Cloud Computing Management Architecture for Digital Health Remote Patient Monitoring

Hsuan Su
Department of Electrical Engineering
National Taipei University of Tech.
Taipei 10618, Taiwan
t108319004@ntut.edu.tw

Leehter Yao
Department of Electrical Engineering
National Taipei University of Tech.
Taipei 10618, Taiwan
ltyao@ntut.edu.tw

Dennis Hou
Department of Product Development
Caloudi Corporation
New Brunswick, NJ
dennis@caloudi.com

Miles Sun
Department of Product Development
Caloudi Corporation
Vancouver, Canada
miles.sun@caloudi.com

Janpu Hou
Departmet of Product Development
Caloudi Corporation
San Fracisco, CA
janpu@caloudi.com

Jeffrey Ying
Department of Product Development
Caloudi Corporation
Taipei, Taiwan
wing@caloudi.com

Hsin-Yu Feng
Department of Mathematics
National Tsing Hua University
Hsinchu, Taiwan
sabrina900118@gmail.com

Po-Ying Chen
Department of Mathematics
National Tsing Hua University
Hsinchu, Taiwan
bchenturkey@gmail.com

Raymond Hou, MD
Department of Emergency Medicine
Long Island Jewish Medical Center
Long Island, NY
rhou@northwell.edu

2021 IEEE International Conference on Smart Computing (SMARTCOMP) | 978-1-6654-1252-0/21/$31.00 ©2021 IEEE | DOI: 10.1109/SMARTCOMP52413.2021.00049

***Abstract*—With machine learning, the remote patient monitoring (RPM) devices are no longer just remote data collection devices. In addition to data analytics, data security and systems integration are also core challenges for developers of the next generation of innovative RPM devices. This includes overcoming technological barriers on applying machine learning algorithms to patient data directly on devices and regulatory barriers on patient data privacy. To address these challenges, this study proposed a unified edge-cloud computing architecture to effectively integrate all the RPM devices in use by the individual patient. All the remote patient monitoring data are managed by edge computing, only the latent representations are uploaded to the cloud for AI-assisted decision making. The proposed model has three modules. The edge medical image module used a subspace learning model for anomalies detection and unhealthy signs and symptoms classification. The edge medical time series module used spectral residual for anomalies detection and scattering wavelet network for severity classification. The cloud telehealth management module used convolutional neural network, recurrent neural network and attention model to provide individual patient treatment plan and medicine delivery schedule. The proposed platform has been tested on various RPM devices to provide AI-based anomaly detection and symptoms classifications. The application of the proposed platform has demonstrated that the on-device training model can enable faster and more accurate diagnosis and treatment. For meso-level organizational interoperability on health information exchange, we will only transmit the latent representation instead of the patient's raw data to reduce cyberattacks and ensure confidentiality of health data.**

***Index Terms*—Remote Patient Monitoring, Intelligent Edge, Cloud Computing**

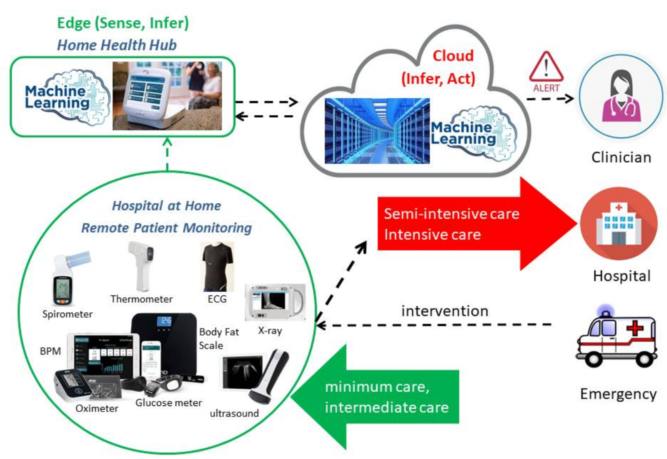

Fig. 1. The proposed edge-enabled cloud computing remote patient monitoring platform

I. Introduction

Chronic diseases, also known as non-communicable diseases, are responsible for approximately 70% of all deaths globally, according to the World Health Organization. The four main categories of chronic diseases are cardiovascular disease, cancer, respiratory diseases and diabetes. When these chronic diseases become severe, they are expensive to treat and negatively impact a patient's quality of life.

