FEEL: FEderated LEarning Framework for ELderly Healthcare Using Edge-IoMT

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***Abstract*— Recent advancements in artificial intelligence (AI) and IoT technology have revolutionized the healthcare industry by providing effective remote healthcare. Furthermore, with the aging of the world's population, remote health monitoring and recommendations are becoming imperative to provide cost-effective healthcare solutions for improving the quality of life of our senior citizens. The explosive growth of wearable sensors (IoT sensors) and health bands has facilitated the interconnection among patients and caregivers to enable assisted living by leveraging AI techniques. This work proposes an end-to-end connected smart home healthcare system (FEEL) for elderly people. Our proposed framework addresses the main challenges of the Internet of Medical Things (IoMT) system namely, the scarcity of labeled data and user's diverse needs. The major contributions of the work are: 1) few-shot learning-enabled novel federated learning (FL) framework for health data and context information analysis and recommendation; 2) user and context-based knowledge graph (UKG) to represent and model health parameters and environmental impacts on recommendations; 3) deep learning architecture for activity monitoring and location estimation of the users; and 4) edge-fog-IoMT collaborative framework to collect, store, and share medical recommendations while protecting the privacy of the users. FEEL is specifically beneficial for elderly homes where several aged people stay together and require constant care. We aim to develop a novel AI module where along with the health parameters, the social context of the home can be augmented to provide an accurate and improved healthcare service. FEEL has been evaluated for three tasks, namely: 1) activity monitoring and location estimation; 2) fall detection; and 3) medical recommendations for unusual health conditions. A customized wearable device has been used to collect, store, and send health-related parameters. The experimental evaluation demonstrates promising accuracy (F1 score 0.86–0.94 range) for the tasks and outperforms the baselines by a significant margin (≈10%–16%).**

***Index Terms*— Edge computing, federated learning (FL), few-shot learning, healthcare, Internet of Medical Things (IoMT).**

I. Introduction

THE ubiquitous use of the IoT sensors and advancements of networking and communication technology [1] has profoundly transformed the healthcare experience by providing digital wellness, remote, and smart healthcare (termed *Healthcare 5.0*) [2]. Internet of Medical Things (IoMT) [3], [4] is conducive to collect, store, and exchange data using short-to-long distance communication path, and contributes to smart and informed health decisions leveraging artificial intelligence (AI) algorithms [5], [6]. Such AI-driven IoMT system [7] is helpful in varied scenarios, namely, continuous health monitoring in smart homes [8], preliminary diagnosis and early notification [9], [10], and intelligent health recommendations [11]. Due to the aging of the world population,[1] there is an increasing need of remote health-monitoring instead of physician-centric environment for the lack of adequate medical facilities and medical professionals, specifically in the developing countries. In this regard, *smart connected homes* integrated with ambient assisted living (AAL) play a pivotal role in reforming healthcare services, specifically for elderly population to provide remote healthcare and monitor their well-being at home [12]. Furthermore, there is a rising number of old-age homes (or, retirement community[2]) across the world, where constant care and monitoring are required for elderly residents.

Motivating Scenario: This article aims to develop an efficient edge-IoMT-based smart healthcare for elderly people, specifically living in an old age home or assisted living. It is reported that almost 40% of injury-related deaths occurred from falls in elderly citizens [13]. Therefore, *fall detection* is one of the most crucial services in smart connected homes. Furthermore, along with health parameter analyzing, activity monitoring is important to progressively monitor the well-being and health status of the individuals and notify the caregivers and medical practitioners. It may be noted that video-based activity monitoring and fall detection has privacy concerns and are often cost-intensive. Therefore, it is essential to develop an automated, adaptable, and privacy-preserving elderly healthcare system leveraging IoMT solutions. Our proposed framework, *FEEL* facilitates an end-to-end smart-healthcare system for three tasks: 1) activity monitoring and location estimation without camera/video feed; 2) fall detection; and 3) effective and timely health recommendations. Fig. 1 provides a pictorial view of the applicability of FEEL in a real-world setting.

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[1]The number of people aged 65 or older number will reach 1.5 billion by 2050: https://www.un.org/development/desa/en/news/population/our-world-is-growing-older.html

[2]https://en.wikipedia.org/wiki/Retirement_community

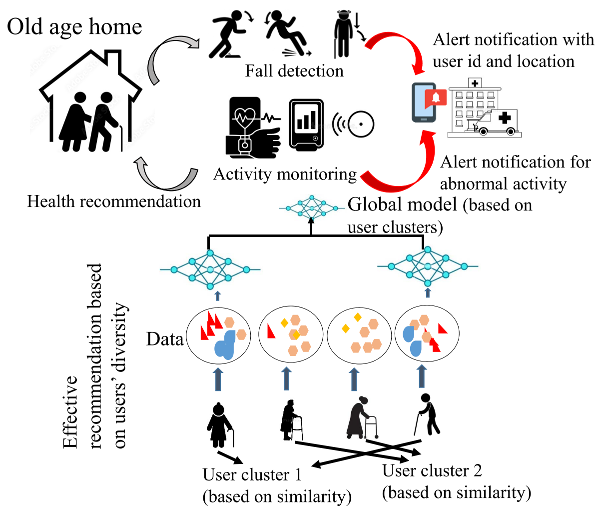

Fig. 1. Motivating scenario for FEEL. Different users have different attributes and aggregated model captures user similarity for recommendations.

