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SERP: Smart Edge-Assisted System for Real-Time Pain Monitoring

THESIS

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MASTER OF SCIENCE

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by

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DEDICATION

I dedicate this thesis to my lovely parents and brother whom I haven't seen for a long time, but they have always been there to support me, motivate me, and give me sincere advice. Undeniably, I owe all my academic achievements to them, and this dedication is the smallest gratitude that I could express to them.

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ABSTRACT OF THE THESIS

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In the healthcare sector, there is a strong demand for accurate objective pain assessment as a key for effective pain management. Real-time and accurate objective pain assessment help caregivers and hospital staffs decide the proper dosage of pain medication to be provided to a patient in a timely manner. The state-of-the-art automatic and objective pain assessment techniques in the literature can be classified into two main categories: physiological-based and behavioral-based. The first-class monitors the changes in patients' physiological data such as heart rate (HR), heart rate variability (HRV), Electrocardiography (ECG), Electromyography (EMG), Photoplethysmography (PPG) to identify autonomic nervous system reactions to pain, while the second class utilizes behavioral reactions to pain such as techniques using computer vision-based techniques by extracting features from patients' head poses and facial expressions. Recent pain monitoring systems have recently gained attention on multi-modality meaning that they deploy a combination of both approaches to improve pain monitoring accuracy. Although such complex models are highly accurate in pain monitoring, they are more computationally intensive imposing feasibility limitations to implement them on wearable devices in terms of energy efficiency (battery life) as well as computation latency. A smart and self-aware system capable of adaptively making a decision at run-time in response to the changes in pain level and context can minimize energy consumption by dynamically offloading tasks to the gateway devices at the edge layer. For this reason, in

this work, a self-aware system is proposed for the continuous assessment of pain intensity at the edge layer. Using the BioVid heat pain dataset, this approach demonstrates a promising reduction in terms of energy consumption with a negligible accuracy loss compared with its non-adaptive counterpart.

Chapter 1

Introduction

Pain is a single major reason for people seeking medical care and is associated with many illnesses [33]. In acute pain management, pain assessment is critical for optimal treatment of pain and evaluation for decisions on intervention. However, pain, as a multivalent, dynamic, and ambiguous phenomenon is difficult to quantify [26], in particular, at times when patient has limitation in his/her communication (e.g., during critical illness, infants and preverbal toddlers, patients under sedation or anesthesia, persons with intellectual disabilities, and patients at the end of life) [7]. At present, a wide variation exists in how pain is assessed and managed at the bedside, and the prevalent practices remain sub-optimal [12]. The pain assessment "gold standard" relies on a patient's self-report of their pain intensity on a scale of 0 to 10, where 0 refers to no pain, and 10 represents the most severe pain. This is done through tools such as Numerical Rating Scale (NRS), Visual Analogue Scale (VAS), and Verbal Rating Scale (VRS). However, these unidimensional assessment tools have been questioned and debated for their oversimplification and limited applicability in noncommunicative patients since they require interactive communication between patient and caregiver [17]. It is thus imperative to develop an objective pain assessment tool to improve the well-being and care processes of noncommunicative patients. Such a tool can also benefit other patient populations with a more accurate assessment and more timely treatment.

While pain is a highly subjective experience, there are behavioral and physiological manifestations of pain that can be objectively measured. There have been efforts in developing objective pain assessment tools through analyzing changes in physiological pain indicators, such as heart rate (HR), heart rate variability (HRV), and electrodermal activity (EDA) [6, 25, 11, 31, 32, 22, 23, 14, 10]. However, pain assessment by using only these signals can be unreliable as there are various other factors causing changes in vital signs [9]. Objective pain assessment, using behavioral signs such as facial expression, has recently gained attention [21]. One way to detect facial expressions is to record patient's faces and use the video as another useful modality. Face detection in a video is improved so much that nowadays, it is possible to detect facial landmarks, head pose tracking, eye gaze, and facial Action Unit estimation. One of the best algorithms that can perform all of these in real-time is called OpenFace [4]. Predictions of pain levels can be leveraged via using both modalities combined.