978-1-6654-1252-0/21/$31.00 ©2021 IEEE
DOI 10.1109/SMARTCOMP52413.2021.00049

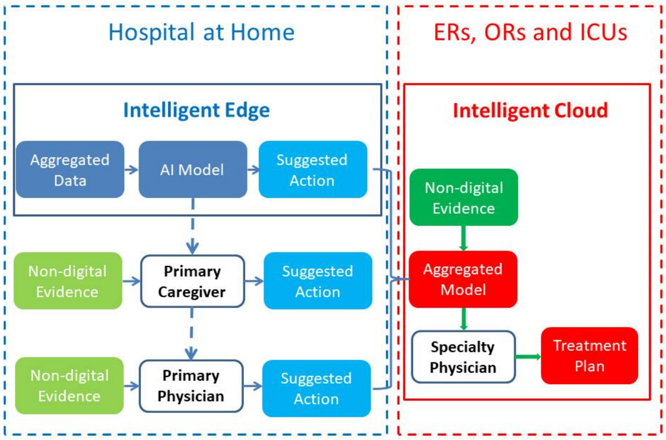

Fig. 2. Application of proposed platform for digital health remote patient monitoring

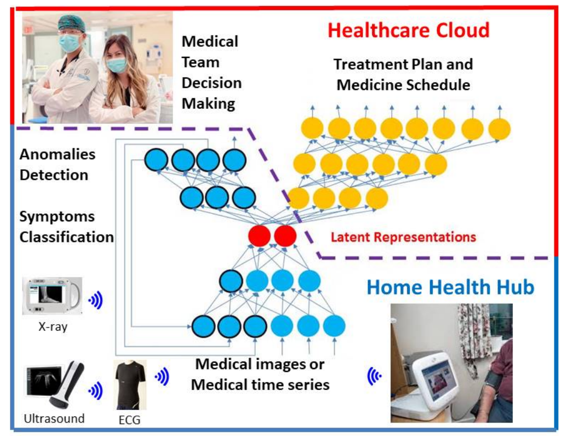

Fig. 3. Framework of edge-cloud platform for smart healthcare

Currently, over 50 million persons in Europe have more than one chronic disease, and this number will increase dramatically in the near future. European Union (EU) 2020 project SELFIE (Sustainable intEgrated care models for multi-morbidity: delivery, Financing and performancE) will contribute to the current state of knowledge and provide applicable policy advice on integrated care for persons with multi-morbidity. In the US, the Centers for Medicare & Medicaid Services (CMS) executed an innovative Acute Hospital Care At Home program in November 2020, providing eligible hospitals with unprecedented regulatory flexibility to treat eligible patients in their homes as shown in Fig. 1.

CMS believes that treatment for more than 60 different acute conditions, such as asthma, congestive heart failure, pneumonia and chronic obstructive pulmonary disease (COPD) care, can be treated appropriately and safely in home settings with proper monitoring and treatment protocols. [1-3]

It is important to note that patients will only be admitted to the program from emergency departments and inpatient hospital beds, and an in-person physician evaluation is required prior to starting services at home as shown in Fig. 2.

North Shore University Hospital of Northwell Health (NY)affiliated with one of the author was approved for Acute Hospital Care at Home Programin December 2020. By May 2021, 56 healthsystems, 129 hospitals in 30 states have been approved by CMS to treat eligiblepatients in their homes on Acute Hospital Care At Home program platform. In this study, we will address two of the issues laid out in the SELFIE project on technologies and medical products, (1) Micro-level digital health tools for electronic medical records from patient monitoring devices, (2) Meso-level organizational interoperability on health information exchange.

The subspace learning model is proposed to be used as the digital health tools to provide on-device training on portable imaging devices for remote patient monitoring. The spectral residual for anomalies detection and scattering wavelet network for severity classification are proposed for time series remote patient monitoring devices. All the patient monitoring data and severity analysis are managed by edge computing. Only the latent representations are uploaded to the cloud and further analyzed to provide AI-assisted decision making to the physicians.

II. Methodology

Traditional commercially available remote patient monitoring software relies on patient-reported data, as well as connected devices. For example, a patient can connect their blood glucose meter to upload data, as well as input their temperature. This is fine with a single device updating the discrete information continuously. But with the advancement of the Acute Hospital Care At Home program, multiple devices are required to monitor multiple image and video information.

We proposed to update and integrate such a traditional control and measure device with the edge imaging module and edge time series module to have edge computing leads the measure and process for all remote patient monitoring devices at a patient's home or nursing home.