To address the privacy issue, *federated learning* (FL) is one of the feasible solutions that facilitate on-device training and share the model parameters without exchanging the data itself [14]. Nevertheless, most of the existing FL technologies ignore the data sparsity issue. For instance, when an IoMT system is installed in a smart home, the sparse data samples fail to produce an effective model. Most importantly, *user diversity* affects the performance of the modules as varied body characters such as height, weight, habitual motions, age, gender, and preferences impact the *falling patterns* of different users. Accordingly, *health recommendations and alerts* are significantly different for diverse health attributes of the users (e.g., a low blood pressure may not be alarming for a user, while it may be a vital sign of illness for other users). Furthermore, most of the existing FL-based works focus on system design and algorithm optimization, however, disregards the *semantic aspect* in the model architecture. For instance, contextual information, such as environmental factors, food, and quality of caregivers may impact the health of a large number of users in old age homes. Moreover, users having chronic diseases such as diabetes, asthma, hypertension, and so on need to be monitored in a different way by continuously measuring varied health-related parameters (blood pressure, weight, and blood sugar) and providing different health recommendations compared to users without such health issues. Such causal relationships are important to improve the overall quality of living. Motivated by the challenges, the major contributions of this article can be summarized as follows.

1) *FEEL: Edge-IoMT System:* We propose an end-to-end edge-IoMT collaborative system, named *FEEL*. The proposed system is capable of collecting, storing, and analyzing several information including location, health parameters, and environmental features (air temperature, humidity, and so on) while protecting user's privacy in a distributed way. To the best of our knowledge, FEEL is the first framework that can be used in an old age home to provide effective remote healthcare.
2) *User and Context-Based Knowledge Graph (UKG):* We propose a UKG to represent user's unique as well as shared (common) characteristics. This modeling is helpful for identifying clusters among the users based on their similar health parameters and helpful for making recommendations while unseen conditions arise.
3) *Few-Shot-Enabled FL:* To address the issue of sparse data and labeled data scarcity, we propose few-shot-enabled FL for IoMT using UKG and reinforcement learning (RL) network. This presents the step toward very popular but overlooked cases in IoMT where labeled training data is insufficient and tasks (healthcare recommendations) are different.
4) *Experimental Evaluations:* We have developed a customized wearable band for collecting data (body temperature, SPO2, blood pressure, heart rate, and motion-related parameters) in a continuous manner. The experimental evaluations on three different tasks, namely activity monitoring and location estimation (F1 0.938), fall detection (F1 0.905), and health recommendations (F1 0.86) demonstrate the efficacy of FEEL.

The rest of the article is organized as follows. Section II discusses relevant existing works and our contributions toward the literature. The proposed system and algorithms are described in Section III. We present the experimental evaluations in Section IV. Finally, the article is concluded in Section V with future research avenues.

II. Related Works

Table I highlights few significant research works and our contributions in this research domain. Machine learning [23] algorithms have been used for pattern recognition from heterogeneous data-sources. A centralized server is required for training purposes in standard machine learning techniques. FL enables mobile phones to collaboratively learn a shared prediction model while keeping all the training data on the device. Furthermore, deep learning models are powerful tools for extracting unknown patterns using multiple layers between input and output. In general, multilayer perceptrons (MLP), convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are the major categories of deep learning architecture. On the other side, RL denotes how intelligent agents take actions in an environment in order to maximize the notion of cumulative reward.

A. Activity Monitoring and Recommendations

Sethuraman et al. [11] propose a framework named, *MyWear* to monitor continuous vitals of patients. The authors present the design of a smart garment that can collect and monitor physiological data, and predicts the risk of heart failure. Rachakonda et al. [24] present an intelligent device, iLog that can automatically identify food intake monitoring and stress level of the users leveraging IoMT solution. A hierarchical domain adaptation learning model has been proposed in [15] and applied to the electroencephalogram (EEG) diagnosis of epilepsy. The authors have proposed the

TABLE I

COMPARISON OF THE PROPOSED FEEL FRAMEWORK WITH THE RELEVANT EXISTING WORKS (IN THE CONTEXT OF IoMT). **A**: ACTIVITY MONITORING AND RECOMMENDATIONS; **B**: FALL DETECTION; **C**: DATA SPARSITY ISSUE; **D**: FL ENABLED; AND **E**: USERS' DIVERSITY

Publication Reference	Highlights	Feature				
		A	B	C	D	E
Sethuraman et al. [12]	MyWear, a smart garment, capable of analyzing muscle activity, stress levels, and heart rate variations and predict risk of heart failure from abnormal variations in vitals	✓	✘	✘	✘	✘
Yuan et al. [21]	Fuzzy-GBDT algorithm for heart disease prediction by reducing data complexity and generalization of binary classification	✓	✘	✓	✘	✘
Chakraborty et al. [22]	IoMT based cloud-fog diagnostics for heart disease using ML-based algorithms	✓	✘	✘	✘	✘
Nath et al. [23]	Stress detection framework for older adults using wrist smartband	✓	✘	✘	✘	✘
Musci et al. [24]	Software architecture for fall detection running on onboard wearable device	✘	✓	✘	✘	✘
Mauldin et al. [25]	Ensemble deep learning method for fall detection trained on simulated scenarios	✘	✓	✘	✘	✘
Xu et al. [20]	FEDMSQE, federated learning framework for IoMT and achieves higher accuracy and lower quantization error	✘	✘	✘	✓	✘
Wu et al. [26]	FedHome, a cloud-edge based framework for in-home health monitoring to reduce communication cost by using generative convolutional autoencoder	✘	✘	✘	✓	✘
Alzubi et al. [27]	Cloud-based and blockchain enabled federated learning for privacy preservation of electronic health records	✘	✘	✘	✓	✘
Lian et al. [28]	DEEP-FEL, decentralized, privacy-enhanced federated edge learning framework, to collaboratively train global model from different institutions without data exchange	✘	✘	✘	✓	✘
FEEL (proposed framework)	Few-shot enabled federated learning for elderly healthcare service in old age home setting to resolve privacy concerns, data sparsity and user diversity issues.	✓	✓	✓	✓	✓

model by utilizing the common knowledge between source and target domains. Yuan et al. [15] propose a Fuzzy-gradient-boosted decision tree (GBDT) algorithm for heart disease prediction. The authors claimed that their proposed method achieved promising accuracy in both binary and multiple classification predictions. Chakraborty and Kishor [16] presented a cloud-fog-based IoMT system for heart disease prediction using machine learning classification techniques. A deep learning-based fusion network is proposed for medical image fusion [25]. The proposed fusion architecture is unsupervised and therefore does not require fusion rules to be designed manually. The framework can be used for several applications in healthcare. Nath and Thapliyal [17] proposed a novel model for stress detection for older adults by devising a smart wristband. The model achieved an f1 score of 0.92 in detecting stress levels as well as obtaining feedback about their vitals.

