AN EFFECTIVE EDGE REGISTERING METHOD BASED ON EXCHANGE LEARNING FOR HOME HEALTH MONITORING

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ABSTRACT: The health-care gets huge stress in a pandemic or epidemic situation. Some diseases that cause a pandemic is highly spreadable from an infected person to others. Therefore, providing health services at home for noncritical infected patients with isolation shall assist to mitigate this kind of stress. In addition, this practice is also very useful for monitoring the health-related activities of elders who live at home. The home health monitoring, a continuous monitoring of a patient or elder at home using visual sensors is one such nonintrusive sub-area of health services at home. Here, we propose a transfer learning-based edge computing method for home health monitoring. Specifically, a convolutional neural network-based VGG16 model is loaded into the AI sensors which is connected to the edge cloud servers for predicting the image and its accuracy. Therefore, on-site computing of visual data captured by thermal sensor could be possible in an affordable way. As a result, raw data captured by these types of sensors is not required to be sent outside from home. Therefore, privacy, security, and bandwidth scarcity shall not be issues. Moreover, real-time computing for these purposes shall be possible in an economical way.
Keywords: *AI-enabled Health Monitoring, Ambient Intelligence, Computer Vision, VGG-16, Deep Learning, Edge Computing, Transfer Learning, Visual Sensors.*

1. INTRODUCTION

In India, only 1.9 millions hospital beds in all kind hospitals are currently available for population around 1.35 billion [1]; that is, only 1.4 beds per 1000 peoples. This situation is also not far better in other countries [2]. In addition, those countries that are comparably on top of that list also may not be able to cope with the challenges arising from a pandemic. Therefore, home health services need to be improved to cope with a pandemic or epidemic situations. Moreover, as the percentage of aged people(elders) is increasing steadily [3], so home health services, are also very useful health practice for elders who live at home. As Artificial Intelligence (AI) is augmenting human capabilities for many human-centered tasks [4], [5], [6]. Therefore, AI could also assist home health services in many ways [7], [8]. Automated patient or elders monitoring (in short we are calling it 'Home Health Monitoring') one such non-intrusive and economical sub-area of these services; these sub-area may include activity monitoring, sleep monitoring, respiration monitoring, fall detection, facial expression understanding, speech recognition, hand hygienic practice monitoring, etc.

For these kind of tasks, deep learning (DL) and computer vision (CV) are very effective as studied in [10], [11], [12]. But DL especially for tasks of CV, required GPU-enabled computing devices, which may not be available for every household.

Fig.1 Home health monitoring system

To address this issue, one approach is to leverage cloud computing technique, where data needs to be sent to a remote cloud server for processing outside from home. But in this case, privacy, security and bandwidth scarcity are big issues and real-time computing may not be possible. These disincentives motivate to use the new technology of Edge Computing (EC). EC could be used to compute data of home health monitoring inside the home or house. However, some challenges also exist as edge devices (ED) are generally small and have low computing capabilities. In addition, the DL-based model usually takes a large amount of data which is also a big challenge for health sectors.

2. LITERATURE REVIEW

Human-centered artificial intelligence: Reliable, safe & trustworthy

Well-designed technologies that offer high levels of human control and high levels of computer automation can increase human performance, leading to wider adoption. The Human-Centered Artificial Intelligence (HCAI) framework clarifies how to (1) design for high levels of human control and high levels of computer automation so as to increase human performance, (2) understand the situations in which full human control or full computer control are necessary, and (3) avoid the dangers of excessive human control or excessive computer control. The methods of HCAI are more likely to produce designs that are Reliable, Safe & Trustworthy (RST). Achieving these goals will dramatically increase human performance, while supporting human self-efficacy, mastery, creativity, and responsibility.

A Nurse-Driven Method for Developing Artificial Intelligence

To offer practical guidance to nurse investigators interested in multidisciplinary research that includes assisting in the development of artificial intelligence (AI) algorithms for "smart" health management and aging-in-place. Methods: Ten health-assistive Smart Homes were deployed to chronically ill older adults from 2015 to 2018. Data were collected using five sensor types (infrared motion, contact, light, temperature, and humidity). Nurses used telehealth and home visitation to collect health data and provide ground truth annotation for training intelligent algorithms using raw sensor data containing health events.

The practical implementation of artificial intelligence technologies in medicine

The development of artificial intelligence (AI)-based technologies in medicine is advancing rapidly, but real-world clinical implementation has not yet become a reality. Here we review some of the key practical issues surrounding the implementation of AI into existing clinical workflows, including data sharing and privacy, transparency of algorithms, data standardization, and interoperability across multiple platforms, and concern for patient safety. We summarize the current regulatory environment in the United States and highlight comparisons with other regions in the world, notably Europe and China.

