors. FedSWP proposed by the authors addresses some of these aspects using federated learning (Li et al., 2021), which is a distributed learning paradigm that enables individuals (e.g., SWP) to collectively train a global model published by the central server. The application of federated learning can effectively reduce privacy exposure risks for SWP by performing facial fatigue monitoring (FFM) tasks locally. However, model parameters are still processed in a central server, and this centralized setting decreases fault tolerance. If the central server is compromised, the complete SWP systems face a risk of single-point-of-failure (SPoF), which might readily expose personal information. Furthermore, suppose malicious SWP systems submit erroneous or poor model parameters to the central server. In that case, the convergence of loss or accuracy deteriorates, which can reduce the SWP system's FFM performance, ultimately affecting the safe equipment operations.

To address these challenges, this study introduces smart work package learning (SWPL), which aims to form a consortium blockchain-based decentralized SWP network with distributed learning to improve the accuracy of FFM with high-level privacy-preserving. Model updates can be shared and verified via this network but built independently on private data at each SWP. To this end, three objectives are designed accordingly: (1) To create an SWPL model for decentralized and privacy-persevering FFM; (2) To develop consortium blockchain for SWPL to avoid SPoF and ensure the quality of model updates; (3) To evaluate the SWPL in FFM with real-life datasets.

The remainder of this study is organized as follows: Section 2 reviews the state-of-the-art literature on FFM, SWP, and federated or distributed deep learning. Section 3 establishes the methodology for SWPL. An experiment using real facial fatigue datasets is to demonstrate and evaluate the performance of the proposed method in Section 4. Section 5 compares with existing works to discuss innovations and drawbacks in this study. Finally, conclusions and future works are presented in Section 6.

2 RELATED WORK

2.1 Facial Fatigue Monitoring (FFM)

Construction equipment operators (CEOs), such as crane operators, paver, and truck drivers, should be physically strong and have agility in the hearing, vision, and reactions for safe and productive operation (Tam and Fung, 2011). However, these capacities will be degraded when CEOs fall into fatigue or drowsiness. Previous studies have made efforts to develop various fatigue monitoring systems for detecting and alerting driver's or operator's fatigue operation, which mainly uses equipment trajectory, facial expression, and physiological signal to judge the level of fatigue (Thiffault and Bergeron, 2003; Ji and Yang, 2002; Borghini et al., 2014). Equipment trajectory can be measured by movement speed, acceleration, path deviation, steering, and turning angle. The physiological signals mainly collect electrocardiogram (ECG), electroencephalogram (EEG), electromyogram (EMG), electrooculogram (EOG), and heart rate, as the measurement. However, many disturbances (e.g., operation faults owing to inexperience, ineffective communication with site signallers) may impact construction equipment operation trajectory, and the physiological signals are aggregated in an inconvenient and invasive manner for CEOs. As a result, fatigue monitoring through facial expressions (e.g., eye state, yawning, nodding) may be a more practical, speedy, and cost-effective method. After deep learning is boosted, FFM has a high level of accuracy. For instance, Zhang et al. (2015) employed a convolutional neural network (CNN) to extract yawning features in the nose rather than the mouth due to the impact of head turns. However, it can be difficult to discern between fatigue states, such as blinking and closing eyes. Huynh et al. (2016) used the 3D-CNN as a more realistic method by taking into account more face features as well as temporal features in sequential video frames. However, It is still challenging to discriminate lengthy dependent statuses on the face, e.g., talking and yawning. Guo and Markoni (2018) and Lyu et al. (2018) improved the model with temporal features extractor by combing CNN with a Long Short-term Memory (LSTM) that enables the detection of long-term dynamic features over consecutive frames. Li et al. (2019) further considered backward dependencies learned from reverse-order frames to develop deep bi-directional LSTM for learning dependencies of periodic fatigue facial expression in the crane operations (e.g., discriminate the fatigue nodding and head slant to track the crane hook movements, yawning and talking with signallers). However, monitoring the CEO's facial fatigue in each construction equipment has a great privacy exposure risk. Particularly in the global privacy crisis, privacy-preserving deep learning solutions are demanding to avoid contemporary data privacy scandals (Newman, 2015; Tuttle, 2018). At the same time, a growing number of regions or countries have promulgated laws policies, or regulations to respond to the issues of privacy and security in data, such as European Union issued the General Data Protection Regulation (GDPR) (Voigt et al., 2017) and Personal Information Protection Law by China (Determann et al., 2021). As a result, technical solutions for monitoring the CEOs' facial fatigue while preserving personal information are urgently needed.

2.2 Smart Work Package (SWP)

SWP can be defined as the smallest distributed agent to facilitate tasks planning and executions with smart capacities, e.g., perceiving, computing, networking, inferencing, and predicting. SWPs can be performed in an autonomous manner, resilient to dynamics in their real-world situation, and real-time interaction with the other SWPs and environment (Li et al., 2019b). Many approaches have been developed in SWP to enhance modeling, optimizing, and monitoring data for distributed construction workers. For instance, the hybrid SD-DES model in SWP is developed to assist the dynamic assessment of the impacts of construction workers' task execution constraints on project performance, e.g., schedule (Li et al., 2019c). Furthermore, by calculating the dynamic distance between crane loads and site dynamic obstacles (e.g., walking workers), the probabilistic roadmap using A* embedded in SWP can assist operation decision optimization (Li et al., 2020). Additionally, SWP's hybrid deep neural networks have been successfully employed to monitor and predict CEOs' fatigue (Li et al., 2019a; Li, 2019).

Instead of providing a new workflow in workers' FFM, SWP can enable current workflows with smart properties, such as adaptivity, sociability, and autonomy (Li, 2019). The CEO FFM required in heavy equipment operations is one of the applications to leverage SWP's autonomy with proactive tracking, updating, and predicting. Previous investigations by the authors have looked into the SWP-enabled FFM service, and the service system architecture is presented in Li et al. (2019c, 2021). The infrastructure and functions of this service are enabled by construction resources with embedded IoT sensors, namely, smart construction objects (SCOs) (Lu et al., 2021) and the smart building information modeling (BIM) platform (Li et al., 2022). To facilitate the efficiency in data provision and capture, the SCOs are developed by empowering objects, such as human (operator), machine (crane cabin, helmet), material (prefabricated components) with multimode IoT sensors, e.g., bio-medical ped, camera, IMU, temperature, and humidity sensors. SCOs can also help enrich the semantics of BIM or exchange information with BIM. SWP can then be enabled to perform the FFM tasks after the trigger from CEOs through the human-machine interfaces. Models and approaches developed into SWP may frequently require data sharing or aggregating from each construction worker. However, widely using CEOs' private data may expose them to privacy risks. The privacy concerns expressed by CEOs may stymie the adoption of SWP and other wearable innovations at construction sites.

2.3 Distributed Learning

In COHS, previous studies mainly rely on training worker-related data, including massive private information, such as location, motion, and images. But direct worker-related data gathering is not always easy or allowed in real-life construction sites. Thus, the emergence of Federated Learning (FL) addresses some of these aspects. After being introduced by Google (Konečný et al.,2016), FL quickly received attention from researchers and pushed forward its revolution, such as communication cost optimization and heterogeneity improvement (Sattler et al., 2019), advanced encryption and differential privacy algorithms (Ali et al., 2019), and applications in a wide field including medicine data in healthcare, IoT data in industrial engineering, financial and personal data in mobile devices (Li et al., 2020a). In FL, in each round of model training, each participant downloads an initial global model, completes local model training, and transmits local model parameters to the central server without submitting data. The central server then combines all updates from local trained models to form an aggregated global model, which is subsequently released to the local. This process is repeated iteratively until convergence is achieved. However, FL for SWP-based FFM may present the following issues: (1) the centralized model updates may suffer from the SPoF; (2) malicious SWPs can provide erroneous or poor model parameters to the central server.

To address the above issues, the latest studies have made efforts to use blockchain with distributed databases, consensus mechanisms, and encryption algorithms to incentivize participants to share data parameters and verify them. By combining blockchain with federated learning (FL), Kang et al. (2019) used blockchain to achieve tamper-proof reputation management for an incentive mechanism in model learning. The reliability of FL is also improved in further investigation (Kang et al., 2020). Lu et al. (2020a) developed an asynchronous FL scheme with blockchain for private data sharing on the internet of vehicles, and this scheme is also extended to the digital twin application (Lu et al., 2020b). Qu et al. (2020) evaluated the performance of blockchain-based FL, including latency, consensus delays, cost of communication, and computation for optimal block generation rate. Moreover, they adopted this blockchain FL framework for cognitive computing (Qu et al., 2020b). Zhao et al. (2021) created a Blockchain FL system by using a reputation mechanism to incentivize customers in data provision to facilitate the manufacturers of home appliances in training machine learning models. Qi et al. (2021) also established an FL framework with a consortium blockchain by involving a noise-adding mechanism-based differential privacy method to improve privacy preservation of traffic flow prediction. Although previous studies investigated many privacy-preserving methods, those methods normally protect privacy by sacrificing model performance or system efficiency, and these methods are difficult to be directly applied to FFM of CEOs due to the statistical heterogeneity. Inspired by the concept of swarm learning (Warnat-Herresthal et al., 2021), this study explored a consortium blockchain-based distributed learning method among SWPs, namely SWP learning, to protect privacy and ensure the data quality shared in CEO-FFM.