B. Fall Detection

Saadeh et al. [26] presented a framework for the fall prediction and detection system using single sensor IoT system. The system triggers an alarm to the caregivers through the internet. The system achieved 97.8% and 99.1% sensitivity and specificity, respectively. Musci et al. [18] proposed a fall detection algorithm leveraging RNN on wearable device data. Ding and Wang [27] presented a WiFi-based fall detection system using discrete wavelet transform (DWT) and RNN. Paolini et al. [28] proposed a 3-D tracking and fall detection method using using a Raspberry Pi 3B. The experiments demonstrate that the proposed system is capable of tri-dimensional scanning of a monitored room with decimeter accuracy over the three reference axes. An ensemble deep learning method is proposed in [19] for fall detection. The authors conducted offline experiments on simulated falls and train the model effectively for real-world scenarios using an ensemble RNN model. Luo et al. [29] presented a framework, named P^2Est for fall detection by pose estimation. The authors claimed that their model can efficiently track body orientation and achieves promising accuracy.

Several works have been done leveraging FL for privacy protection in IoMT settings [30]. Lian et al. [22] proposed a framework, named *Decentralized, efficient, privacy-enhanced federated edge learning (DEEP-FEL)* using federated edge learning for healthcare. Can and Ersoy [31] proposed a federated deep learning framework for biomedical monitoring. The authors used heart activity data for stress-level monitoring by preserving the privacy of such records. The framework achieves 81.75% accuracy for detecting stress using the FL-based strategy. Adhikari et al. [32] proposed deep transfer learning for detecting communicable diseases in edge network. The method transfers the knowledge from the trained model and develops a lightweight machine learning model which can be supported in resource-constrained edge-devices. The system achieved 99.8% accuracy in disease prediction. Wu et al. [20] proposed a framework named *FedHome* for in-home health monitoring using generative convolutional autoencoder (GCAE). Alzubi et al. [21] proposed a cloud-based and blockchain-enabled FL architecture to preserve the privacy of electronic health records. A personalized FL system is proposed in [33] for different nonidentical data distributions of clients.

Despite several advancements in FL-based system in IoMT contexts, there are challenges that affect the efficacy of healthcare services. As mentioned before, the data sparsity and diverse behavior of users are not properly addressed in the literature. Moreover, no existing works have attempted to develop an FL-enabled IoMT system for old age homes. To the best of our knowledge, ours is the first work to incorporate users' similarity and contextual information in FL-enabled IoMT system for effective healthcare services in old age home settings.

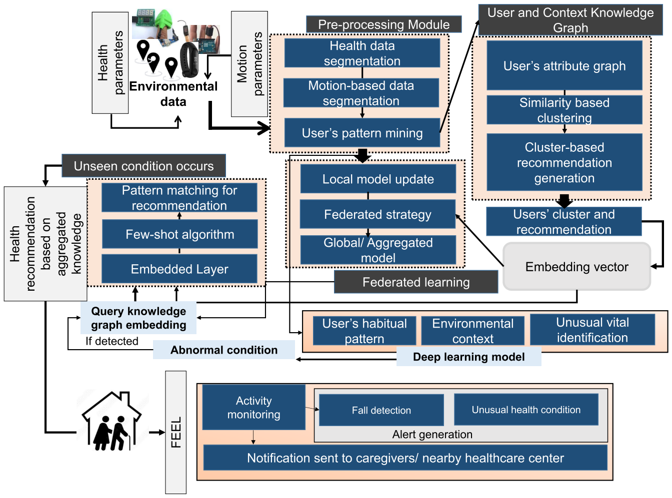

Fig. 2. FEEL: Overall building blocks.

III. FEEL: The Proposed Framework

Fig. 2 depicts the overall building blocks of the proposed framework, FEEL. The "blue" color blocks represent the computational modules and "gray" blocks denote input and outcomes of the computational modules. First, we describe few preliminary concepts as follows.

Activity Node: Activity nodes are represented by $(a_{\text{name}}, [t_s, t_f])$, activity name (a_{name}), and start (t_s) and finish time (t_f) of the activity a_{name}. In this work, we have considered several types of daily activities of individuals such as *having meal*, *listening to music*, or *taking medicine*.

Disjoint and Embedded Activities: The set of activities are termed as disjoint activity set (A_D) and embedded activity set (A_E) if

$$A_D = \left\{ a^i_{\text{name}} \middle| t^i_s \geq t^{i-1}_f \ \forall i \right\}$$
$$A_E = \left\{ a^i_{\text{name}} \middle| \left(t^i_s \leq t^r_s \leq t^j_f \right) \wedge \left(t^r_s \leq t^j_f \leq t^r_f \right) \right.$$
$$\left. \times\, i \in [0, \ldots, j, r, \ldots, n]. \right. \tag{1}$$

Allen's Temporal Calculus: Allens' temporal calculus [34] formalizes and represents 13 basic relations (after, during, meet, and so on) between temporal objects interpreted as intervals. The detailed representation of these temporal relations and activities has been discussed in our previous work [35]. The qualitative temporal relations (Tr) among the activities in this article are represented by these 13 relations.