As shown in Fig. 3, the latent representation of all the parameters monitored at the patient's home will be transferred to the cloud manufacturing management module. The cloud computing will compute and provide all the necessary information needed by the healthcare team to make informed decisions.

A. The edge imaging module

Computer vision is the fundamental building blocks of the edge imaging module. The recent advancement of deep learning algorithms improves characterization and classification of complex patient monitoring. We use the successive subspace learning (SSL) model to replace the standard convolutional neural network (CNN) for image detection and classification on the edge.[4, 5, 6, 7]

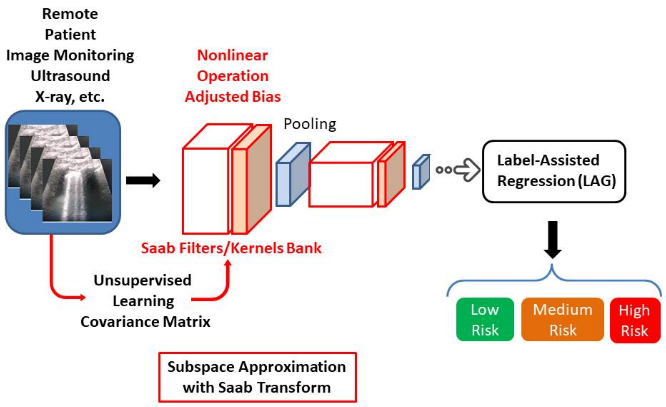

Fig. 4. Succesive subspace learning for edge imaging module

As shown in Figure 4, both models have similar processes to create feature maps, convolution operation, nonlinear operation and pooling operation. The difference is CNN needs backpropagation to update filter weights and needs more computing power where SSL using subspace approximation that computes filter weights on feed-forward fashion with minimum computing requirement. With this simplified model on-device training can easily be implemented without the overhead of traditional CNN deep learning frameworks such as tensorflow or pytorch. No AI accelerator chip will be needed.

Anomaly detection is the fundamental building block of the edge time series module for remote patient monitoring systems.

B. The edge time series module

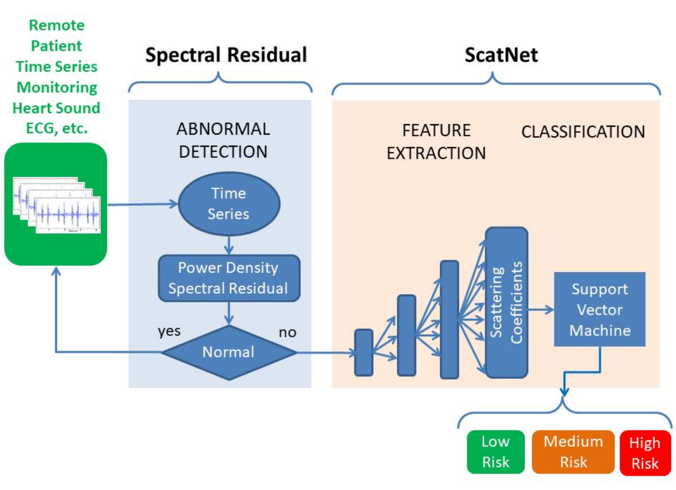

Fig. 5. Spetral residual and wavelet scattering network for edge time series module

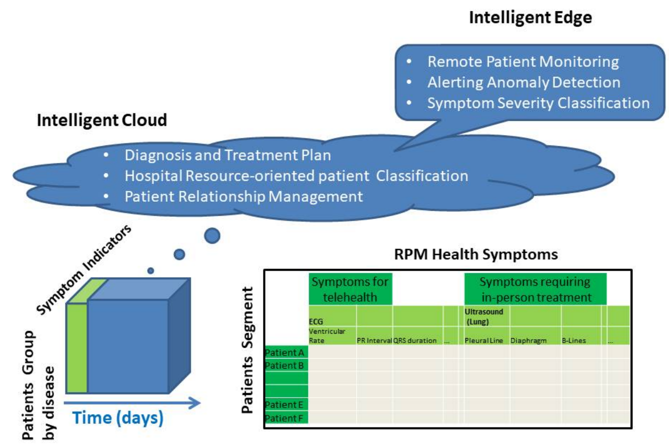

Fig. 6. Smart remote patient monitoring will provide anomaly detection and symptom severity classification alerts to the healthcare cloud for further actions

While you have multiple RPM devices at home, there is no need to upload all the normal data to the cloud continuously.