Internet-of-Things (IoT) devices, including wearables, play a significant role in objective pain monitoring systems. These devices are in charge of delivering real-time measurements of physiological signs reflecting pain as well as processing these signals to be able to classify pain levels automatically and objectively. At the same time, to be feasible in real settings, these devices need to have reasonable battery lives. However, because of computationally intensive tasks, accurate real-time pain monitoring is not a long term solution in wearable technologies. Some tasks, such as modern Computer Vision or Deep Neural Network inference, are not suitable to be executed on such resource-constrained devices. One way of addressing the resource constraints in IoT devices in terms of computation power and energy consumption is through offloading the computation to the gateway layer, often called Edge or Fog computing [27]. This approach can help improve performance and energy consumption to enable IoT devices can deliver real-time services.

Although continuous offloading tasks can deliver high-quality real-time services to end-users, the continuous sensing and data transmission over the network can, however, dramatically reduce battery lifetime. To be able to cope with such stringent constraints, a monitoring system needs to be aware of its context and its internal state to be able to adaptively adjust its sensing energy and accuracy at run-time when a power-saving opportunity arises [30, 2, 1]. Self-Aware monitoring systems are capable of making smart decisions at run-time by sensing parameters from the environment as well as their state (e.g., battery lifetime or pain level of the user) and take proper actions accordingly [16, 28, 5, 3]. They often utilize the Observe, Decide, and Act (ODA) control loop paradigm for real-time observations to dynamically control the system [15].

In this thesis, we propose a real-time pain monitoring system that is designed based on the self and context awareness concepts to provide energy efficiency (longer operation time) and accuracy for long-term monitoring. Our system uses two different models to access pain levels. The decision on what model to be used is taken at runtime by an ODA control loop. The models have different characteristics in terms of prediction accuracy and energy consumption. The first model is a pain assessment approach based on physiological signals, particularly ECG, EMG, and GSR signals. The second model is a multi-modal pain assessment approach utilizing an aggregation of facial expressions (video) and Physiological signals. The proposed self-aware pain monitoring system can deliver real-time service in the long-term by dynamically offloading tasks at the Edge. This thesis makes the following contributions [24].

- We propose a self-aware pain monitoring system to enable a real-time long term service using battery constrained wearable devices.
- We evaluated the pain monitoring system using the biopotentials and multi-modal models in terms of accuracy and energy consumption on the edge devices.

The rest of this thesis is organized as follows. In Section 2, the pain assessment approaches are explained then in Section 3, our proposed self-aware system is introduced in terms of system architecture and self-awareness algorithm. In the rest of the sections, the pain monitoring system, experimental setup, and our results are explained and discussed.

Chapter 2

Objective Pain Assessment Methods

Pain Assessment is a challenging task. Current pain assessment tools rely on a patient's self-reported level of pain intensity, which is subjective. In this work, we focus on objective methods, in particular, two popular methods for pain intensity classification which are based on: i) processing subjects' physiological signs, and ii) analyzing captured video of patients using computer vision and deep learning.

2.1 Pain Assessment using Physiological Signs

To this date, research in the estimation of pain intensity has mainly focused on physiological features. They are extracted from channels that include Electromyography (EMG) from facial expressions, Electrocardiography (ECG), Photoplethysmogram (PPG), and Galvanic Skin Response (GSR). After raw signals are extracted, they are then preprocessed often using Butterworth filters and adaptive non-linear noise cancellation techniques. The final step of the preprocessing is the segmentation and feature extraction of these signals. Once the features are obtained, they are then normalized and concatenated to a feature matrix. Each set of normalized physiological features in the feature matrix is associated with a particular pain level. For instance, in the experimental design of [18], three pain levels are used: No pain, Mild pain, and Moderate/severe pain. A patient's pain levels can then be predicted using machine learning models based on the labeled feature matrix.

2.2 Pain Assessment using Behavioral Parameters: Computer Vision

There are several research studies regarding visual features and the fusion of bio-physiological and visual features for pain intensity estimation. To improve the robustness of the pain-level classifiers and achieve invariance to different face poses and subject identity, two sets of features from videos from head pose and facial expressions are extracted: geometric-based features and appearance-based features. The steps in extracting features from a video are to detect a face and then locate facial landmarks. In this regard, one of the most popular methods is OpenFace [4], which is capable of detecting facial landmarks, estimating head pose, recognizing facial action units, and estimating eye-gaze. The computed facial landmarks consist of 68 points on the face which describe mouth, nose, and eye areas as well as the shape of the detected facial regions. Then we can represent the face in numerical embedding using a deep neural network. OpenFace trains each image to produce 128-dimensional facial embeddings that represents a generic face. Once all the relevant visual features are obtained, specific Machine Learning based methods like Random Forest or Neural Network can be employed for pain classification. It should be noted that the computer vision-based techniques are orders of magnitude more power hungry and computationally intensive compared to the approached processing vital signs, although they offer another essential modality for pain assessment.