Root Activity and Sub-Activity: The sub-activities (Act_S) are the unit-level activity; which cannot be broken down further. The root activities (Act_R) are the sequences of sub-activities

$$\text{Act}_S = \left\{ a^i_{\text{name}}, [s_1, \ldots, s_a], t^i_s, t^i_f \forall i \right\}. \tag{2}$$

The sub-activity is recognized from a list of sensors $(s_1, \ldots, s_a)$ placed in different parts of the users' body

$$\text{Act}_R = \left\{ a^i_{\text{name}}, \left[A : a^1_{\text{name}}, \ldots, a^n_{\text{name}} \right.\right.$$
$$\left.\left. \times \text{ and } A \in \text{Act}_S \right], [A, \text{Tr}, \text{Cv}], t^i_s, t^i_f \forall i \right\}. \tag{3}$$

The context information (such as temperature, humidity, and light intensity) is denoted by Cv. The root activity is comprised of a subset of sub-activities (A), and these sub-activities maintain a temporal sequence (Tr). Table II presents different types of activities and fall types analyzed and detected in this work.

TABLE II
Types of Activities and Fall Detection

Type	Activities
Mobility/ Motion-based	Standing, Sitting, Lying, Walking, Running, Exercising, Walking Upstairs, Walking Downstairs, Jogging, Jumping, Falling
Regular Activity	Cooking, Having meal/ breakfast/ dinner, Taking medicine, Taking Bath, Sleeping, Reading, Watching TV, Listening to music
Handheld device	Making/ receiving calls, Text messages, sending alerts, checking health notifications
Fall detection	Kneel and fall, sit then fall, walk then fall, trip, slip

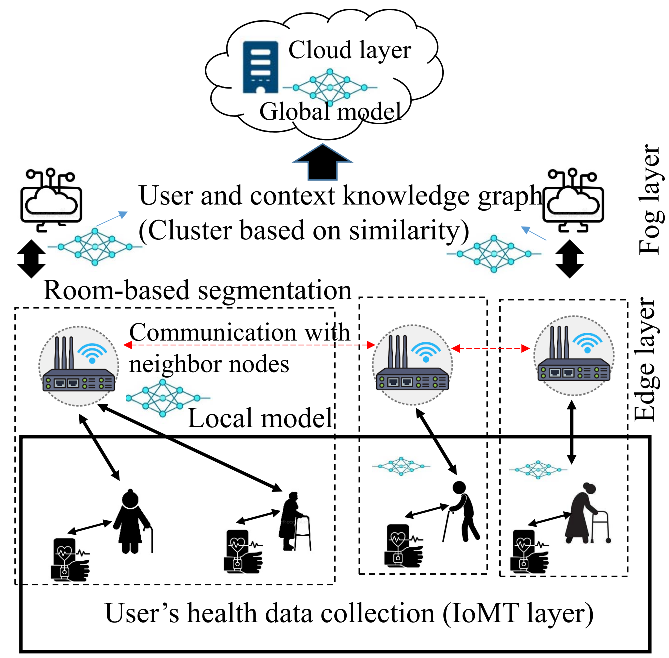

Fig. 3. FEEL: Hierarchical and collaborative Edge-IoMT architecture.

A. Proposed Edge-IoMT Architecture

FEEL presents a collaborative hierarchical *fog-edge-IoMT* architecture which has three layers (see Fig. 3). In the bottom layer, data are collected from users using wearable devices and smartphones of the users. As such data are sensitive in nature, centralized, or cloud based approach has privacy issues. Moreover, time-critical applications, such as fall detection can be affected due to network latency or interruption if cloud-based method is used. Here, a connected in-home (old age/retirement community) health-monitoring system is considered where in each segment of the smart home, one or more than one user can stay. In each room, edge computing nodes (such as smart home gateway, or small cell base stations) are deployed. Say, the total number of such edge nodes is E_n, and the total number of users is U. Now, at each floor (or segment), a fog node is deployed which stores other contextual information

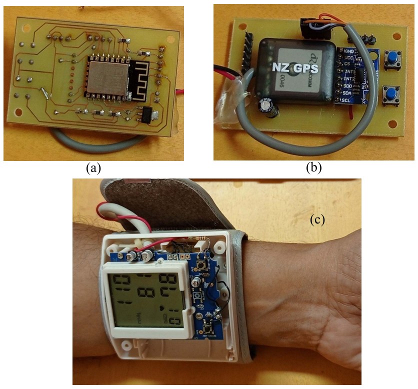

Fig. 4. Customized low-cost wearable device. (a) NodeMCU ESP8266 CP2102 Board, (b) accelerometer (ADXL345), and (c) recording health parameters.

about the area. Now, given a specific task, namely, activity recognition or fall detection, FEEL learns the machine learning model utilizing data collected from U users $\{u_1, u_2, \ldots, u_U\}$. Each user can either select to process the data in a local device (smartphone) or offload in local trustworthy edge nodes. The fog nodes are used to cluster and maintain user and context knowledge graph by processing the user-specific features (medical history, existing health issues, recommended medical guidelines, and so on). The edge nodes can communicate with each other if an exigency situation (fall detected or abnormal health status predicted) arises and send the notification to the nearest fog device. By proposing FL, users can manage their local models in the global model without exchanging sensitive information. Furthermore, the data from the users of the old age home with similar medical attributes help to develop accurate local models for the users with limited data (or in unseen condition) by utilizing the data/recommendations already available.

To support the system, a low-cost customized wearable device has been developed (See Fig. 4). The device consists of several sensors namely, pulse meter, blood pressure, accelerometer, body temperature, pulse oximeter, NZ-GPS, and wifi modules. The device outputs serial data at 9600 baud rate in ASCII format [36]. The body vitals can be visualized using a smartphone of the users and the medical practitioners can monitor in real-time. The major objectives are: 1) continuous monitoring of body vitals; 2) processing data in regular interval and update the local model; 3) communicating with neighboring edge and fog nodes, if any unusual condition arises; and 4) sending alerts to caregivers in the case of emergency.