In summary, an ideal scenario is that sufficient image data could be available locally, and deep learning algorithms can be performed locally in each SWP. However, each SWP may collect image data only from an individual construction site, single construction equipment, or even one operator resulting in data shortage, which requires gathering data into the cloud to train and test better deep learning models. This data centralization issue can lead to data privacy exposure risks. Although FL-based methods have raised great attention with advantages in only aggregating the model parameters and keeping data locally, it still has a centralized structure with a fixed global model to aggregate parameters, which not only have parameter exposure risks but also increased the communication cost in exchanging parameters between global and local model.

3 SMART WORK PACKAGE LEARNING

3.1 Problem Statement

This study considers the CEOs as the entities in facial fatigue monitoring (FFM). Each CEO corresponds to an SWP with the sensory camera. This study uses the SWP (See Fig.1) to represent CEOs entities in the proposed SWPL framework. Each SWP includes specific CEOs' facial fatigue image datasets. SWPL aims to prevent privacy exposure and improve FFM accuracy by sharing model parameters among isolated SWPs in the consortium blockchain network. The SWP set is denoted by $W = \{W_1, W_2, \cdots W_N\}$, while SWPs' datasets are defined by $D = \{D_1, D_2, \cdots D_N\}$. Let t and O_t stand for the t-th timestamp of temporal data and the t-th facial fatigue state. Let

$f(t, D)$ presents the function for FFM, and the followings are problem definitions for privacy and accuracy:

3.1.1 Privacy

Privacy in this study is defined as the avoidance of model parameters leaking, which may potentially lead to revealing sensitive facial image data. For example, model parameters are always processed in a central server, even for an FL model. If the central server is compromised, it may suffer from SPoF risk. The local datasets in each SWP in this study will be used to train its local model, and SWP shares the model parameters via the consortium blockchain, and parameters are aggregated by a dynamic leader SWP rather than submitting the parameters to a fixed central cloud.

3.1.2 Accuracy

The accuracy is defined in this study as achieving better performance in classifying CEOs' facial fatigue levels in each SWP. SWPL approach share all model parameters $P = P_1 \cup P_2 \cup \cdots \cup P_N$ to train a model locally and compute $O_{t+s} = f_i(t + s, D_i)$ for each SWP and its accuracy is defined as A_{SWPL}, where s is the prediction frame at t. For the traditional method, if there exists data insulation, the accuracy of training model locally and conducting classification individually can be represented by A_{SWP}. This study's hypothesis is to see if the accuracy of SWPL outperforms the method on individual SWP, which can be denoted in Equation (1)

$$A_{SWPL} - A_{SWP} > 0 \tag{1}$$

3.2 Overview of SWPL framework

Inspired by the swarm learning in Warnat-Herresthal et al. (2021), this section introduces smart work package learning (SWPL) to share model parameters via smart work package chain (SWPC) and train deep learning models on private facial image data locally at SWPL nodes. SWPC is achieved via consortium blockchain, and each SWP should be defined and authorized before parameters sharing. The framework of SWPL is presented in Fig.1(a), which includes SWPC node, SWPL node, SWP control interface (SWPCI) node, license server, and server node. SWPC nodes form the Ethereum-based consortium blockchain network to broadcast and keep global state information from model updates while not holding the whole model. SWPL nodes run the deep learning models to train and update models in FFM. SWPCI is the command interface tool to view, control, and manage the processes of parameter sharing, merging, and updating via application programming interface (API) ports. SWPC nodes can obtain license tokens from the license server for running the SWPC network and SWPL nodes. Sever nodes use the SPIRE (SPIFFE Runtime Environment, SPIFFE refers to Secure Production Identity Framework for Everyone) framework to provide SVID (SPIFFE Verifiable Identity Document) and trust bundles to SWPC nodes and SWPL nodes. The process of SWPL is shown in Fig.1 (b). A new SWP joins through smart contracts in blockchain, receives the model, and trains the model locally until defined synchronization conditions are satisfied. Before initiating a new round of training, model parameters are shared through an API in SWPCI and aggregated to build an updated model. For each SWP (see Fig.1(c)), SWPL is composed of layers of application, middleware, and infrastructure. The CEO-FFM task is one of the application scenarios. The middleware layer contains blockchain and deep learning models. The infrastructure layer includes a containerized API for executing SWPL in hardware environments.

3.3 Deep neural networks in SWPL

This study leverages and makes improvements of hybrid deep neural networks for FFM in the authors' previous work (Li et al., 2021). As shown in Fig.2, the private facial data (e.g., image or video) from each SWP is considered as the input data, which would be preprocessed locally by a face detector and a spatial feature extractor. The MultiTask Cascaded Convolutional Neural Network (MTCNN) can achieve real-time face detection with high accuracy and robustness (Zhang et al., 2016). Thus the face detector in this study used MTCNN to retrieve bounding boxes and facial landmarks with three-stage models: P-Net, R-Net, and O-Net. As MobileNets are compact, low-latency, low-power models and can be parameterized to facilitate real-time fatigue feature extraction, the latest MobileNet V3 Large is applied as the spatial feature extractor to proceed common features, e.g., eyes, mouth, head, on the face through start stage: one convolutional layer (Conv 1), middle stage: a mobile block with two expansion layers and several depthwise separable convolution layers (Conv 2-18), later stage: one average-pooling layer (Avg pooling), and two convolutional layers (Conv 19 and 20) (Howard et al., 2019). The MTCNN and MobileNet V3 Large are used to preprocess data locally, which indicates, in backpropagation, their parameters will not be updated.

FFM involves the periodicity of temporal data, especially for repeating fatigue patterns. Bidirectional LSTM (Bi-LSTM) can play a critical role to help extract high-level dynamic temporal features by learning both forward and backward long-term dependencies (Greff et al. 2016). Thus, this study will update and share parameters of Bi-LSTM during the training process. The sigmoid activation function is used to normalize the classification output to a probability distribution.

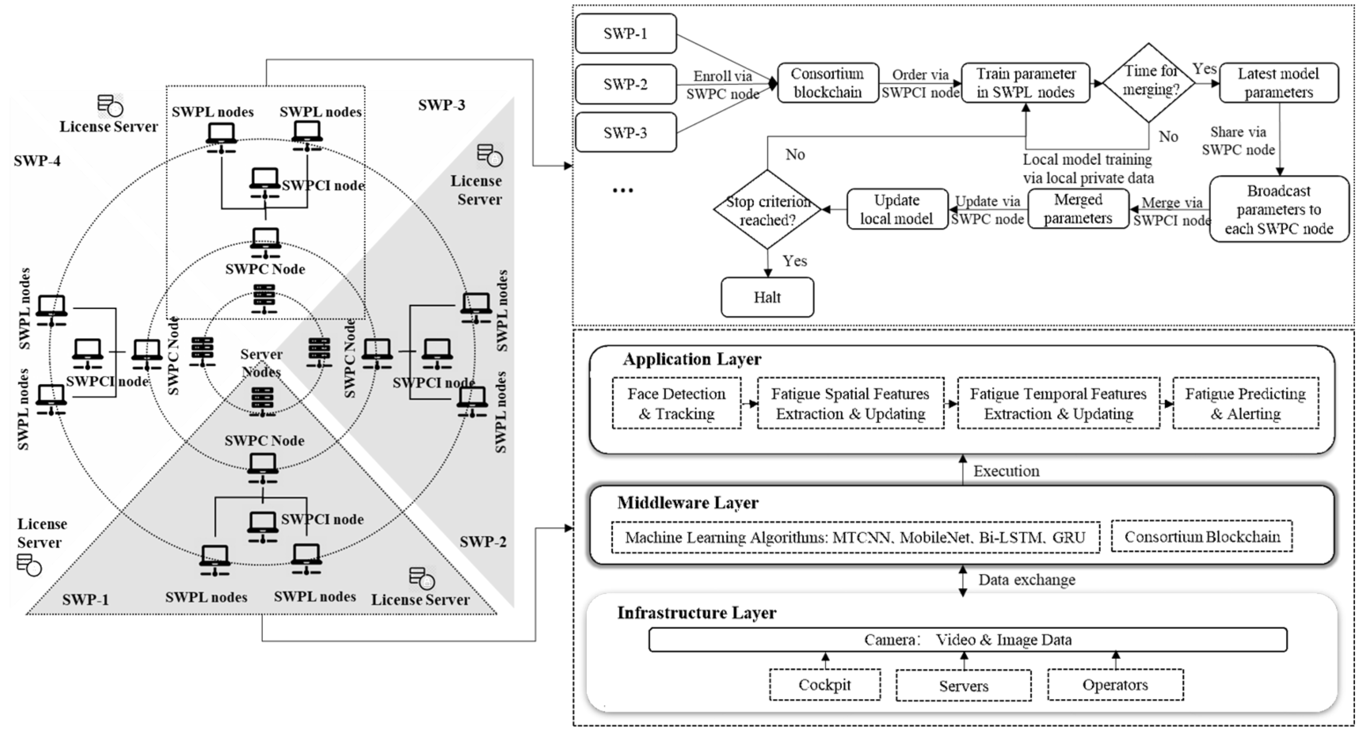


FIGURE 1. SWPL framework for decentralized and privacy-preserving facial fatigue monitoring of CEOs