Chapter 3

Self-Aware Energy Management

Power and energy are constraints in IoT devices that perform computational tasks at the Edge. Self-Aware computing leverages a set of techniques to deal with multiple constraints such as power and performance. These techniques exist at application-level and system-level. Approximate-able applications can be one of the examples used in application-level techniques that can sacrifice the quality of service to obtain a real-time service. System-level techniques can reduce energy consumption by decreasing computational demands. In this thesis, we proposed a system that leverages an application-level self-awareness framework. In this manner, we propose an IoT device that continuously delivers pain level predictions by executing two different machine learning models with different quality of service at the Edge. The system architecture and self-awareness framework are explained in the following subsections.

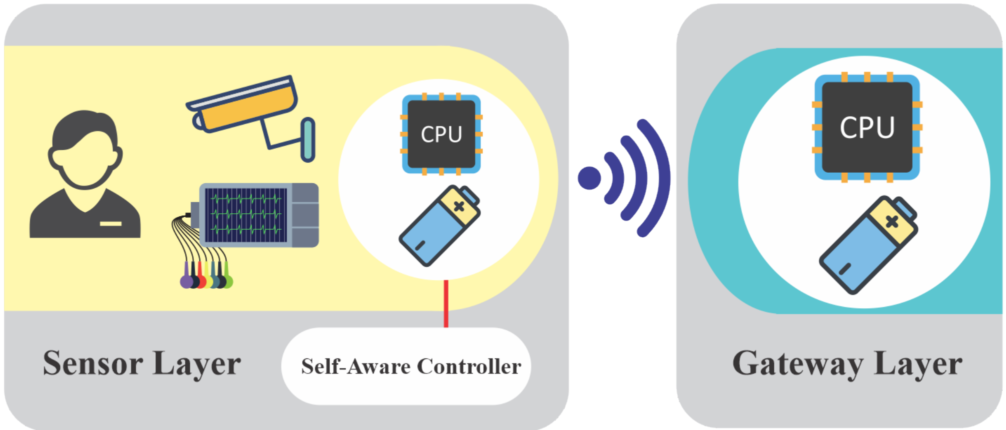

Figure 3.1: Edge System Architecture

3.1 System Architecture

In our system architecture, we leverage the concept of edge computing. The Edge consists of two layers, which include the processing unit, communication infrastructure, storage, to name a few. The first layer is the sensor layer, which continuously senses and collects raw data from end-users. The layer is resource-constrained in terms of battery life, computational power, and communication bandwidth. The second layer is the gateway layer, which offers more resources for computations closer to the sensor layer. In this thesis, an IoT node which is connected to a camera recorder and Physiological signal acquisition device constitutes the sensor layer while a gateway which can offer high computational power constitutes the gateway layer as shown in Figure 3.1.

3.2 Self-Aware System

A Self-aware system makes a decision based on the changes in its internal parameter as well the environment and context surrounding it often using the Observe, Decision, Act (ODA) model. Our approach also exploits the same model where the loop measures the system state, performs decision making, and applies changes in the system's behavior [15, 5]. In