Remote patient monitoring: a comprehensive study

Healthcare is a field that is rapidly developing in technology and services. A recent development in this area is remote monitoring of patients which has many advantages in a fast-aging world population with increasing health complications. With relatively simple applications to monitor patients inside hospital rooms, the technology has developed to the extent that the patient can be allowed normal daily activities at home while still being monitored with the use of modern communication and sensor technologies. Sensors for monitoring essential vital signs such as electrocardiogram reading, heart rate, respiration rate, blood pressure, temperature, blood glucose levels and neural system activity are available today. Range of remote healthcare varies from monitoring chronically ill patients, elders, premature children to victims of accidents. These new technologies can monitor patients based on the illness or based on the situation. The technology varies from sensors attached to body to ambient sensors attached to the environment and new breakthroughs show contactless monitoring which requires only the patient to be present within a few meters from the sensor. Fall detection systems and applications to monitor chronical ill patients have already become familiar to many. This study provides a review of the recent advances in remote healthcare and monitoring in both with-contact and contactless methods. With the review, the authors discuss some issues available in most systems. The paper also includes some directions for future research.

Vision-based patient monitoring: a comprehensive review of algorithms and technologies:

Vision-based monitoring for assisted living is gaining increasing attention, especially in multi-modal monitoring systems owing to the several advantages of vision-based sensors. In this paper, a detailed survey of some of the important vision-based patient monitoring applications is presented, namely (a) fall detection (b) action and activity monitoring (c) sleep monitoring (d) respiration and apnea monitoring (e) epilepsy monitoring (f) vital signs monitoring and (g) facial expression monitoring. The challenges and state-of-art technologies in each of these applications is presented. This is the first work to present such a comprehensive survey with the focus on a set of seven most common applications pertaining to patient monitoring. Potential future directions are presented while also considering practical large-scale deployment of vision-based systems in patient monitoring. One of the important conclusions drawn is that rather than applying generic algorithms, use of the application context of patient monitoring can be a useful way to develop novel techniques that are robust and yet cost-effective.

3. IMPLEMENTATION

EXISTING METHOD:

Existing researches of e-health has the potential of providing real-time medical services for the countryside with body sensor networks (BSN), but there are two limitations. On one hand, because of the medical services requiring not only low-latency but also high-quality, constructing an AI e-health service on resource-constrained fog with edge AI is necessary but unsolved. On the other hand, because of the regional differences in disease risk, there is a lack of an effective mechanism to provide a customized AI e-health service for patients in different regions. Firstly, semantics-based lightweight and meticulous load management mechanism is designed to reduce data load and involve medical semantic. Secondly, model-ensemble based AI collaborative analysis mechanism is proposed for load balance and knowledge integration.

Limitations:

- A major limitation is that this method has not been validated for clinical usefulness. Literature is scarce regarding: (a) anomaly detection categories, (b) the association between motion characteristics, specific diagnoses, and sensor activation combinations, and (c) AI algorithms capable of identifying changes in health states.

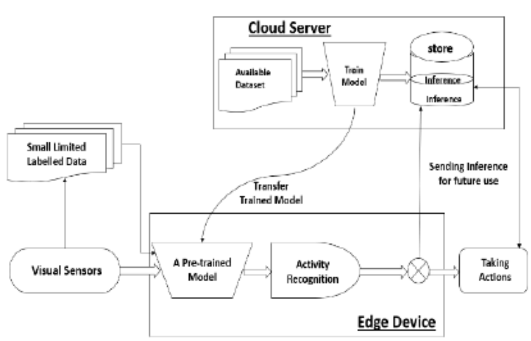

Fig.2: System architecture

PROPOSED METHOD:

In this work, we propose a transfer learning-based edge computing method for home health monitoring. Specifically, a pre-trained convolutional neural network-based VGG-16 model can leverage edge devices with a small amount of ground-labelled data and fine-tuning method to train the model. Therefore, on-site computing of visual data captured by RGB, depth, or thermal sensor could be possible in an affordable way. As a result, raw data captured by these types of sensors is not required to be sent outside from home. Therefore, privacy, security, and bandwidth scarcity shall not be issues. Moreover, real-time computing for the above-mentioned purposes shall be possible in an economical way.

Advantages:

- Real-time computing for these purposes shall be possible in an economical way.