B. Activity Monitoring and Recognition

In this section, the activity data analysis is carried out to obtain individual's preferences and abnormal activity sequences. Algorithm 1 states the steps of learning the activity sequences and detection of abnormal activities. We will start with the generation of activity and health profile, followed by activity sequence learning.

1) User and Context Knowledge Graph: First, we develop a knowledge graph (UKG) incorporating user's features such as age, gender, height, weight, medical history (existing illness),

Algorithm 1 : Recognizing the Activity Sequences and Detection of Abnormal Activities in FEEL

Input: List of devices RS, Contextual Variables G, Temporal relations E_s, Time Interval E_T

Output: $< G_k, REC >$ ▷ Output: Abnormal Activity sequences and recommendations

$function\ MAPPER(E_s, E_T, G[])$
for $all\ b_i \in RS$ **do**
  $L \leftarrow RemoveSpikes(b_i)$ ▷ Eliminate accidental spikes from the data using median filter
  $EMIT(f, t)$ ▷ Emit features and t: Temporal information
end for
function COMBINER$(S_Q)(m)$ ▷ This method finds out the appropriate/regular patterns of activities
  for $i = 1$ to 3 **do**
    Initialize model AR^i_{LSTM} ▷ AR: Activity recognizer model, TS: temporal sequence
    for $j = 1\ to\ |TS|$ **do**
      $F \leftarrow computeFeaure(TS[j])$
      $Train\ AR^i_{LSTM}(F)$ ▷ Given all the training instances, train the LSTM learner
      $Update(AR^i_{LSTM})$ model using the loss function
    end for
    $ConcatL(AR^{1,2,3}_{LSTM})$ ▷ Ensemble the LSTM learners using Bagging method
  end for
  $MLTG_3(N[\,], E[\,]) \leftarrow NULL$ ▷ Initialize MLTG
  for $i = 1$ to $length(T)$ **do**
    $Create\_node(MLTG_3.N_i \leftarrow (mobility))$
    $M : MLTG_3.N_i[id] \leftarrow p$ ▷ Current activity sequence
    $MLTG_3.N_i[p][label] \leftarrow T[i].t_{S1}$
    $Create\_edge(MLTG_3.N_i \leftarrow (id, label))$
    $M : MLTG_3.E_i[id] \leftarrow d$ ▷ Connect Previous k-layers
    $MLTG_3.N_i[d][label] \leftarrow T[i].t_{S2}$
  end for
end function
$function\ Sorter(MLTG, AR_{LSTM})$
Sort the activity sequence based on temporal value
$G_k \leftarrow ComputeThres(MLTG, A)$ ▷ A: Input sequences
for each user u **do**
  Construct REC(MLTG,H) ▷ H: Health profile
end for
$Print < G_k, REC >$ ▷ G_k: Abnormal activity sequence, REC: Recommendation list

recommended guidelines, and so on. At the edge level, individual user's attributes are modeled in a user graph, where the attributes are presented as nodes. Apart from that, the user graph also stores impact of varied variables (environment, medicine, food, and so on) on user's health. Therefore, user-graph modeling and stored information at edge nodes provide user characteristics and recommended guidelines by medical practitioners. If the medical guideline is not available, a *null* value is stored in that node. In brief, user graph creates a causal relationship (such as one activity triggers health status, which needs specific medical recommendations, and so on) using the available data for each user. In fog level, several user-graphs from different edge nodes are aggregated. Here, we first devise similarity computation score based on the nodes' values and causal relationships presented in the edges of the graph. We deploy a semantic matching model where the semantic similarity among the nodes and edges is computed using a feedforward network. Based on the similarity values, users are clustered into different groups. The users of a cluster represent similar medical and health features. UKG is represented by triplets where activities and health status are nodes and edges represent the causal relationships between varied entities of the knowledge graph.

It may be noted that peoples' daily activities are complex in nature and consists of many sub-activities. These sub-activities are unit-level activities which can be identified from various sensor readings. In the initial phase, we segment varied sensor data and generate a multilayer temporal graph (MLTG) for each individual. Here, the input data from varied sources are: 1) BAN or Body Area Network (body temperature, blood pressure, pulse rate, SpO2, breathing rate, and diabetes); 2) mobility-related data (movement, acceleration, direction, and proximity); and 3) context information of the surroundings (humidity, room temperature, light intensity, and audio-level). It may be noted that an effective activity recognition system should not rely on a specific type of data, rather it needs to analyze information from various modalities to analyze complex human activities. The activities which are mainly considered in this article are listed in Table II. While the mobility-based and regular activities are recognized from sensor readings and other context information, the log of handheld devices (smartphones or tablets) are analyzed to detect the usages/preferences of the individual at different time scales.

Next, the information from varied sources is modeled into a MLTG. In a typical multilayer graph, the vertices of one graph are correlated with the vertices of the other graph by node-mapping function. MLTG is defined by three layers of an interdependent graph. The proposed MLTG differs from the conventional multilayer graph. Here, in the first two levels, the mobility-related information and the activity data form a hidden Markov model (HMM).

We define an activity context by the hierarchy of the present activity (levels of concurrent activities) and the sequence followed by the individual. As a user's mobility can be characterized by various stochastic processes, we aim to model user's activity-based mobility profiling as *HMM*.

$\lambda = \{A, B, \pi, L\}$ is introduced to characterize the HMM, where the transition matrix A is an $N \times N$ matrix of $l_i \in L$ level activities and $A_{ij} = P(s_{j:t+1}|s_{i:t}), 1 \leq i, j \leq N$, and the emission probability matrix B is an $N \times M$ matrix $B_{ij} = P(o_{i:t+1}|s_{j:t}), 1 \leq i \leq M, 1 \leq j \leq N$; π is a $1 \times N$ vector for each level and $\pi = [p(s_1), p(s_2), \ldots, p(s_N)]$. Here, *Allen's temporal calculus* is used to define the level of activities.

The HMM-based MLTG associates with three basic inference problems.