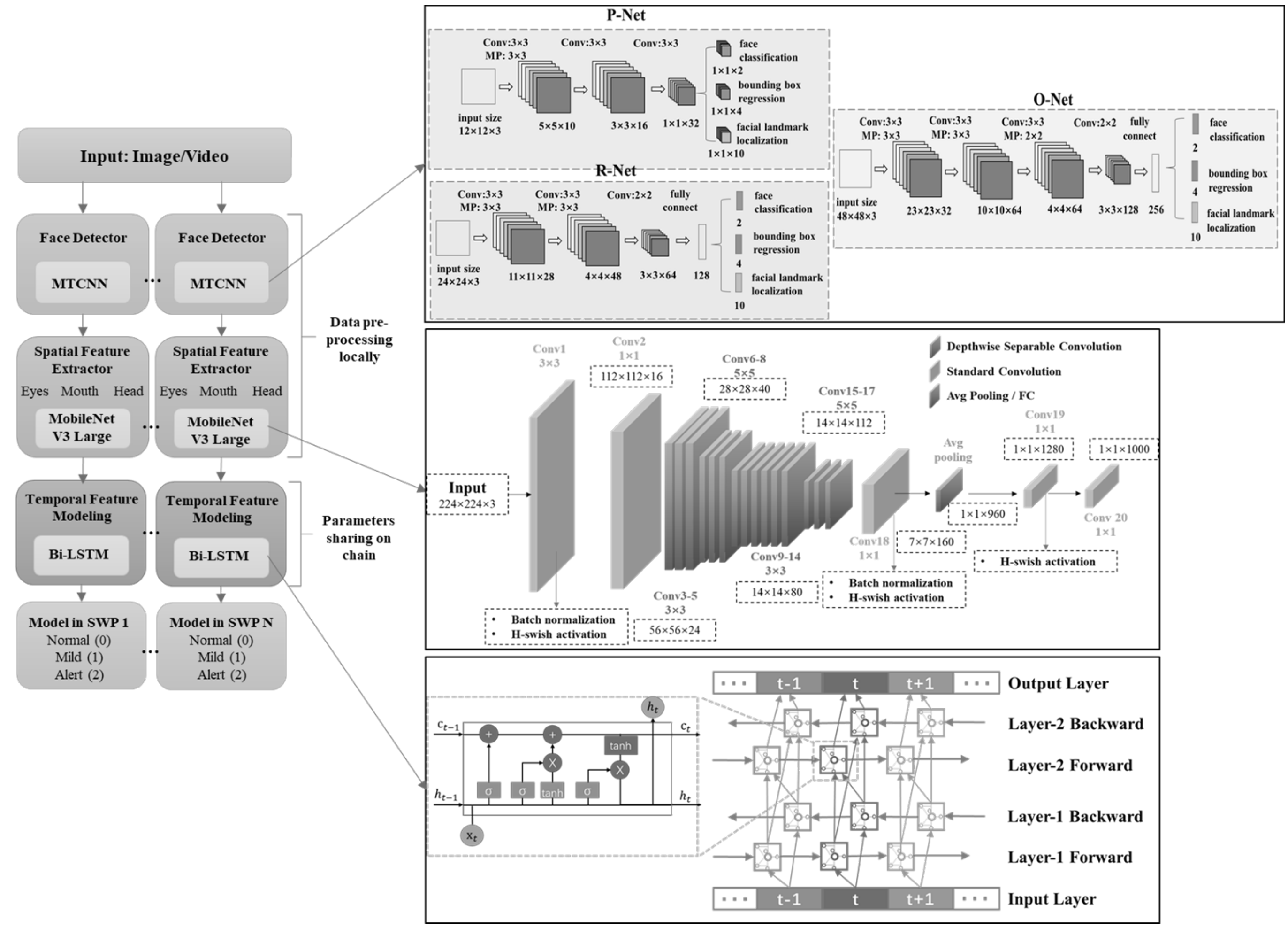


FIGURE 2. Deep neural networks for facial fatigue monitoring

3.4 Consortium Blockchain for SWPL

As shown in Fig.3, a permissioned blockchain, namely SWPC, is configured to realize the decentralized SWPL. To facilitate SWPL functionality, SWPC nodes are first registered on the blockchain network using the API. Then, SWPC nodes can interact with other SWPC nodes using blockchain for parameter sharing and can control the local model training process through related SWPL nodes. Thirdly, instead of depending on a confirmed central aggregator in federated learning, a dynamic selection mechanism of shifting aggregators is implemented at each parameter merging round through smart contracts to make SWPL decentralized. Moreover, a package of state-of-the-art security technologies, e.g., network encryption, trusted execution environment, secure containment, is applied to preserve facial images from direct unauthorized access. Since the SWPL network is typically configured starting from its lower boundary at its early stage, two SWPC network nodes, four SWPL nodes, and two SPIRE server nodes are established for this study. With the implementation of this setting in consortium blockchain, SWPL can be performed including the following stages:

- *Model training on SWPL nodes*—Firstly, each SWPL node uses its local datasets to train the Bi-LSTM model to get the latest local updates and provide these parameters to the nearest SWPC node.
- *Parameters merging on SWPC*—Secondly, when a leader is dynamically selected (the first node to finish its training is set as the leader in each epoch) among SWPC nodes, the leader will aggregate their parameters and generate a new data block in which all model parameters will be stored.
- *Parameters synchronizing between SWPC nodes*—Finally, the new block with merged parameters is stored on the SWPC, responsible for sharing block data to each SWPC node. And each SWPL nodes compute their model using the latest merged parameters until meeting the determined performance metrics.

As shown in Fig.4, a consensus process is designed for the consortium blockchain of SWPL.

- *Initialization*—It begins with the enrollment of a set of construction equipment operators' SWPs to formulate the operational and legal requirements of the decentralized system, which includes consensus on model training performance, parameter sharing agreements and synchronization frequency, incentive mechanism, and deep learning model to be used.
- *Configuration*—All the SWPs install the SWPL function on their SWPC nodes to form the SWPC network, which overlays the underlying IP network (See Fig.3) connection between SWPC nodes.
- *Training*—(1) SWPL training starts with each SWPL node enrollment via smart contract. Each SWPL node can record its information (e.g., uniform resource identifier (URI)) in the ledger to facilitate its trained parameters extracted by other nodes in SWPC. (2) Then, SWPL nodes iteratively train the local replica of the model over numerous epochs. For each epoch, each SWPL node trains a local model through various data batches for the defined iterations. Upon reaching the iteration number, it notifies the SWPC nodes that it is ready for parameter sharing. (3) When the number of SWPL nodes ready for parameter sharing comes to a minimum threshold determined in initialization, parameter sharing begins. After each epoch, the elected SWPC node leader retrieves the trained parameters via URI and aggregates them. (4) All aggregated parameters are merged through predefined methods, e.g., mean, weighted mean, and median, and the leader notifies other SWPC nodes when the merging process is completed. Each SWPC node can then download the latest merged parameters and update the local models of its SWPL nodes. (5) All SWPL nodes evaluate the model performance, e.g., accuracy and loss, using the smart contract. After completing the validation process in each SWPL node, the leader of SWPC nodes will aggregate all local validation metrics and get the global performance.
- *Testing*—Testing new local datasets can be conducted when the training process reaches a reasonable performance. Otherwise, the SWPL nodes start the next training batch with the merged parameters.