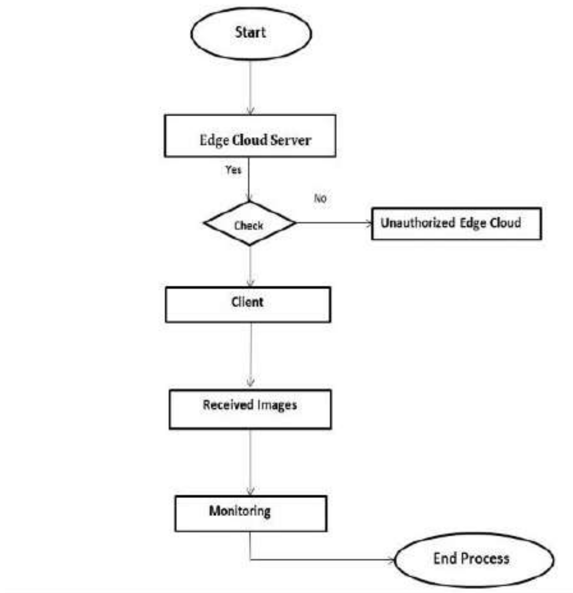

Fig.3: Dataflow diagram for Edge Cloud Server

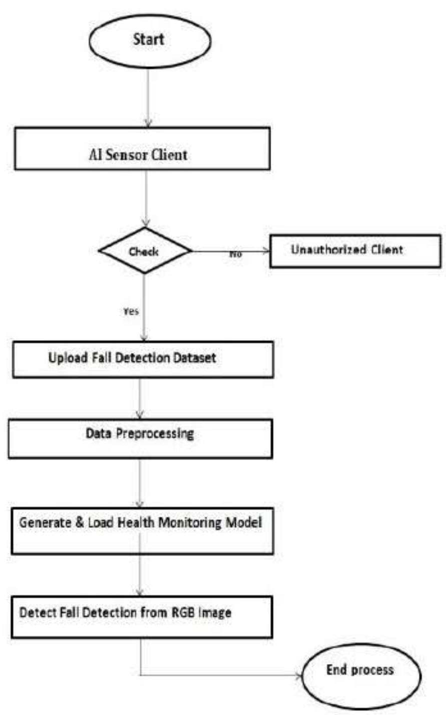

Fig.4: Dataflow diagram for AI Sensor Client

MODULES:

To implement this work, we have designed following modules

1) Edge Cloud Server: this is a cloud application which received images from client and display to medical peoples for monitoring

2) AI Sensor Client Application: this module we will upload dataset to train AI model and then load the model and whenever user upload any images then it will predict condition and report to cloud server.

A possible working scenario of TL-EC-HM is depicted in Fig. 5, where how a caregiver center, cloud server, ED, and IoT device(sensor) are connected to each other to form a system is shown. The highlights of this article are listed as below:

• We provide a study on health and activity monitoring for patient as well as elders at their home for mitigating health crisis.

• We propose a method (TL-EC-HM) based on DTL and EC for home health monitoring.

• We analyze the proposed privacy-preserving TL-EC-HM for on-site visual computing.

• We provide some future research directions.

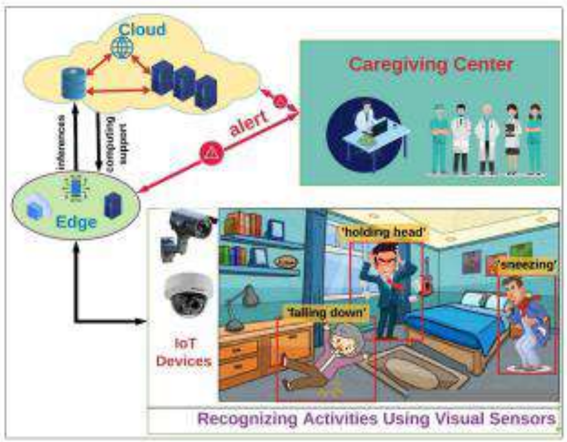

Fig.5: A working scenario of TL-EC-HM

4. ALGORITHMS

The proposed TL-EC-HM is works with association of some technical components such as sensor, EC, and DTL. These are directly relevant to this work, therefore these are first briefly mentioned, then the propose pipeline is discussed.

Type of Sensor May Used:

In order to do home health monitoring, mainly five types of sensors, i.e., RGB, Depth, Thermal (Inferred), Sound, and Wearable sensors may be used. As our proposed TL-EC-HM focuses on non-intrusive vision-based monitoring, so we pay attention to compute spatial data captured by first three type sensors that are visual in nature. Among these three types of sensors, RGB could give more details.

Edge Computing (EC):

Computing is the necessary functionalities to make desired inference from the data sensed by sensors. As mentioned, EDs that embedded with sensors have very limited computing capabilities, so, cloud or sometimes fog computing may be used. But in both cases, data needs to be sent outside of the home, so, privacy, security, latency, etc. become a huge problem and that leads towards the edge computing.