1) *Evaluation:* It computes the likelihood of an output sequence $o_{i:t}$ (observed activities) for a particular HMM λ.
2) *Decoding:* Identify the most likely sequence of hidden states $s_{i:t}$ for a particular model $\lambda = \{A, B, \pi, L\}$ and given output sequence $o_{i:t}$. The task is to find out the maximum value of $p(s_{i:t}|\lambda, o_{i:t})$ over all possible hidden state sequences. The *Viterbi algorithm* is used by extending it using time relationships among the possible sequences. The existing data are utilized to adjust model parameters. Finally, the parameters along with the model $\lambda = \{A, B, \pi, L\}$ represents the activity profile of the individual. An iterative version of the expectation–maximization algorithm is used for parameter learning.

Finally, the top-most layer is constructed by the BAN data of the users. Formally, MLTG is defined as follows:

$$\text{MLTG} = (g_1, g_2, g_3, M), \text{ where } g_a = (N_a, E_a), \ a \in 1, 2, 3 \times M_{i,j} : N_i \times N_j \leftarrow [0, 1] \quad (4)$$

where M denotes the node mapping function having 3×3 dimension, and each layer ($g_1, g_2,$ and g_3) has set of nodes (N) and links (E) among the nodes. In the next step of FEEL, we aim to learn the normal sequences of activities in the daily life of a user and recognize the activities performed by the user. In this direction, we have used *adaptive and stacked long short-term memory (LSTM)* network, which is effective in the given scenario. In the preliminary step, the features are extracted from varied sensor readings using the temporal sliding window approach. The window size is incremented from 5 to 15 s, with 10%, 20%, 30%, 40%, 45%, and 50% overlap. After several iterations, a sliding window with 8 s and 50% overlap is selected. The framework then finds out the best 15 features from the input data. The LSTM network maps an input sequence to an output sequence by computing the network activations in different time instances. Our framework uses tanh for cell input–output activation functions, and *softmax* as network activation function. FEEL utilizes multiple stacked LSTM networks, where varied individual learners that are each trained on different modalities (mobility/contextual) of the sample data.

FEEL uses a varied number of layers in the deep LSTM architecture, where each layer has a linear recurrent projection layer. This n-layer deep architecture finds out the correlation of activities (temporal and sequential) in an iterative and hierarchical manner. First, it learns the effect of previous sequences of activities along with other parameters such as temporal duration, effects of contexts among different activities, and then extracts the activity patterns as a consequence of previous activities and context information in the input log. The output of the architecture is regular activity sequences (and embedded activities) and activity duration of all these predicted activities of an individual. Furthermore, the network is capable to detect

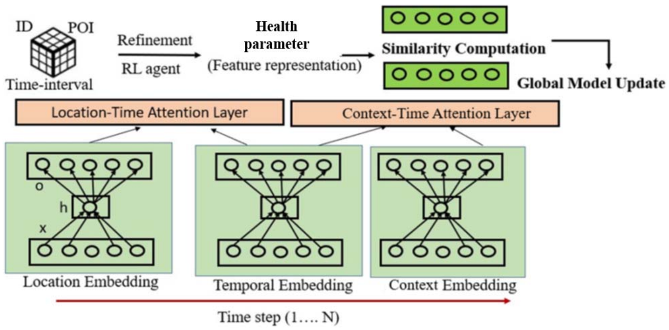

Fig. 5. Few-shot enabled FL architecture.

any other abnormal activity sequence, after the training is completed.

C. Few-Shot Enabled FL: Fall Detection and Recommendation Generation

Few-shot learning is implemented by reinforcement learner agent. Fig. 5 depicts the building blocks of the learning architecture. A three-layer attention module has been devised to identify similar traits amongst users' attributes to effectively model and embed the information.

Few-shot learning aims to learn a generic model to classify or predict unseen tasks with very few labeled samples. FEEL explores few-shot classification and recommendation tasks. Furthermore, given an unseen condition (abnormal health status), FEEL aims to recommend health recommendations based on already available medical guidelines. The overall steps of the learning algorithm are presented in Algorithm 2.

In general, the mapping of feature space from the source-to-target domain is carried out (for data sparsity or scarcity of labeled data), which is termed as *feature representation* transfer. The representations of each users' feature space are obtained from the deep learning architecture, and the dimensionality of the representation is reduced by deploying multilayer perceptron. In the next step, the transfer of the knowledge of instances by addressing the empirical risk minimization problem [37]

$$\kappa^* = \arg\min_{\kappa} \sum_{(x,y)\in \mathrm{TG}} P(G(\mathrm{TG})) lf(x, y, \kappa) \tag{5}$$

where $P(G(\mathrm{SG}))$ is the marginal probability distribution of users' aggregated data, $lf(x, y, \kappa)$ is the loss function and κ is the set of optimal parameters in the learning set-up. Since the target and source tasks are different, and $P(G(\mathrm{SG})) \neq P(G(\mathrm{TG}))$, we rewrite the above optimization problem as follows:

$$\kappa^* = \arg\min_{\kappa} \sum_{(x,y)\in \mathrm{SG}} \frac{P(G(\mathrm{TG}))}{P(G(\mathrm{SG}))} P(G(\mathrm{SG})) lf(x, y, \kappa). \tag{6}$$

To solve this objective function, we need to estimate $(P(x_{\mathrm{SG}_i})/P(x_{\mathrm{TG}_i}))$ for each instance. Initially, FEEL deploys *domain adaptation* technique as the source instances and target data instances are from a different distribution. The intuitive idea is to utilize the labeled data instances of the source task to classify unlabeled instances of the target task. FEEL proposes an *RL*-based transfer learning technique here. To be specific, the instance weighting and instance adaptation are carried out by learning the *reward and policy*. Here, an *agent* attempts to predict the information about the transition from one health condition to another as well as the recommendations at different stages. *Actions* are represented by the user's activity at a time instance. The users and health status of the UKG represent the *environment* denoted by the pair of user knowledge graph and the user $<\mathrm{UKG}, u_i>$. The *reward* is defined by the similarity score of the real and the predicted activity transitions. For policy learning, we have used a variant of deep Q-Network [38] and potential-based reward shaping technique in [39], as we have to perform the transfer learning on UKG. The key components of the framework are described as follows.