Only the abnormal ones are needed. For minute-level time series, we use the 2-stage approach as shown in Fig. 5. . In the first stage, we take the Fourier Transform of the autocorrelation of the time series and use power spectral density residual for abnormal detection. In the second stage, we use a simplified scattering network for feature extraction and classification. The scattering network has similar operation as convolutional neural network.[8, 9, 10] It uses a low pass filter for pooling, wavelet function as filter weight and norm as nonlinear activation. It can extract significant features without GPU-based computational hardware.

C. The cloud remote patient monitoring management module

All the hospitals and healthcare providers have their own medical triage and diagnosis systems in their daily practices. The cloud remote patient monitoring management module can be easily integrated into their system as part of their workflow. The digital healthcare cloud provides the platform for healthcare teams to interact with its associated testing laboratories, pharmacies and patients. Other than exceptional emergency cases, based on the status of the patients, the healthcare team needs to forecast treatment schedules for patients and order prescription schedules for pharmacies. The healthcare operation management cube is shown in Figure 6. The daily report generated from all the patients by the edge computing modules contains various symptoms and severity analysis and their treatment schedule, prescription medicine inventory status, symptoms severity status, etc. Both symptom and symptom severity classification are generated for every patient. The cumulative daily reports as shown in Fig. 6 are the input for the healthcare analytics by cloud computing.

The cloud healthcare management module will take the operation management cube as input and generate status prediction for any given individual patient.

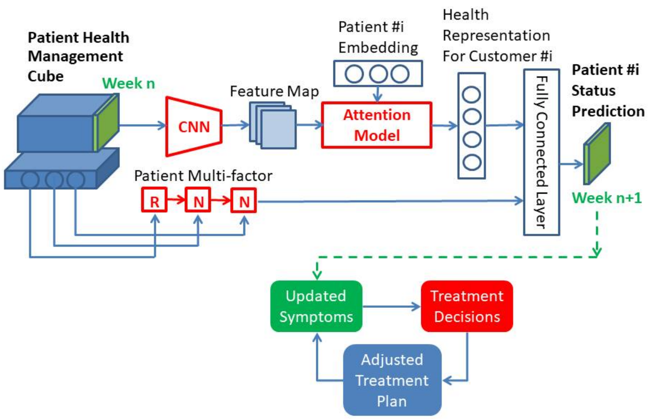

Fig. 7. Convolution and recurrent neural networks for the cloud remote patient monitoring management module

As shown in Figure 7, we use the combination of convolutional neural network (CNN), recurrent neural network (RNN) and attention model to forecast individual patient treatment and prescription drug delivery schedule.[11,12]

This combined RNN-CNN model is an approximation of the nonlinear dynamic system of treatment-symptom for all the similar patients with similar symptoms from all the patients using the edge RPM devices. The similarity scores can be calculated from the latent representation transmitted from the edge directly, without reconstructing the original images or time series. There are many factors that help the medical team to decide what individualized treatment plan to be established. Risks: What are the risks or problems associated with treatment? What are the side effects and potential for complications? What are the financial costs? Benefits: What are the potential benefits? Does the treatment address the problem? Evidence: How much evidence (research or experience) exists? Does it support the efficacy and safety of the treatment? In addition to all the American Medical Association (AMA) treatment guidelines, Centers for Disease Control (CDC) guidelines on the treatment and management, all the healthcare providers have their own treatment guidelines in their own system. All these guidelines can be integrated with the treatment plan workflow. A cohort is defined as a subset of the general population that shares one or more defining characteristics. The analysis of cohorts has proven effective in the medical community for identifying factors that affect patient recovery and treatment. In clinical applications, cohorts can be defined by utilizing patient data collected through remote patient monitoring. Cohorts of patients formed from RPM data have the potential to be used for "patients-like-me" comparisons, in which proper clustering can define a cohort with attributes similar to a given target patient. A few personalized treatment options can be recommended from this analysis.