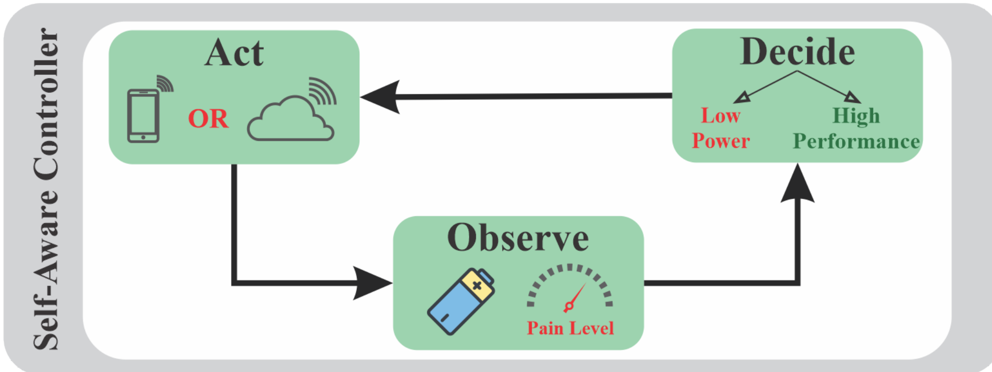

Figure 3.2: ODA Loop Architecture

this context, it measures the system's battery life and observes the user predicted pain level and makes a decision to determine which layer is the most efficient one to execute the pain assessment. Then, it applies the decision of whether to keep the execution at the sensor layer or offload it to the gateway layer. The loop structure is shown in Figure 3.2, and the algorithm is explained in Algorithm 1. This algorithm will be discussed in more detail in the following section.

Algorithm 1: Self-Aware Pain Monitoring Algorithm

```
painLevel ← 0;
averageMeasurement ← 0;
state ← Sensor Layer Computing;
while batteryPercentage do
    batteryPercentage ← Battery Remaining;
    if batteryPercentage < 20% then
        state ← Senor Layer Computing;
    else
        if averageMeasurement == NOPAIN then
            state ← Senor Layer Computing;
        else
            state ← Gateway Layer Computing;
        end
    end
    if state == Sensor Layer Computing then
        painLavel ← Prediction from Bio-Potential Model at Sensor Layer
    else
        painLavel ← Prediction from Multi-modal Model at Gateway Layer
    end
    averageMeasurement ← Last five pain predictions;
end
```

Chapter 4

Pain Monitoring System

In this section, we conduct an experiment to evaluate our proposed real-time self-aware pain monitoring approach as a real-life case study. The first subsection explains the dataset which is used to train and test machine learning models. Then it describes how features are extracted to be used in the models. The second subsection describes the models used to evaluate the proposed method.

4.1 Dataset & Feature Extraction

The BioVid Heat Pain database [34] is analyzed in the study. A total of 85 subjects participated in the experiment and a total of 5 pain levels were recorded (baseline, level 1, 2, 3, 4). Every subject randomly underwent 20 times of trials of each pain intensity and 20 times of a no-pain baseline, resulting in a total of 100 samples. Each pain stimulus was held for 4 seconds and then, paused for 8-12 seconds. Five channels of physiological signals and high-resolution video were recorded during the experiments [19], which were electromyogram (EMG) at the trapezius, corrugator and zygomaticus muscles, electrocardiogram (ECG) and

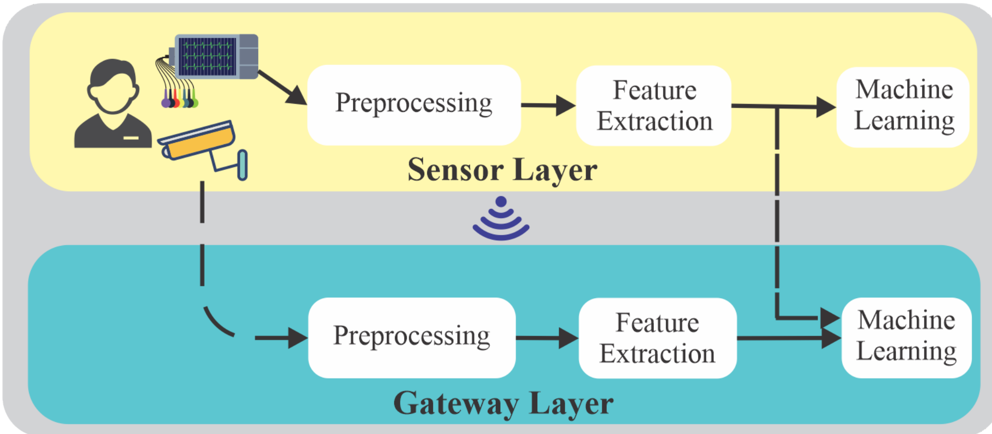

Figure 4.1: Pain Monitoring System

galvanic skin response (GSR).

The EMG and ECG signals were filtered with a Butterworth bandpass filter with cutoff frequencies [20,250] Hz and [0.1,250] Hz, respectively to reduce noise, such as movement artifacts and electrical stimulus pulses.