Agent: FEEL considers agent as the next activity predictor/planner of the user. Given the input (current health and motion parameters) of the user and the environment, agent predicts the next transition (health values and next activity) along with the recommendation.

Actions (α): Actions are defined in two-folds: 1) $\alpha = (1, p_a, i)$: user performs activity p_a while health value is

Algorithm 2 : Few-Shot Enabled FL Algorithm

Input: U users and corresponding dataset $\{u_1, u_2, \ldots, u_U\}$, c: communication round, l: learning rate
Output: $< G_m, L_m >$ ▹ Output: Aggregated and local model

function USER LOCAL MODEL(L_m)
  Each user/client computes feature representation based on data and corresponding labels
  Refine model parameters and update to obtain new prediction model (L_m)
  Generate UKG and return (UKG, L_m)
end function
function USER CLUSTERING($UKG_1, UKG_2, \ldots, UKG_U$)
  Compute user similarity score (U_{score})
  Semantic matching model (U_{score})
  Obtain clusters ($clust$) and embedding of users' features for each cluster
end function
Sample few-shot tasks FT from base classes
Adapt current local model L_i based on user similarity score to the sampled task ($clust$)
Optimize the model using gradient descent
function AGGREGATED MODEL(G_m)
  for each round $i = 0, 1, 2, \ldots$ **do**
    for each cluster $cl \in clust$ **do**
      Select user set randomly from a cluster
      Distribute model parameters and update user model
      Predict labels for "unlabelled samples" in each user
    end for
    Obtain learned global/aggregated model parameters (G_m)
  end for
end function

recorded i and 2) $\alpha = (0, p_a, t)$: user shows unusual health value p_a for t time-duration. Here, the action space is the set of activities. The first element of α denotes whether the activities are normal or not.

Environment (En) and State (se): The environment of the framework is composed of $\mathrm{En} = (\mathrm{UKG}, U)$. Here, the elements are user-knowledge graph and the users (users with their activity traces available) of that duration.

Reward (Rd): The reward function is the key factor of the RL, as it determines the direction of the optimization. In our set-up, the reward is the weighted sum of the factors: 1) dtra: the reciprocal of the similarity scores between the real and predicted activity; 2) durS: the reciprocal of the real and predicted time-duration spent for each activity; and 3) act: whether the fall detection at a time instance is correctly predicted. The reward is computed for the complete activity trace (say, the trace comprises n activities)

$$\mathrm{Rd} = \mathrm{wr}_1 \times \sum_{j=1}^{(n-1)} \mathrm{dtra}_j + \mathrm{wr}_2 \times \sum_{j=1}^{(n)} \mathrm{durS}_j + \mathrm{wr}_3 \times \sum_{j=1}^{(n)} \mathrm{act}. \quad (7)$$

In the next step, we attempt to transfer the *relational-knowledge*. Since the user knowledge graph captures the relations of users' habitual preferences and health-based recommendations, we exploit this structure to transfer the relational knowledge from the source to the target task and predict when unseen conditions arise. In this regard, Mihalkova et al. [40] propose a transfer learning approach to map the relations from the source to the target domain using Markov logic networks [41]. We follow a similar approach; however, the relations are represented by similar health recommendation facts or relations of UKG instead of the Markov logic network. The model complexity depends on the number of unique activity instances of the users and linear to the multiplication of number of levels in UKG and unique activities performed at each level.

In summary, *Transductive transfer learning* is implemented over the representation to label the activity segments and health values in the target domain. For domain adaptation, we have used RL agent to learn the movement behavior of the users at the target region exploiting the knowledge from the source region.

IV. Performance Evaluation

To validate the proposed approach, a testbed has been built which consists of handheld-devices, wearable sensors (collects health and movement data), fog device, and cloud server. We have used the Google cloud platform (GCP) for the computation and storage of the global model. Furthermore, an API endpoint communicates with the edge devices and provides the recommendations to the user. Here, we discuss the efficacy of our proposed framework to recognize several activities and detect the abnormal sequence of activities as well. We have tested the *FEEL* framework for 17 activities performed by the individuals on a regular basis. Along with our collected dataset from volunteers using the customized wearable device, we have used publicly available dataset MobiAct [44] for human activity recognition in order to do fair comparisons. The accuracy of activity recognition is measured by *precision*, *recall*, and *F1-measure*. Fig. 6 shows the average accuracy of four activities and two types of fall detection and Fig. 7 represents the average accuracy when unseen condition arises, in terms of precision, recall, and F1-measure. It is observed that for the average precision value lies in the range of 0.94–0.96 and recall value is in the range of 0.91–0.92. The accuracy of fall detection is also quite high (in the range of 0.903–0.94). The key reason for the efficacy of our framework is that the activity recognition method does not only rely on a specific type of sensor readings, rather it effectively models and analyzes human habitual preferences and activity sequences.

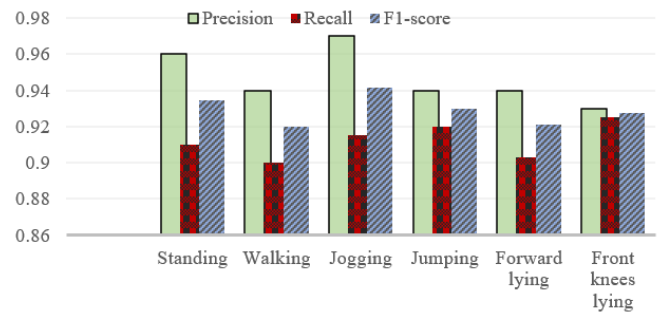

Fig. 6. Performance of FEEL: Average precision, recall, and F1 score.