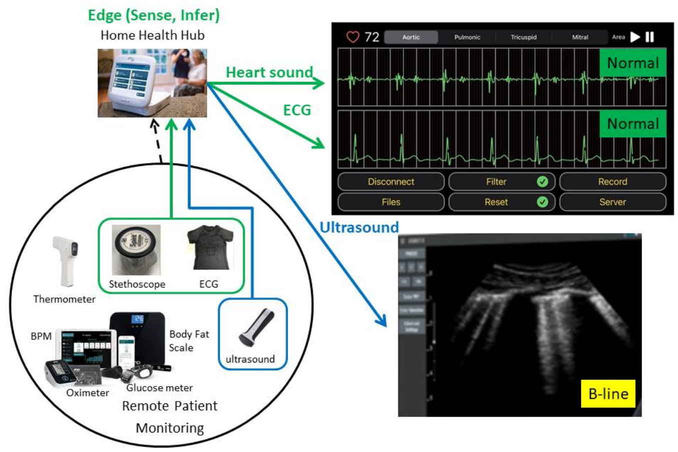

Fig. 8. Integration of edge time series module to a digital stethoscope for heart sound monitoring, and to ECG smart cloth for heart condition monitoring can yield 98.3% accuracy

III. Results and Discussion

Based on the private by design concept, the edge remote patient monitoring modules can be integrated into all the monitoring devices for the remote patients. Alternatively, both imaging modules and time series modules can also be implemented in the home healthcare hub, so the patient's raw data still stays at the patient's home.

A. The edge imaging module

Physicians have used handheld ultrasound devices for monitoring pneumonia patients in developing countries and other places with limited X-ray equipment. And unlike a static X-ray, ultrasound produces many images per second, allowing the provider to see a real-time "movie" of the lungs in action. Analysis revealed that ultrasound had correctly identified almost all of the pneumonia cases, whereas X-rays identified only about two-thirds of them. Yet while correctly capturing most of the true cases, ultrasound also was more likely than X-ray to yield a "false positive". These are the decisions the healthcare team needs to decide. As far as patient monitoring is concerned, to accurately indicate the level of severity of the patient and send an alarm to the healthcare team is all it requires. We integrated the successive subspace learning (SSL) model with the portable ultrasound system[14] and can be used to monitor if a covid-19 patient's lung is recovering or getting worse[15] as shown in Fig. 8.

B. The edge time series module

We applied the proposed two-stage algorithm for ECG wearable devices for abnormality detection.[16,17,18] By combining the spectral residual and wavelet scattering network, a Fast Fourier Transform (FFT) based SR-ScatNet algorithm required much less computation and can be done on smart cloth ECG

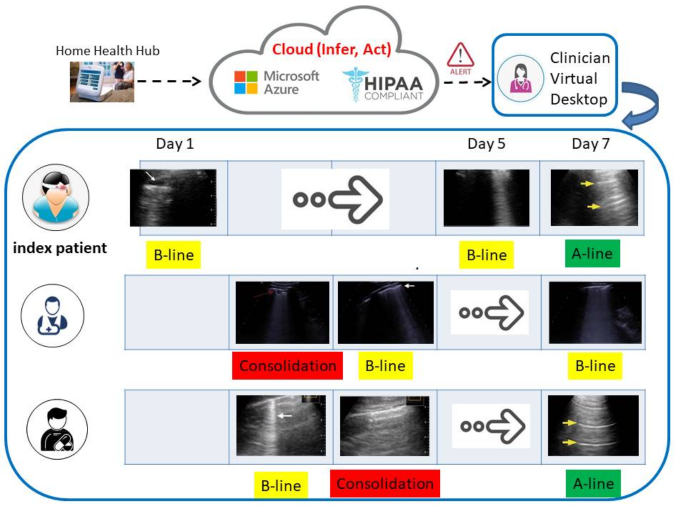

Fig. 9. The cloud remote patient monitoring management module has been integrated with Azure, patients' ultrasound images and symptom progression can be easily reconstructed in the cloud and shared through Azure virtual desktop

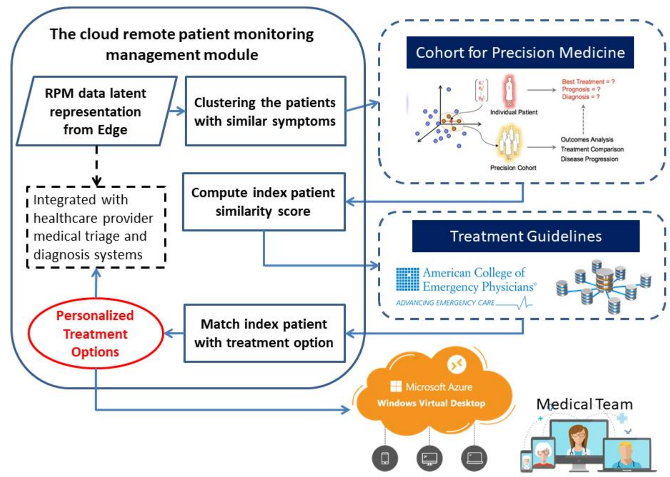

Fig. 10. The cloud remote patient monitoring management module, interconnected to healthcare cloud with precision medicine cohort and medical cloud with treatment guidelines, can provide personalized treatment options in the cloud and shared with all the members of medical team through Azure virtual desktop