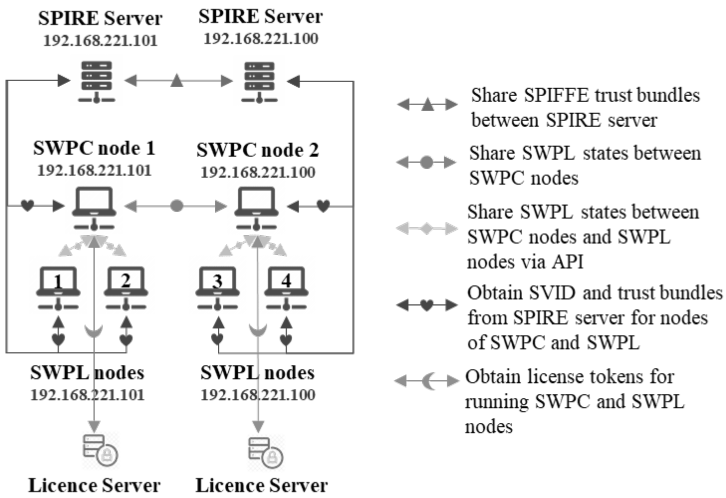


FIGURE 3. Consortium blockchain architecture for two-node SWPC

4 EXPERIMENT

Experiments are conducted in this section to assess the SWPL's performance in accuracy and privacy for FFM, which is one of the most privacy-concerned operations for CEOs in COHS. The datasets, implementation details, and results analysis are presented below.

4.1 Facial Fatigue Monitoring Dataset

YawDD, as a popular public dataset for the vehicle operator (Abtahi et al., 2014), is used in this study's experiment and evaluation process. The justification for using this dataset are threefold: (1) The authors have tested a similar hybrid model (MTCNN, MobileNet, LSTM) on existing public datasets (e.g., NTHU-DDD, UTA-RLDD, YawDD), which the YawDD outperforms others in accuracy and loss (Liu et al., 2021);

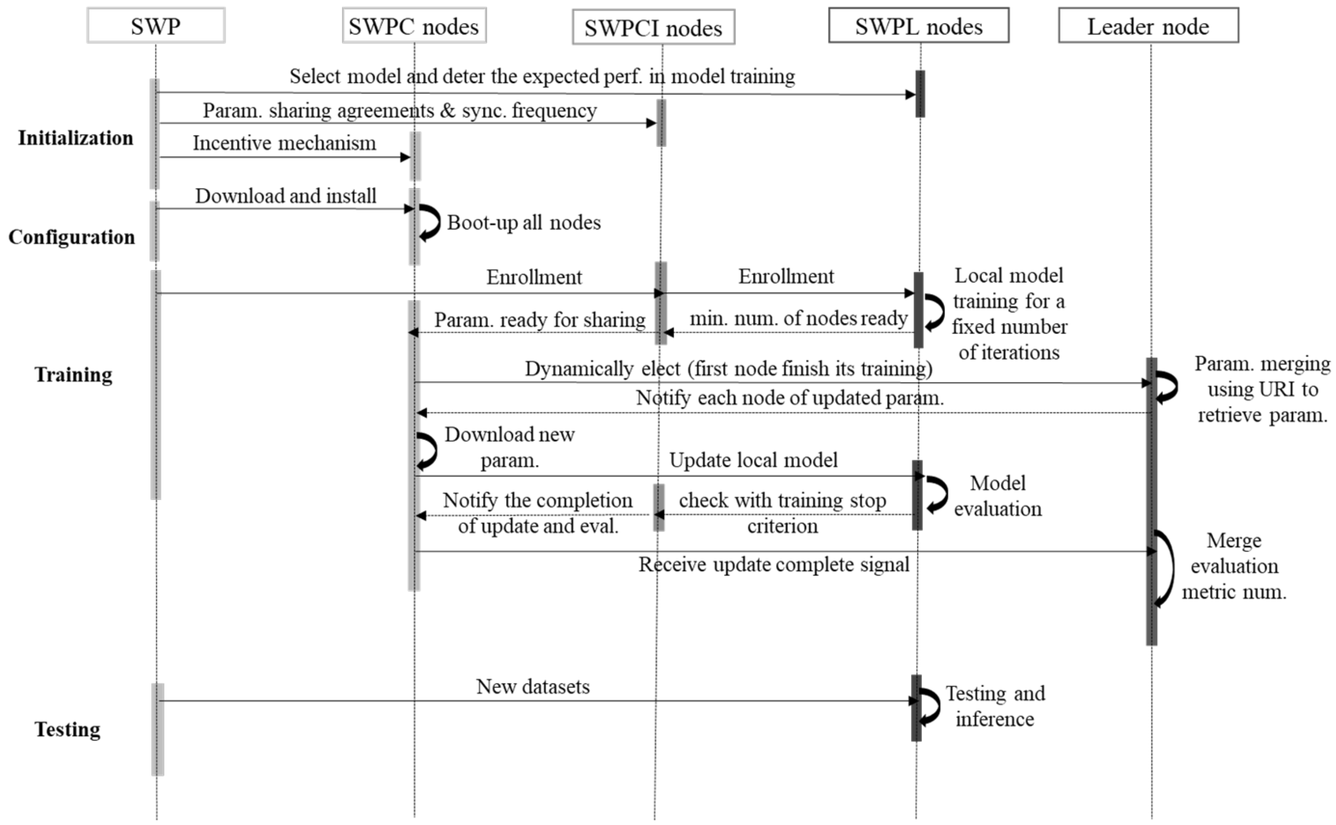


FIGURE 4. The consensus process for the consortium blockchain of SWPL

(2) monitoring of CEOs' facial fatigue statuses are nearly the same as the scenarios for vehicle operators, where operators sit-in cockpit for operating vehicles or equipment; (3) it will be easier to compare the performance of SWPL with previous centralized or federated learning methods as training and testing on the same dataset. YawDD has two datasets of videos (640×480 pixels resolution and 24-bit true color (RGB) without audio) that are recorded by in-cockpit cameras and captured in a variety of lighting conditions within natural environments. Each dataset includes various facial features, e.g., talking, laughing, singing, normal stillness, yawning, nodding, slow blink rate of eyes, different gender, with and without glasses/sunglasses, and various ethnic groups. The first dataset includes 322 videos for 90 participants (47 male and 43 female), which all are captured through a video camera installed in the front mirror of the cabin. Each participant is documented with three or four videos, each of which covers normal, talking/singing, and yawning facial expressions. The second dataset includes 29 videos (one for each participant, namely, 16 male and 13 female), which are recorded via a video camera positioned on the dashboard of the cabin. YawDD datasets contain five scenarios, including Bareface, Glasses, Sunglasses, Mustache, and Breard, all of which were captured at a window size of 30 fps (frames per second). In datasets, each participant presents different combinations of fatigue expressions (yawning, nodding, slow blink rate of eyes) and normal signs (talking, singing, laughing, normal stillness). All details of YawDD have been summarized in Table 1. A two-node SWPC scenario with four SWPL nodes is established. Each SWPL node is assigned with uneven videos to simulate the real-world situation, where each SWP may include different CEOs in single construction equipment or a construction site that creates such COHS data that is subject to local privacy regulations

TABLE 1. YawDD Details

Participants	Behavior	Illumination	Camera Type	Scenarios	Camera Position
119	•Normal Stillness •Talking or Singing •Yawning •Sleepy Blinking •Nodding	Day (from early morning till sunset)	RGB	•Glasses •Sunglasses •Mustache •Beard •Bare Face	Front mirror & Dashboard

4.2 SWPL Implementation Details

4.2.1 Experiment Environment Settings

The experiment environment includes 2 virtual machines within a Linux Ubuntu 20.04 system to run the training and evaluation process. The computer configurations and development package specifications for this experiment are listed in the following:

- Hardware: 20 cores, 64GB of RAM, 256 GB SSD, and 2TB HDD
- Network: Up to 3 open ports in each node
- Architecture: AMD64
- Container hosting platform: Docker 18.01.0
- CPU: Intel (R) Xeon (R) E5-2640 v4@ 2.40 GHz (20 CPUs)
- GPU: NVIDIA GeForce GTX 1080

- Deep learning framework: Python 3.73, Keras 2.3.1, Tensorflow 1.15.0
- Image operation cross-platform: OpenCV-Python

4.2.2 Facial Fatigue Data Pre-processing

Firstly, the MTCNN is applied locally in each SWPL node to recognize the faces and extract the frame landmarks. After that, the MobileNet v3 is used to transform the face frames to feature embeddings (512). The features for facial fatigue status can be presented by the expressions of the eyes, head, and mouth. The temporal fatigue features are easy to be identified in each video as long-term dependencies, indicating that accurately predicting each frame's state should make good use of frames from preceding or succeeding seconds. However, within a few seconds, these facial expressions (e.g., closing eyelids, yawning, and nodding) on a sequence of frames would still be detected as fatigue symptoms if they had just remained expressions to alert following fatigue states. To accurately distinguish the temporal states between normal and fatigue, the YawDD is relabeled accurately with two fatigue levels: (1) Normal (label: 0): the participant shows no indicators of facial drowsiness. (2) Fatigue (label: 1): it indicates that the participant exhibits facial sleepiness. As indicated in Table 2, the behaviors that are least connected to facial fatigue include stillness, looking away, normal blinking and chatting, talking, laughing, and singing. Thus, the frames with such behaviors can be labeled to 0. As for obvious behaviors of facial fatigue, such as closing eyes, yawning, and nodding, they can be labeled as 1.