Feature selection was then applied to obtain a full rank feature matrix. For the EMG and GSR channels, 39 features were extracted, which among them all, there were 97.6%, 80%, 70% and 70% empty values for four features, so we excluded them.

For ECG channels, three features of heart rate variability were included. In addition to this, Walter et al. demonstrated that there was a significant difference in the heart rate variability features among females and males, so the gender of the participants was recorded [35]. Thus, in total, there were 156 features selected. After feature selection, we standardized the data with a mean value of 0 and a standard deviation of 1.

Additionally, head pose features and facial expressions were extracted from videos of the BioVid heat pain database. The first step in extracting features from a video is to detect the face in each frame. Next, facial landmarks needed to be located on the mouth, right eye, and right eyebrow [36]. In this regard, one of the most popular methods is the OpenFace library, which can detect facial landmarks, different head poses, and eye gaze. The computed facial landmarks consisted of 68 points on the face, which describe mouth, nose, and eye areas. OpenFace produces 128-dimensional facial embeddings that represent a generic face. In literature, a number of fusion strategies [20, 29] are employed. Since this is not our primary focus in this thesis, we used an early fusion strategy, which combines the features of different modalities prior to the learning phase.

4.2 Data Analytics using Machine Learning

For the classification of pain intensity levels in this study, we focused on using biopotential data at the sensor layer along with a multi-modal fusion of biopotential and video signals at the gateway layer. In this regard, for the following experiments a selected classical Machine Learning algorithms, Support Vector Machine (SVM) and Random Forest (RF) were chosen as a classifier from the extracted features and OpenFace [4] deep learning to extract visual features on the gateway. SVM classifies data by maximizing the margin of the hyperplane that separates the classes. It can work effectively in high-dimensional data and maintain sufficient flexibility [13, 8]. An RF classifier constructs a multitude of decision trees each performing the classification and picks the mode class as the model's predicted value. The OpenFace library detects the face from the input image and isolates it from the background. Then it calculates 68 landmarks on the face and projects these facial landmarks to a Deep Neural Network (DNN) to extract 128 embedding features. We can predict a pain level among five levels, given the needed features, the features calculated from biopotential data or 128-dimensional visual features returned from DNN. Our present work focuses on the 10-fold cross-validation method to evaluate the results. Although no additional learning phases are included, it can be considered as an applicable scenario in the real world.

Chapter 5

Experimental Setup & Evaluation

In this section, the setup and experiments conducted to evaluate the self-awareness method are described. The system includes a sensor node and a gateway node. The sensor collects 30 frames-per-second videos along with the EMG, ECG, and GSR channels from the patient. A Raspberry Pi and NVIDIA Jetson TX2 are used to deploy the self-aware monitoring at the Edge (sensor layer and gateway layer, respectively). Furthermore, the system's behavior is elaborated at runtime. The specifications for both devices are listed in Table 5.1.

	Raspberry Pi 3 Model B	NVIDIA Jetson TX2
Processor	Quad-core Broadcom BCM2837 64bit	Quad-core Cortex-A57
Architecture	ARM	ARM
Speed	1.2 GHz	2.0 GHz
GPU	—	256-core Pascal
RAM	1 GB	8GB
External Storage	16GB eMMC	32GB eMMC

Table 5.1: Platforms specifications

Stimulus		EMG	ECG	GSR	All Biopotentials	All Bio + Video
0 vs. 1	SVM	0.74	0.49	0.55	**0.76**	0.74
	RF	0.78	0.50	0.54	**0.79**	0.76
1 vs. 2	SVM	0.52	0.52	**0.56**	0.53	0.50
	RF	**0.53**	0.52	0.49	0.52	0.51
2 vs. 3	SVM	0.54	0.54	**0.56**	0.54	0.49
	RF	**0.56**	0.50	0.53	0.55	0.50
3 vs. 4	SVM	0.58	0.54	0.58	**0.60**	0.55
	RF	**0.61**	0.53	0.56	0.60	0.55

Table 5.2: Support Vector Machine and Random-Forest classification accuracy of bio-potential data and bio-potential+video data with self-aware method on the edge devices

As is described in Section 2, we use Support Vector Machine (SVM) and Random Forest (RF) classifiers as our selected classifiers performing a prediction on biopotential data and video signals. The accuracy of these classifiers between two adjacent pain levels is shown in Table 5.2. In this study, two different sets of experiments have been carried out to investigate the behavior of the proposed method using an individual model trained on biopotential data on the sensor layer and a multi-modal model trained on bio-visual data on the gateway.