sensor platform. The detection itself can be done on device without the need to transfer all the personal ECG data to the cloud as shown in Fig. 8

The purpose of wearing ECG monitoring smart cloth is for early detection not for diagnostic potential heart disease.

It is more important to know the level of risk when we detect any abnormal ECG signals, so the proper action can be taken. Whether it is the need to call an ambulance rush to the hospital emergency room or the need to call upon a family doctor for further examination. Here we try to aggregate the different abnormal signals into three different levels, high risk, medium risk and low risk. The satisfactory result of integrating the edge time series module into the smart ECG cloth is shown in Fig. 8

C. The cloud remote patient monitoring management module

Before implementing the cloud remote patient monitoring management module, the healthcare provider had a huge amount of live images and time series data gathered from various monitoring devices just for a single patient, in addition to all the treatment plans with medications. The cloud remote patient monitoring management module provides a platform to keep the patient's monitoring data and related decision making stay on the patient's home with edge computing. Only the necessary latent representations of the patients need to be uploaded to the cloud for interactive analysis for the hospitals and pharmacies. Latent representations of the patients can be used to create the digital copy of the patient's conditions at home in the cloud as shown in Fig. 9 for symptom progression monitoring.

In the cloud remote patient monitoring management module, the latent representation of images and time series symptoms from the edge modules can be used to directly compute the similarity between symptoms. The module is interconnected to healthcare cloud with precision medicine cohort and medical cloud with treatment guidelines, and can provide personalized treatment options in the cloud and shared with all the members of medical team through Azure virtual desktop as shown in Fig.10.

Based on the key feature information from the edge computing, now the cloud computing will utilize the RNN-CNN model to approximate the progression of the index patient. The model predictive control can be used to update the treatment options form symptom-treatment relationship for medical team to consider as shown in Fig.11.

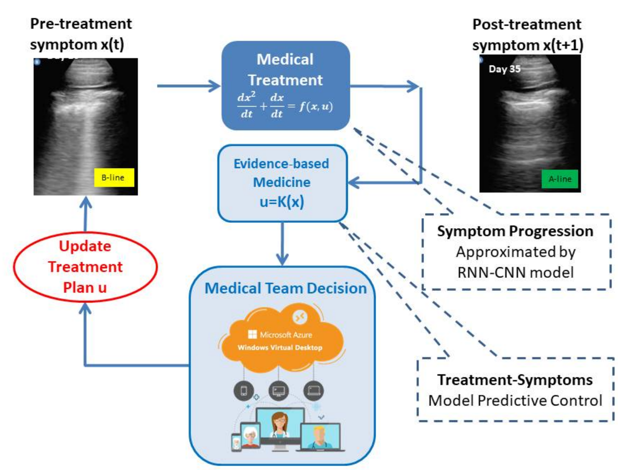

Fig. 11. The cloud remote patient monitoring management module can provide the updated sympotoms for medical team to update their treatment plan. The suggested treatment options can be shared with the medical team through the Azure virtual desk

The medical team can visulize and discuss individual patient's conditions and treatment plans from each physician's virtual desktop.

IV. Conclusion

We demonstrated a cloud computing management architecture for a digital health edge-driven remote patient monitoring system. The platform was built around the Acute Hospital Care At Home program required by US Centers for Medicare & Medicaid Services (CMS).

Successive subspace learning model based on the paradigm of successive learning of representations followed by a decision layer is used to build an edge image module.

A spectral residual based anomaly detection network in which the representation is formed in a wavelet scattering manner is used to build edge time series modules.

Once the cloud remote patient monitoring management module received the latent representations from both edge image and time series module, it uses both feedforward and feedback neural networks to predict the treatment schedules and medication delivery schedules.

The proposed platform collaborates with edge and cloud computing to use edge devices to maintain the workflow in remote patient monitoring at patient's home, and use cloud service to interact with clinician and pharmacies.