Table 3 and Figure 4 present the statistical details for samples and datasets on YawDD (image array n= 78,081), which is divided into well-separated training datasets (75%) and a test dataset (25%) that are applied for validating models developed by SWPL and at individual nodes. All the participants with different scenarios are assigned to each SWPL node (node 1 (23): female with glasses, node 2 (17): female with non-glasses, node 3 (26): male with glasses, node 4 (25): male with non-glasses, test node (28%): all scenarios). For the training dataset, it is randomly and unevenly assigned datasets for the SWPL nodes (node 1: 20%, node 2: 14%, node 3:18%, node 4: 23%). Within training and testing data, samples with varying distributions were maintained at each of the SWPL nodes, for simulating real-world scenarios. The ratio between positive (fatigue) and negative (non-fatigued) samples are also presented in Fig.4.

TABLE 2. Label details on YawDD

Behavior	State	Fatigue Level
Talking, laughing, singing Looking aside Normal blinking Stillness	Normal	0
Closing eyes Yawning Nodding	Fatigue	1

TABLE 3. Statistical information on samples for each node

Scenario	Participant	Status	Instance	Type	Shape	Source
Original	90	2	322	Videos	(:, 640, 480, 3)	Mirror
	29	2	29	Videos	(:, 640, 480, 3)	Dashboard
SWPC node1	23	2	15675	Array	(:, 30, 512)	SWPL node 1
	17	2	10864	Array	(:, 30, 512)	SWPL node 2
SWPC node 2	26	2	14352	Array	(:, 30, 512)	SWPL node 3
	25	2	17603	Array	(:, 30, 512)	SWPL node 4
SWPC Test node	28	2	19587	Array	(:, 30, 512)	SWPL Test node

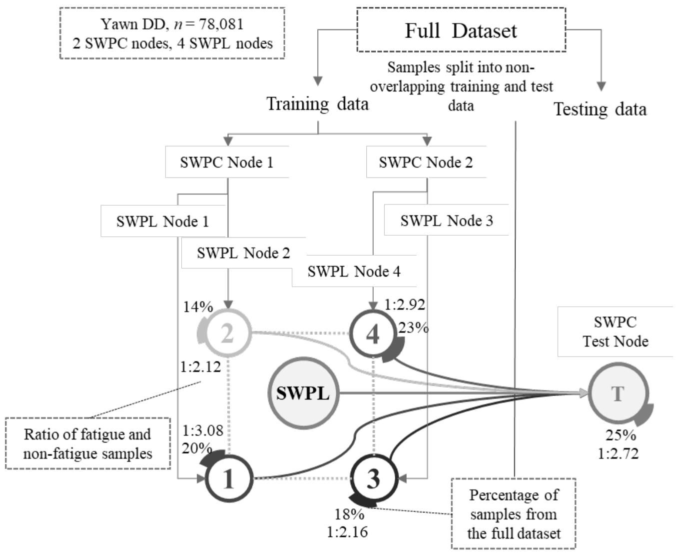


FIGURE 5. Statistical information on Datasets

4.2.3 Decentralized Training

Neural network algorithm. The hybrid deep neural networks that developed in the authors' previous works are leveraged (Li et al., 2019a, 2021; Liu et al., 2021) and there is an improvement in the spatial feature extractor of the hybrid model by using MobileNet V3 instead of Mobile Net or VGG-16. The layers for the face detector (MTCNN) and temporal feature extractor (Bi-LSTM or gated recurrent unit (GRU)) have also been improved and are shown in Table 4. MTCNN and MobileNet V3 are processed locally in each SWPL node, and only the parameters of Bi-LSTM/GRU are trained and are shared through the blockchain network. The trained LSTM-2 model consists of one input layer, 3 hidden layers, and one output layer. The input layer is processed by two hidden LSTM layers with 512 cells, a rectified linear unit activation function, and a dropout rate of 50%. The output layer is densely connected and consists of one node and a sigmoid activation function. The model is configured for training with RMSprop optimization and to compute the binary cross-entropy loss between true labels and predicted labels. The model is used for training both the individual nodes and SWPL nodes. The model is trained over 200 epochs with a batch size of 32 and a learning rate of 0.001.TABLE 4. The detailed layers of the hybrid model

TABLE 4. The details layers of the hybrid model for decentralized training

Trainability	Model Name	Layers
Non-trainable	MTCNN (Face Detector)	P-Net(12,12,3) R-Net(24,24,3) O-Net(48,48,3) Input_1(:,224,224,3) Conv_1(:,112,112,32) …
Non-trainable	MobileNet V3 (Spatial Feature Extractor)	Conv_13(:,7,7,1024) Global_average_pooling2d_1(:,1024) Reshape_1(:,1,1,1024) Dropout(:, 1, 1, 1024) Conv_preds(:, 1, 1, 1000) Softmax(:, 1, 1, 1000) Dense_1(:, 1, 1, 512) Flatten_1(:, 512)
Trainable	Bi-LSTM/GRU (Temporal Feature Extractor)	LSTM/GRU_1（:, 30, 512） LSTM/GRU_2（:, 256） Dense_1(:,128) Dropout_1(:,128) Dense_2(:,1)

Parameter tuning. The model hyperparameters are fine-tuned to get better performance (e.g., higher sensitivity). For example, to improve accuracy and loss, the dropout rate is reduced to 10% and increased the number of epochs to 200. The optimal window size is 30. The parameter merge frequency can be changed through API, which dynamically impacts the efficiency of model convergence to reduce training time.

Parameter merging. Leader node coordinated parameter merging at each synchronization interval (3000 times training). The parameters are merged using a weighted average method, and it is denoted in Equation (2):

TABLE 5. Hyper-parameter tuning results

Hyper-parameter	Explanation/Usage	Scope	Optimal values
Learning rate	Determines the step size at each iteration while moving toward a minimum of a loss function	{5-3, 8-3,10-3,5-2,8-2,10-2} (Trenta et al., 2019; Shih et al., 2016; Guo et al., 2021)	0.001
Batch size	Determines the number of samples utilized in one iteration	{2^k k=1,2…12} (Dua et al., 2021; Huynh et al., 2016)	32
Epoch	Determines the number of times that the model processes all training data	{50, 100, 200…1000} (Lyu et al., 2018; Yu et al., 2018)	200
Dropout	It is a regularization technique that randomly selected neurons are ignored during training	{10%, 20%, 30%…60%} (Li et al., 2021; Warnat-Herresthal et al., 2021)	10% &50%
Activation function	Trigger non-linearity transformation in the model structure	{sigmoid, Relu, elu} (Liu, 2021; Li et al., 2019)	Sigmoid
Optimizer	Adjusts model parameters to minimize the loss	{Adam, RMSprop, Nadam, sgd, adagrad} (Michielli et al., 2019)	RMSprop

$$P_M = \frac{\sum_{k=1}^{n}(W_k \times P_k)}{n \times \sum_{k=1}^{n} W_k} \quad (2)$$

Where P_M stands for merged parameters, P_k presents the kth SWPL node's parameters, W_k denotes the kth SWPL node's weight, and n indicates the number of nodes joining the merging.

4.2.4 Evaluation Metrics

The evaluation in this study is aim to compare SWPL's performance with individual nodes. As the hybrid deep neural networks for SWPL is a binary classification model, the performance of SWPL can be evaluated quantitatively through metrics of accuracy, F1 score, AUC, sensitivity, specificity, and loss, which are calculated after the test. Bootstrapping is applied to estimate all performance metrics with 95% confidence intervals. The one-sided Wilcoxon signed-rank test with continuity correction is used to examine the differences in performance metrics. Each performance metric can be estimated in Equation (3) - (7):

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (3)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (4)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \quad (5)$$

$$\text{F1 score} = \frac{2TP}{FP+FN+2TP} \quad (6)$$

$$\text{loss} = -\sum_{1}^{n} \hat{y}_i \log y_i + (1-\hat{y}_i)\log\left((1-\hat{y}_i)\right) \quad (7)$$

where TP denotes true positive, FP represents false positive, TN indicates true negative and FN is false negative. The predicted fatigue level can be denoted by y_i and the ground truth value of the label is represented by $\hat{y}_i$. The number of samples (video frames) for facial fatigue prediction can be defined as n.