Deep Transfer Learning (DTL):

Modern AI technologies largely depends on DL. To train a DL model from scratch, it requires a massive amount of training data whereas medical data is not easily available. Moreover, the DL-based model usually requires large computing power such as GPU-enabled high resource consumption machine which is a big challenge for EC. On the other hand, DTL is a technique which uses features of an already trained DL model to solve new task with required fine-tuning. DTL significantly reduces the requirement for training data and computing resources for a target domain specific task.

VISUAL GEOMETRY GROUP-16 (VGG-16):

After detecting the fall actions, those action images are fed into a VGG16(Visual Geometry Group16) network for action recognition that is fall or not. VGG16 is a famous DL network architecture, and it has proven that VGG16 has good defect recognition results. Thus, the proposed method builds a VGG16 network to recognize the fall images.

Visual Geometry Group16 (VGG16) is a convolutional neural network model proposed by K. Simonyan and A. Zisserman from the University of Oxford in the paper "Very Deep Convolutional Networks for Large-Scale Image Recognition". The model achieves 92.7% top-5 test accuracy in ImageNet, which is a dataset of over 14 million images belonging to 1000 classes. It was one of the famous models submitted to ILSVRC-2014. It makes the improvement over AlexNet by replacing large kernel-sized filters (11 and 5 in the first and second convolutional layer, respectively) with multiple 3×3 kernel-sized filters one after another. VGG16 was trained for weeks and was using NVIDIA Titan Black GPU's.

The VGG16 network has five blocks. The first two blocks have two convolutional layers and one max-pooling layer, while the remaining three have three convolutional layers and one max-pooling layer. At the end of the last block, a global average pooling (GAP) layer is added for vectorization, and a classification layer is connected to the GAP. The architecture of the VGG16 network.

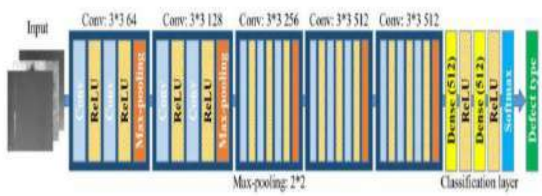

Fig.6: Architecture of the VGG16 Network

5. EXPERIMENTAL RESULTS

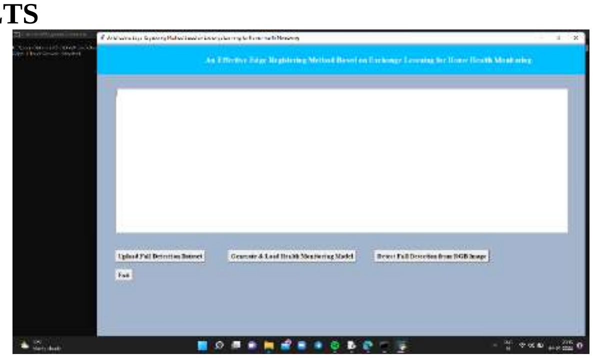

Fig.7: Home screen

In above client application user can click on 'Upload Fall Detection Dataset' button to upload dataset and get below output

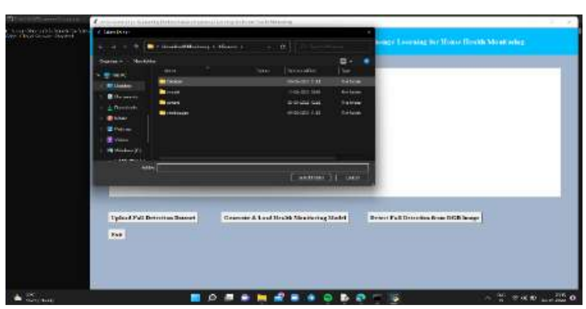

Fig.8: Upload dataset

In above screen selecting and uploading 'Dataset' folder and then click on 'Select Folder' button to load dataset and get below output.