The COVID-19 pandemic has not only forced many professionals to work from home, but also pushed people suffering from various ailments to opt for home health care services instead of going to hospitals for treatment. We believe the home health care system has a lot to offer as more intelligent remote patient monitoring devices become available in the future.

References

[1] J. Guo et al., "Cyber–Physical Healthcare System With Blood Test Module on Broadcast Television Network for Remote Cardiovascular Disease (CVD) Management," in IEEE Transactions on Industrial Informatics, vol. 17, no. 5, pp. 3663-3670, May 2021

[2] T. Zhang et al., "A Joint Deep Learning and Internet of Medical Things Driven Framework for Elderly Patients," in IEEE Access, vol. 8, pp. 75822-75832, 2020

[3] D. Hayn et al., "Telehealth Services for Home-based Rehabilitation of Cardiac Patients," 2020 Computing in Cardiology, 2020, pp. 1-4

[4] Y. Zhu, S. Suri, P. Kulkarni, Y. Chen, J. Duan and C. -. J. Kuo, "An Interpretable Generative Model for Handwritten Digits Synthesis," 2019 IEEE International Conference on Image Processing (ICIP), 2019, pp. 1910-1914

[5] Y. Chen, M. Rouhsedaghat, S. You, R. Rao and C. . -C. Jay Kuo, "Pixelhop++: A Small Successive-Subspace-Learning-Based (Ssl-Based) Model For Image Classification," 2020 IEEE International Conference on Image Processing (ICIP), 2020, pp. 3294-3298

[6] X. Zhang et al., "Image Coding With Data-Driven Transforms: Methodology, Performance and Potential," in IEEE Transactions on Image Processing, vol. 29, pp. 9292-9304, 2020

[7] Y. Ding et al., "Saak Transform-Based Machine Learning for Light-Sheet Imaging of Cardiac Trabeculation," in IEEE Transactions on Biomedical Engineering, vol. 68, no. 1, pp. 225-235, Jan. 2021

[8] J. Bruna and S. Mallat, "Invariant Scattering Convolution Networks," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 35, no. 8, pp. 1872-1886, Aug. 2013

[9] H. Zhou et al., "Weight-Variable Scattering Convolution Networks and Its Application in Electromagnetic Signal Classification," in IEEE Access, vol. 7, pp. 175889-175896, 2019, doi: 10.1109/ACCESS.2019.2957519.

[10] M. Khulbe, S. Kanaujia and M. R. Tripathy, "Wavelet Transforms and Neural Network for medical diagnosis," 2019 9th International Conference on Cloud Computing, Data Science & Engineering (Confluence), 2019, pp. 444-450

[11] Xiaobin Zhang, Fucai Chen, Ruiyang Huang, "A Combination of RNN and CNN for Attention-based Relation Classification", Procedia Computer Science, Volume 131, 2018, Pages 911-917

[12] Ercolano, G., Rossi, S., "Combining CNN and LSTM for activity of daily living recognition with a 3D matrix skeleton representation." Intel Serv Robotics 14, 175–185 (2021).

[13] D. Hou, M. D. Raymond Hou and J. Hou, "On-device Subspace Learning Chest X-Ray Screening," 2020 IEEE International Conference on Consumer Electronics (ICCE), 2020, pp. 1-5

[14] D. Hou, R. Hou and J. Hou, "On-device Training for Breast Ultrasound Image Classification," 2020 10th Annual Computing and Communication Workshop and Conference (CCWC), 2020, pp. 0078-0082

[15] D. Hou, R. Hou and J. Hou, "Interpretable Saab Subspace Network for COVID-19 Lung Ultrasound Screening," 2020 11th IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON), 2020, pp. 0393-0398

[16] D. Hou, M. D. Raymond Hou and J. Hou, "ECG Beat Classification on Edge Device," 2020 IEEE International Conference on Consumer Electronics (ICCE), 2020, pp. 1-4

[17] Hsin-Yu Feng, "Wavelet Scattering Network Model for Detection and Classification of Myocardial Infarction Electrocardiography (ECG) Signals," M.S. Thesis, Department of Mathematics, National Tsing Hua University, Hsinchu, 2020.

[18] H. -Y. Feng, P. -Y. Chen and J. Hou, "SR-ScatNet Algorithm for On-device ECG Time Series Anomaly Detection," SoutheastCon 2021, 2021, pp. 1-5