The self-awareness method is used to minimize the system's energy consumption. In this regard, according to Algorithm 1, the self-aware controller measures the pain level and remaining battery lifetime during the run-time. Then, it decides to execute either one of the multi-modal models on the gateway or the biopotential model on the sensor layer. In detail, the controller observes the last five predicted pain levels and makes a decision based on average measurements. If it decides to execute the multi-modal model, then the sensor device transmits the collected frames and the biopotential raw data over a WiFi network to the gateway device, and the model is executed at the gateway layer. Otherwise, the biopotential model is executed at the sensor layer in 6 seconds interval. Furthermore, the biopotential model is always executed when the remaining battery is less than 20%. In other words, the system's behavior has two states, low power, and high-performance mode. In the low power mode, the system always executes the low complex model (bipotential model) at the sensor layer and in the high-performance mode, it executes the high complex (multi-modal model) at the gateway layer. Energy consumption and performance evaluation for both low power and high-performance modes are explained in Table 5.3.

	Raspberry Pi 3 Model B	NVIDIA Jetson TX2
Execution Time(ms)	13ms	33ms
Power Consumption in Running	5W	12W
Power Consumption in Idle	1.7W	7W

Table 5.3: The system performance/ power consumption evaluation for bio-potential and multi-modal models on the edge devices

The proposed self-aware system is evaluated in terms of energy consumption considering the BioVid dataset to estimate the pain intensity, as a real-life case study. Two sets of experiments were conducted to test the overall system advantages. These scenarios can be considered as if a real patient with acute pain is lying down on a bed with a pain level of 2 at the normal condition. As they start doing an activity - lifting a leg, coughing, sitting up to name a few, their pain level gets increased and as soon as they stop performing the activity their pain level goes back to the normal situation.

To compare the performance of our self-aware system, a comparison is made between including the self-aware energy management technique or only performing the usual pain intensity estimation on the gateway. The results of the two trained models, the one with physiological signals on the sensor layer and the one with bio-visual fusion data on the gateway layer, are shown in Figure 5.1 and 5.2. As shown in these figures, the model or state of the system which is running is changing based on the Algorithm 1. It can be observed that the energy consumption of these two real-life scenarios is reduced by 45% and 64% with a limited accuracy drop of 2% to 7% comparing to the best classification result from a Linear Support Vector Machine or a Random Forest.