4.3 Experiment results analysis

4.3.1 Performance Analysis

This study firstly compares the performance of SWPL with two comparable temporal feature extractors (LSTM and GRU) as they both use getting mechanisms to learn long-term dependencies and outperform traditional machine learning models for temporal features prediction in FFM (Li et al., 2021). Table 6 with the metric of accuracy shows the results of SWPL-LSTM and SWPL-GRU during 195-200 epochs with the different hidden layers that indicate similar accuracy. Thus, this study uses LSTM with two hidden layers for further analysis as it has more parameters (three gates) compared with GRU (two gates), which can demonstrate whether SWPL is efficient with more parameters.

Fig.6 demonstrates the performance comparison among SWPL, individual node (individual SWP), and central model (traditional centralized deep learning). Fig.6 (a) indicates SWPL is significantly higher than individual nodes in the test accuracy with significance labels (asterisk), which is estimated with the one-sided Wilcoxon signed-rank test. The more asterisks (*) present more significance with smaller p-values. The p-values for each compared group are: node1-vs-SWPL (0.005<0.05), node2-vs-SWPL (0.0081<0.05), node3-vs-SWPL (0.0129<0.05), and node4-vs-SWPL (0.0081<0.05). The F1 score is a measure of binary classification accuracy and its results in Fig.6 (b) also supports the findings that SWPL outperforms individual nodes significantly.

TABLE 6. Comparison of LSTM and GRU performance in SWPL

Model	Hidden Layer	Test Accuracy (95-100 epochs)					
		1	2	3	4	5	6
SWPL-LSTM	1, (256)	0.8899	0.8998	0.9003	0.9053	0.8971	0.8973
	2, (512, 256)	0.8958	0.9057	0.8964	0.8875	0.8905	0.8978
SWPL-GRU	1, (256)	0.8856	0.8838	0.8952	0.8852	0.8933	0.8885
	2, (512, 256)	0.8951	0.9025	0.897	0.8953	0.8924	0.8941

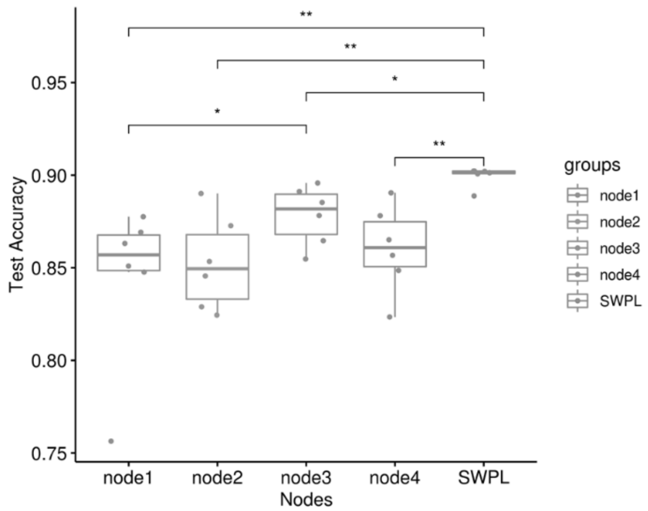


FIGURE 6 (a) Accuracy

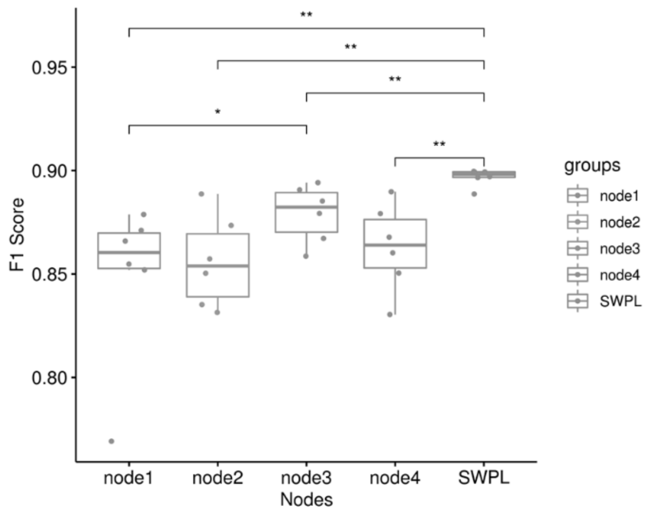
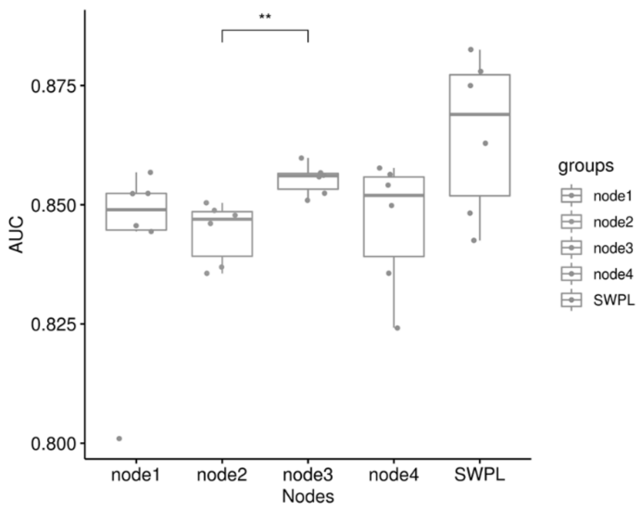


FIGURE 6 (b) F1 Score



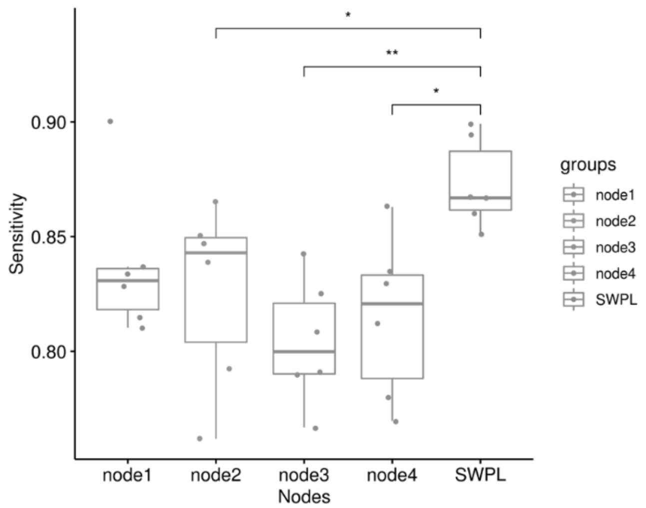
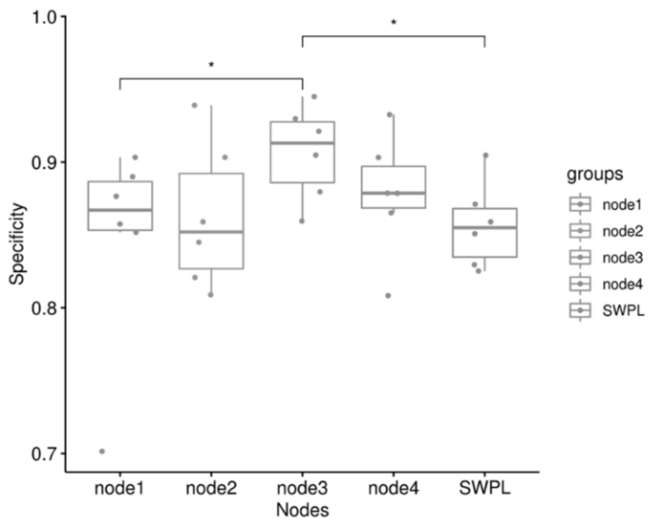