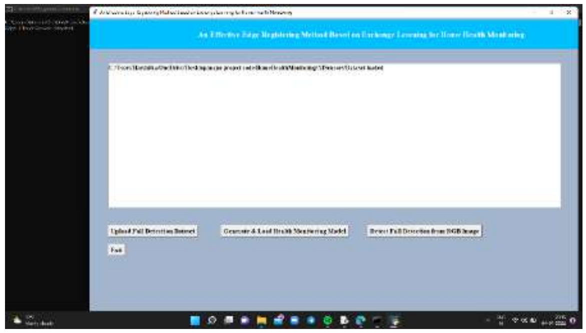

Fig.9: Dataset loaded

In above screen dataset loaded and now click on 'Generate & Load Health Monitoring Model' button to load model and get below output

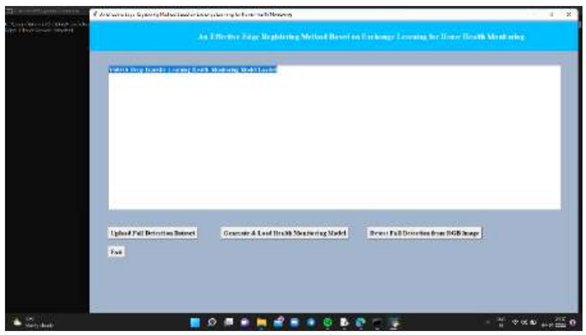

Fig.10: generate & health monitoring model

In above screen VGG16 transfer learning model loaded and now click on 'Detect Fall Detection from RGB image' button to upload image and get below output

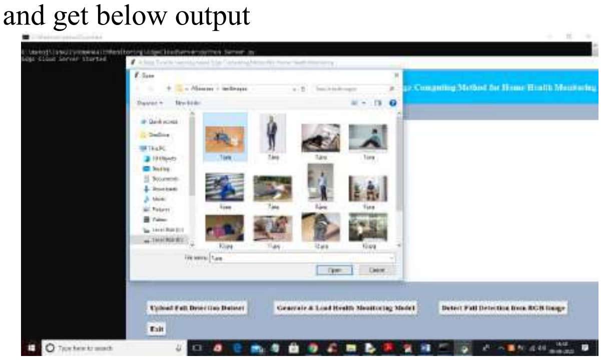

Fig.11: detect fall detection from RGB image

In above screen selecting and uploading '1.jpg' file and then click on 'Open' button to get below prediction result.

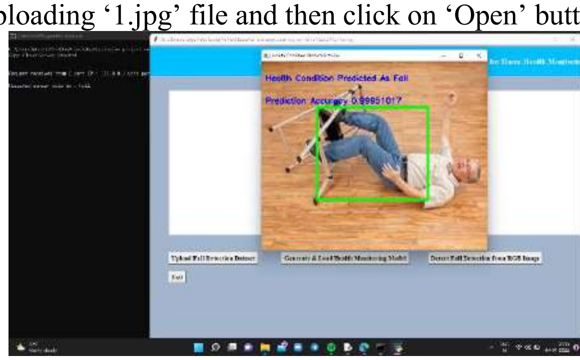

Fig.12: Prediction result-1

In above screen in uploaded image in blue colour text we can see patient in image condition predicted as Fall with accuracy 0.99 and the same output is report to cloud server which we can see in black console and now test another image

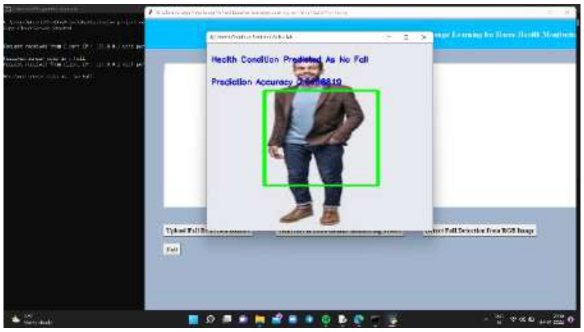

Fig.13: Prediction result-2

In above image also AI predicted as FALL and now test other images.

Fig.14: Prediction result-3

In above screen patient condition predicted as NO FALL and similarly you can upload and test other images. All the above uploaded image we can see inside cloud 'files' folder with result for future monitoring.

6. CONCLUSION

To mitigate the health crises in a pandemic or to take care elders in an affordable way, home health monitoring would be very beneficial. In this article, we have proposed a computer vision-based method where a deep transfer learning is used in edge devices as edge computing. In this approach, the raw visual data continuously capture by visual sensor(s) is not required to be sent outside of home. Therefore, privacy, data security as well as latency are not big issues.

7. FUTURE SCOPE

The proposed method has large scopes of applicability with further investigation. A pilot study by this method including dataset creation, system setup, and data analytics is felt immediate next phase of the study. The main required components of this method are: A VGG-16 based action recognition model, a suitable available dataset for training the model, a small set of ground labeled dataset for fine-tuning, and instruments including IoT based visual sensors-enabled ED, cloud server, caregiver centre, home space, etc. Using this setup, a pilot study shall be carried out. Before pilot study, one may choose a simulation study. Moreover, this visual sensor-based monitoring could also merge with other ambient sensors to add more features in this home health monitoring.

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