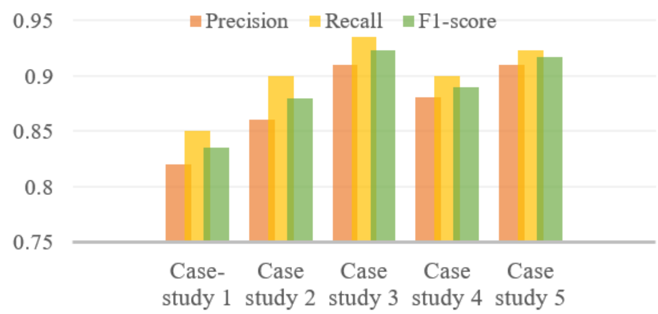

Fig. 7. Performance of FEEL when unseen cases are observed.

Table III shows the average accuracy measures of three tasks (activity recognition, fall detection and health recommendations) of our proposed framework (FEEL) compared to other baseline methods in two different settings. The baselines used here are: support vector machine (SVM), RF, MLP, and CNN. Furthermore, we have presented an ablation study of FEEL framework for demonstrating the impact of each of the modules (UKG, FL, and few-shot technique). It is observed that our proposed framework has outperformed other existing baselines in a large margin for each of the tasks. For instance, FEEL achieves ∼10%–16% more accuracy compared to other baselines. The key reason is that *FEEL* analyzes and models the activity sequences, medical history, and users' preferences effectively along with efficient deep learning model. Fig. 8 depicts the confusion matrix of the activities of an individual.

TABLE III
COMPARISON OF ACCURACY WITH EXISTING MODELS AND FEEL

Methods	Accuracy					
	Activity recognition		Fall detection		Health recommendation	
	Full data	Sparse data	Full data	Sparse data	Full data	Sparse data
Support vector machine	72.08%	64.19%	67.84%	58.32%	61.05%	48.88%
Random forest	76.14%	67.05%	71.97%	65.03%	68.11%	54.20%
Multi layer perceptron (MLP)	84.12%	78.23%	80.90%	73.11%	75.08%	67.14%
Convolutional neural network (CNN)	81.03%	79.05%	78.12%	74.06%	77.12%	68.92%
Ahsen et al. [48]	NA	NA	80.07%	76.78%	NA	NA
Hyunseo et al. [49]	84.81%	80.66%	NA	NA	NA	NA
FEEL (without UKG)	86.08%	81.10%	83.02%	78.16%	79.02%	74.88%
FEEL (without federated learning)	85.43%	82.27%	85.01%	79.25%	80.03%	76.12%
FEEL (without few-shot)	94.02%	87.05%	90.81%	82.04%	85.11%	80.81%
FEEL (FULL)	**96.31%**	**93.81%**	**92.16%**	**90.52%**	**89.05%**	**86.12%**

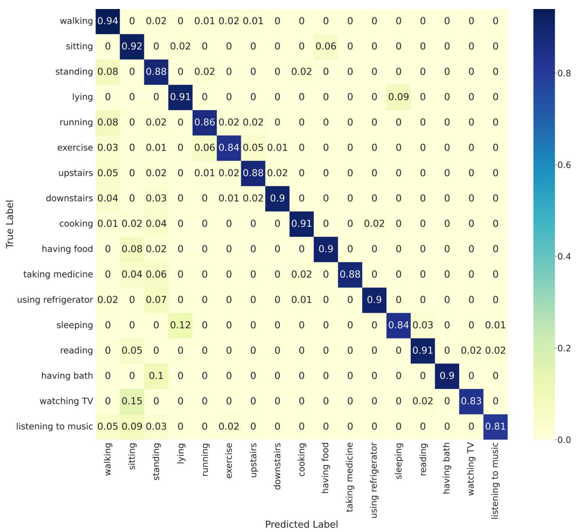

Fig. 8. Confusion matrix of 17 activities of a user.

The purple color depicts higher prediction accuracy of activities. The confusion matrix illustrates the error distribution in activity classification of a user across 17 regular activities. The higher values along the diagonal entries depict better accuracy. Here, the evaluation has been carried out in tenfold cross-validation, where the activity, context, and health data log of one user is split into ten sections. The model is trained for each of the nine sections of data, and the evaluation in done using the remaining part of data. To demonstrate the efficacy of few-shot technique of FEEL, we have conducted experiments based on five case-studies: 1) Case study 1: Activity recognition for a new user registered in the system with very few data samples; 2) Case study 2: New activity occurred for a user; 3) Case study 3: New unusual health status detection; 4) Case study 4: Fall detection for a new registered user with very limited data samples; and 5) Case study 5: Health recommendation for unseen cases. We conducted the experiments to showcase how FEEL works when unseen samples are present in the test dataset. Fig. 7 depicts the average precision, recall, and F1-score for all five case studies. The accuracy values are quite promising (0.84–0.935). It proves the utility of collaborative learning from available samples based on users' similarity and few-shot-based federated approach. FEEL is beneficial in smart hospital settings where health recommendations can be made efficiently even when limited user-specific data are available.

V. CONCLUSION AND FUTURE SCOPES

In the context of privacy preserving healthcare service provision, FEEL presents a novel few-shot enabled FL framework for activity monitoring, fall detection and generating effective health recommendation and outperforms the baselines by $\approx$10%–16% margin. One of the major problems in IoMT domain is scarcity of labeled data and diverse need of users. Our work is a step toward to develop collaborative healthcare model by combining and clustering users' based on their habitual preferences and health status. FEEL is suitable for old age homes where constant healthcare support is required. In future, we would like to explore on-board AI-module implementation for healthcare services and multimodal (voice and medical image) analysis for enhanced remote monitoring. Furthermore, FEEL can be used for monitoring infectious diseases at different geographical regions.

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