FIGURE 6 (c) AUC

FIGURE 6 (d) Sensitivity



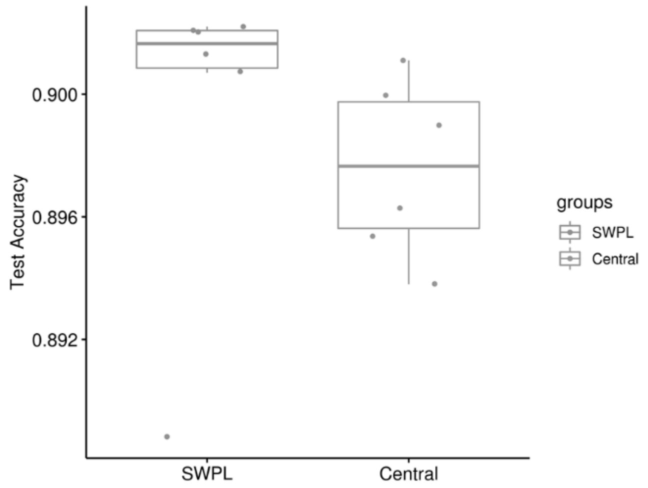


FIGURE 6 (e) Specificity

FIGURE 6 (f) SWPL vs Central Model

Fig.6 (c) uses AUC to express the magnitude or value of separability, which indicates how well the model can discriminate between classes. It shows SWPL has a higher AUC in median than other individual nodes, which means SWPL performs better at distinguishing between normal and fatigue. Fig. 6 (d) and (e) also present the sensitivity and specificity. The former shows that SWPL's ability to predict true positives of each available category is higher than individual nodes in the median value. The latter indicates SWPL's ability to predict the true negatives of each available category is slightly worse than nodes 1, 3, and 4 in the median value. This is because sensitivity and specificity are inversely proportional. As sensitivity rises, specificity falls, and vice versa. More positive values are received when the threshold is lowered, which increases sensitivity while decreasing specificity. Fig.6 (f) compares the test accuracy between SWPL and central model, which shows SWPL evenly slightly outperforms the central model. To show the details for the FFM process, Fig.7 presents a participant's FFM process to support the above results by a specific example. In Fig.7, the predicted results of SWPL (line with diamonds in Fig.7) for each frame keep more aligned with ground truth (line with nothing) than the results from an individual node (Node 1, line with triangles in Fig.7), and is comparable to the central model (line with circles in Fig.7). In summary, SWPL demonstrates better performances for FFM in a decentralized manner compared with performing this task in individual, local, and even central datasets.

Fig.8 and Fig.9 demonstrate the curves of loss and accuracy within 200 epochs during training and test for both SWPL and central model. The weights for two fatigue labels (normal 0, fatigue 1) are tuned at optimum as {0:1, 1:4}. The results show that the central model's training outperforms SWPL in both loss and accuracy, while the SWPL is slightly better in test performance. It may owe to the tradeoff between loss and privacy. As the training of the central model has already set parameters for tunings, such as dropout, batch size, and learning rate, it does not require parameter sharing and merging. However, SWPL may consider more hyperparameters, including synchronization interval, the weighted average for parameters, blockchain rules, and more. Thus, it may sacrifice the loss during the training process to preserve the privacy of these hyperparameters.