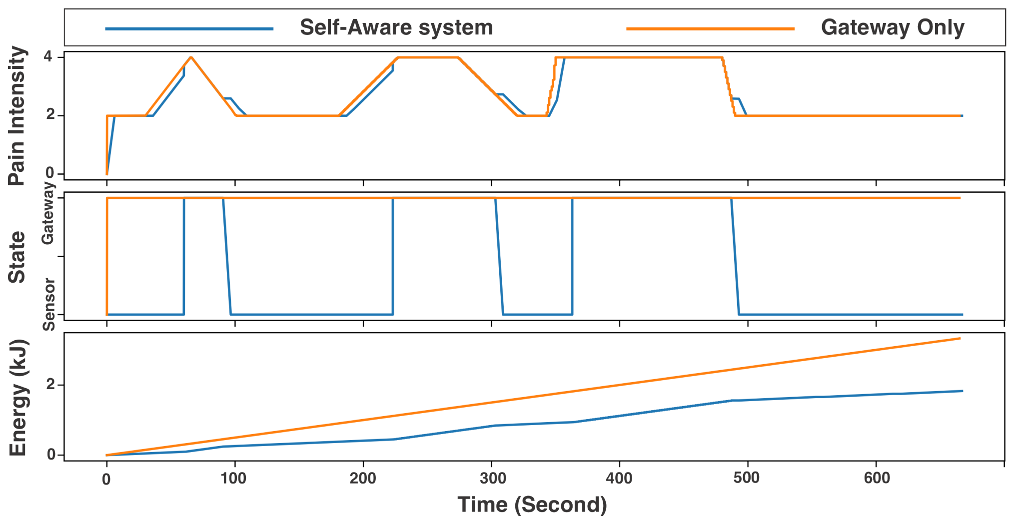

Figure 5.1: Scenario I: Pain Intensity - System Behavior - Consumed Energy

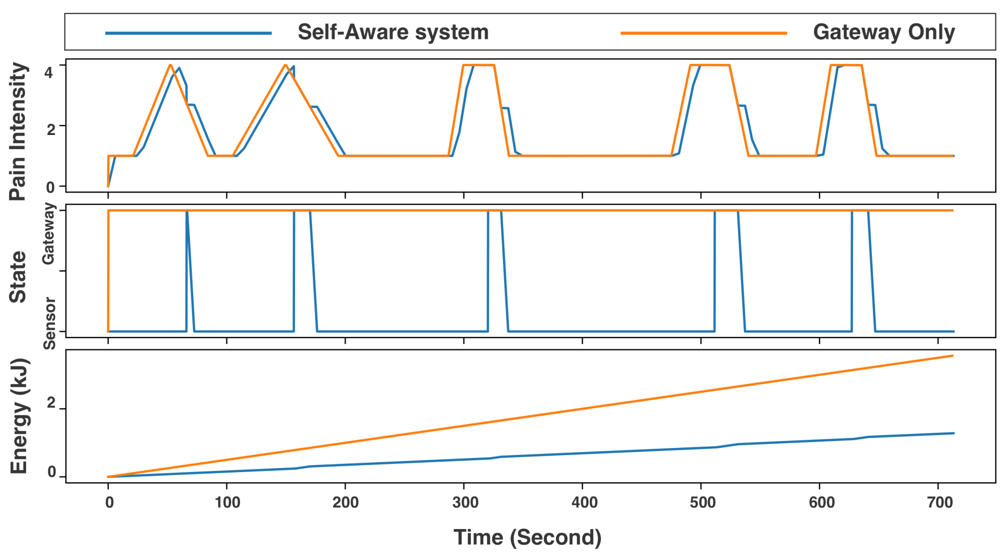

Figure 5.2: Scenario II: Pain Intensity - System Behavior - Consumed Energy

Chapter 6

Conclusion & Future Work

The aim of this thesis has been to develop a smart edge assisted real-time pain monitoring system as highly accurate pain monitoring requires intensive computation on IoT and wearable devices and also offloading tasks to more powerful layers. The signals used for pain assessment are ECG, EMG, GSR, and Video. The signals were collected in 5 different pain levels from no pain to harsh pain. The processed outcomes (features) were then fed separately into different classification models. In this concluding chapter, the contributed highlights of the study will first be presented, followed by limitations and recommendations for future research.

6.1 Significance of the Study

Although offloading can improve the quality of service at the Edge, but continuous data collection and transmission to the upper layers are not feasible for long term monitoring. In this thesis, we proposed a self-aware system for long-term real-time pain monitoring at the Edge of the network. Two pain monitoring models with different characterization in terms of accuracy and computational complexity were deployed at the Edge. We presented a self-aware system capable of observing environmental parameters and making decisions to assign tasks to Edge layers dynamically. As a real-case study, the proposed system was evaluated through two real scenarios showing a significant reduction in sensor layer energy consumption with limited accuracy loss of at most 7%. Our result shows that the proposed system makes long term monitoring feasible on IoT devices by up to 64% energy consumption reduction in different real scenarios.

6.2 Limitations & Future Work

The main limitation is the presence of noise (or incorrect labels), making predictions more prune to errors. Although a certain level of noise has been shown to be positive in order to obtain a more tolerant and robust algorithm, given the real day-to-day data, the noise ratio must be low so that this does not interfere with the learning of the machine. In this study, source of noise is mainly the cognitive difference in pain levels and motion artifacts. These artifacts might come from movement of the electrodes on the skin while the subject is talking. Additionally, thee feature normalization was based on the distribution of the data within each subject. Another limitation is that, this study was conducted with well-controlled pain stimuli with subject sitting on an armchair with few movements. However, in a real life scenario we may encounter many different uncertainties. To overcome the aforementioned limitations of this study we suggest the following approaches:

- Deploy a signal quality checker module to make sure of the quality of signals
- Using novel techniques such as Early Exit to enhance the speed of predictions
- Investigate model compression algorithms to use less complex and computationally intensive

- Using online learning agents in the self-aware management system
- Developing personalized machine learning models
- Comprehensive exploration using full-stack simulator

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