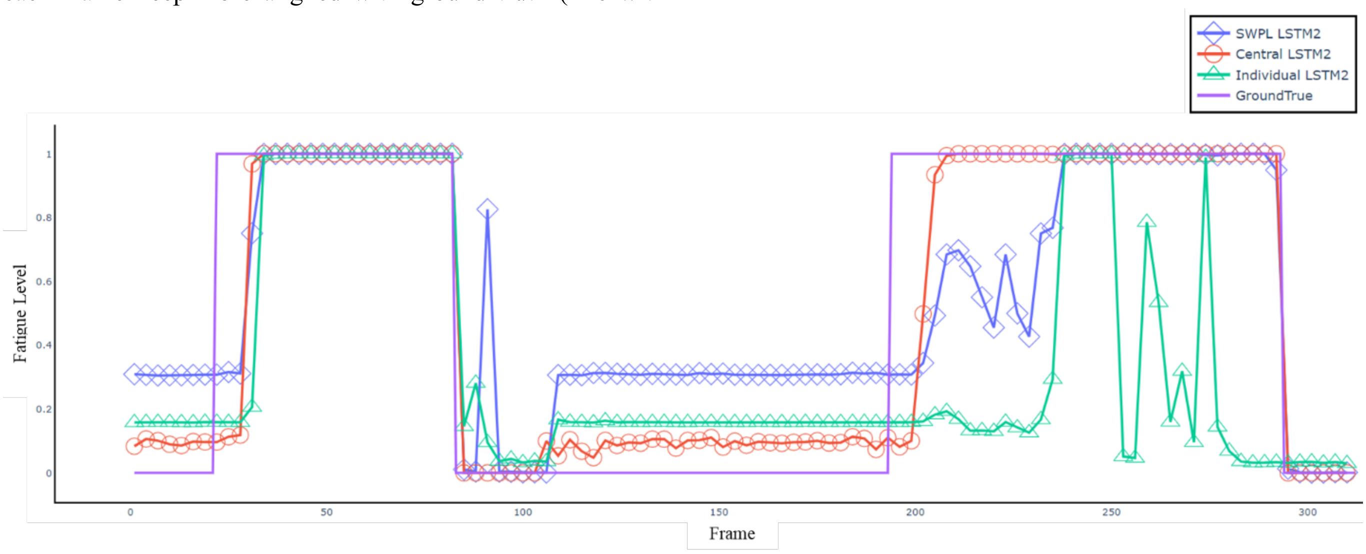


FIGURE 7. Fatigue prediction process

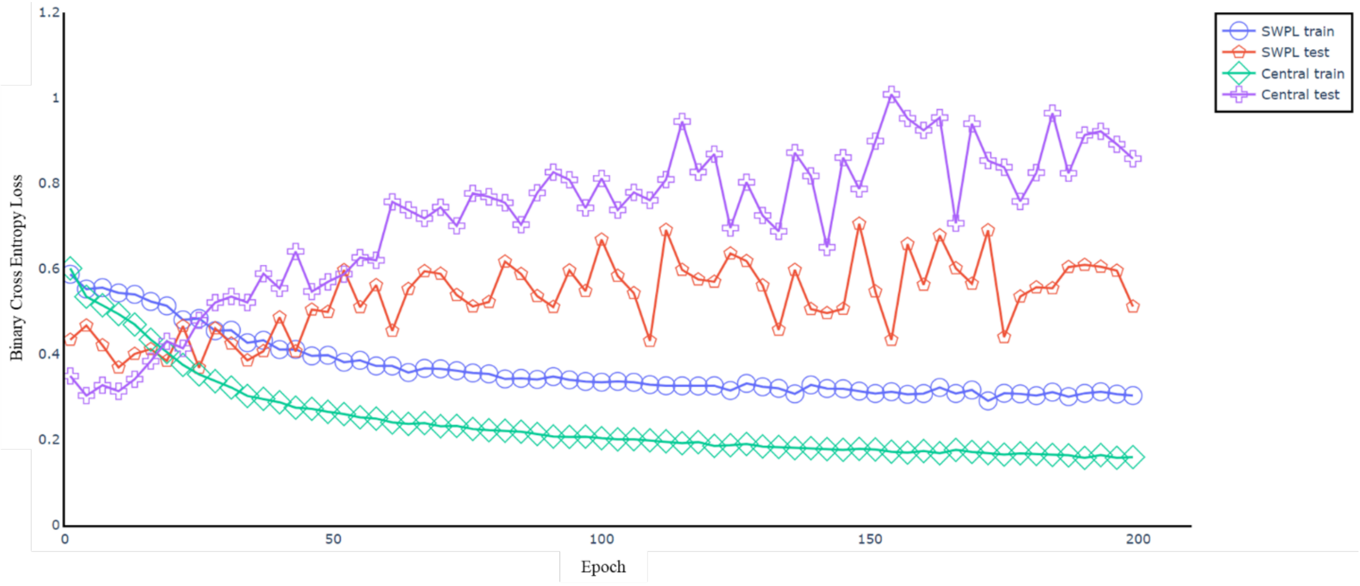


FIGURE 8. Binary Cross-Entropy Loss for SWPL and central model

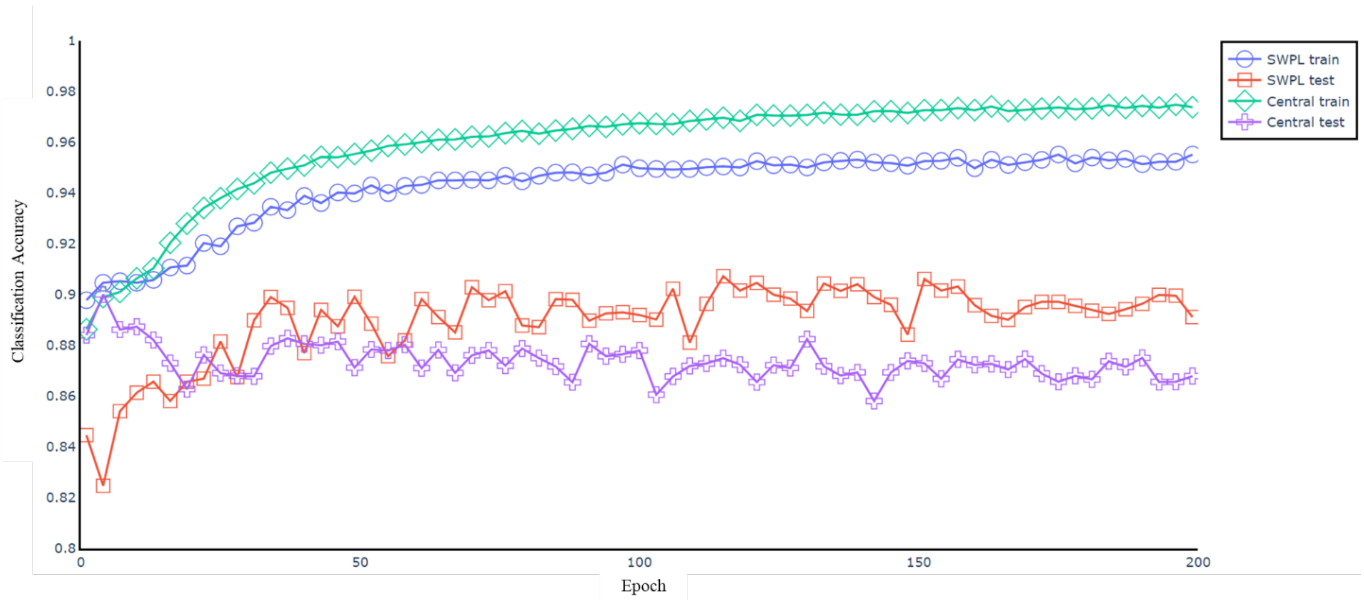


FIGURE 9. Classification accuracy for SWPL and central model

4.3.2 Privacy Analysis

To respond to the privacy issue raised in the problem statement section, the privacy-preserving performance in SWPL can be explained from the following evidence.

- **Data parameters:** this study uses the open-source Ethereum as the permissioned blockchain network. All SWPC nodes register in this network and interact with other SWPC nodes to keep the global state information of the trainable Bi-LSTM model and to track progress. SWPC nodes use the information of parameter merging state and progress to control the training process of SWPL nodes. Thus, this design ensures that the datasets are maintained in each SWPL node locally and all shared data parameters are blockchained. For the security of servers for storing the shared parameters, this study introduces the SPIRE server nodes and the SPIRE Agent Workload Attestor plugin is used to attest the identifies of SWPC nodes and SWPL nodes for ensuring secure interactions between servers and the blockchain network.

- **Model performance:** there is an inherent trade-off between model accuracy and privacy. To improve the model accuracy, increasing tuning hyperparameters is required, such as datasets weights, class weight, learning rate, regularization, batch size, and dropout rate, which results in privacy-preserving burden during these parameters sharing process. If the required level of privacy-preserving is increased, reducing tuning too many parameters is needed thus sacrificing the model performance. However, the results show that SWPL slightly outperforms the central model with the same model parameters, which indicates SWPL achieving good performance in FFM without compromising privacy.

5 DISCUSSION

With expanding endeavors to enhance data privacy and security in the construction industry, and to prevent data traffic in centralized computing and data insulation in distributed computing, a decentralized model will be an ideal choice for processing, learning, analyzing, and predicting distributed construction data. Particularly in COHS, numerous studies have reported that deep learning is successfully applied in construction sites, such as construction equipment detection (Arabi et al. 2020), detection of wearing safety helmets (Shen et al., 2021), and struck-by accidents monitoring (Yan et al., 2021). However, the further advances are blocked by the insufficient datasets and emerging privacy regulations as the COHS data is generated from geographically dispersed construction resources and is more private when involving workers' data. This makes distributed AI system is more appealing to COHS than a centralized one. SWPL is such a decentralized learning model for replacing the centralized or federated data sharing cross construction workers and preserving the private facial information of CEOs for FFM. In summary, there are three aspects to proposed SWPL's novelties compared with existing works.

- Firstly, SWPL is a novel framework that combines permissioned blockchain technology and distributed deep learning for FFM, which is critical progress to enhance privacy and incentivize data sharing in the field of COHS. Li et al. (2021) developed FedSWP using federated transfer learning to avoid data leakage and facilitate construction workers' cooperation in data provision. However, FedSWP still exists issues in a single point of failure as it requires gathering the model parameters to a centralized model. This may expose the model parameters to the risks. In the SWPL process, a leader node will be dynamically elected to coordinate an iteration that does not require a fixed central parameter aggregator, which enhances resilience and fault tolerance.

- Secondly, SWPL provides a more accurate and private deep learning strategy to monitor and predict CEOs' facial fatigue status during their high physical strength operation, as (1) the performance of SWPL presents strong evidence that SWPL outperforms individual nodes and (2) permissioned blockchain governs all rules of interaction between the nodes to ensure SWPL's privacy. In SWPL, it gets such performance without fine-tuning weights and applying these weights to SWPL nodes with different samples or datasets. This indicates that access to more data is also an option to improve performance compared with optimizing a centralized deep learning model.

- Thirdly, SWPL shows a high capacity for performing complex deep learning tasks with more features and data parameters. The previous centralized deep learning strategy in Liu et al. (2021) showed that it trains on one operator's image data and tests on another operator which leads to poor performance. It mainly results from the distribution differences of complex spatial-temporal features between various datasets in FFM. In addition, FedSWP, in the authors' previous work, bears high communication costs as each edge SWP needs to share and communicate with the central model, which may lead to data parameters traffic.

Despite the above innovations, our study still has a few limitations.

- Firstly, this study assumes the permissioned blockchain that provides robust mechanisms against malicious nodes. In-depth privacy and security-related function developments, such as advanced encryption algorithms (Sun et al., 2021), differential privacy algorithms (Jia et al., 2021), and security analysis, have not been investigated in this study.

- Secondly, as limited by the computer nodes for the experiment, SWPL is only trained and tested on two SWPC nodes (four SWPL nodes). In the real-life SWP scenario, each CEO should have an SWP which means hundreds of SWPL nodes will join the blockchain network. Thus, the scalability and parameter merging efficiency among massive nodes have not been measured in this study.

- Thirdly, this study is still lacking the real datasets with multimodality for CEO-FFK, and the SWPL is only tested on the image data in this study. Other bio-signals, such as electrooculogram (EOG), electromyogram(EMG), electroencephalogram (EEG), and electrocardiogram (ECG), are very useful and important in FFM, but they have not been combined as multimodality for training and testing in SWPL.

6 CONCLUSION

Smart work packaging (SWP), in previous studies, provides strong evidence to be an inherently distributed system to equip each construction equipment operator (CEO) with capacities in managing (e.g., modeling, optimizing, monitoring) isolated construction occupational health and safety (COHS) data and provide insights (e.g., analytical results, predicated warnings) ready for each CEO to facilitate their safe operations. However, current centralized or federated deep learning methods used in SWP for monitoring workers' private information (e.g., facial fatigue status) still need to aggregate their private data to a central server or share trained model parameters to a central server. It may expose risks to private data leakage or result in a single point of failure with the central server. These risks could prevent the willingness of data provision from more distributed CEOs or construction sites over the world to further improve the efficiency in monitoring fatigue or other COHS issues in the construction.

This study thus presents the smart work package learning (SWPL) as a new paradigm for CEO-FFM built on distributed deep learning and permissioned blockchain. SWPL is designed with a set of nodes, including smart work package chain (SWPC) nodes for model parameter sharing and SWPL nodes for training deep learning models locally. For the distributed deep learning model, this study customizes the MTCNN, MobileNet V3, and Bi-LSTM to form the hybrid deep neural networks for performing FFM tasks. For the blockchain network, this study registers the SWPC nodes on SWPC using the API, where they can interact with each other using blockchain for parameter sharing and with other SWPL nodes for controlling the training process. For the blockchain consensus, a dynamic selection mechanism is adopted to shift aggregators for each parameter-merge round through smart contracts. The final experiment is conducted in two SWPC nodes with four SWPL nodes and results demonstrate that the accuracy performance of SWPL is quite better than the individual nodes, and even slightly outperforms the central model. Other performance metrics, e.g., F1 score, sensitivity, AUC, and privacy analysis also indicate SWPL is robust and outperforms individual nodes. However, future studies are still needed to further strengthen SWPL in the following aspects:

- In the direction of privacy and security, advanced encryption and differential privacy algorithms should be developed and embedded into SWPL to further enhance the privacy-preserving and security of permissioned blockchain networks.

- In the direction of scalability and resilience, more SWPC and SWPL nodes should be involved to further test its scalability and more varieties of samples for each node, such as the provision of different combinations in gender, glasses/non-glasses, camera positions, ethnic groups, and illumination conditions, should be designed for test the resilience.

- In the direction of data availability and deep learning models, multimode data (e.g., EEG, ECG, EOG, audio data) should be further considered to enlarge datasets for CEO-FFM and the latest advances in deep learning model (e.g., transformer) can be further applied to see better models or access to more enlarged datasets which is more sensitive for performance improvement.

ACKNOWLEDGEMENT

The authors would like to appreciate the financial support from The Hong Kong Polytechnic University Start-up Fund (No. P0039232) and the Fellowship of China Post-doctoral Science Foundation (No. 2021M692169).

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