International Journal for Innovative Engineering and Management Research
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IJIEMR Transactions, online available on 07th Jan 2023. Link :http://www.ijiemr.org/downloads.php?vol=Volume-12&issue=ISSUE-1

DOI: 10.48047/IJIEMR/V12/ISSUE 01/43

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Volume 12, Issue 1, Pages: 485-494

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International Journal for Innovative Engineering and Management Research
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To Improve Health Monitoring at Home Using Deep Transfer Learning and Edge Computing.

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ABSTRACT— In the midst of an epidemic or pandemic, health care systems are put under extreme strain. It is quite easy for an infected individual to disseminate a pandemic illness like COVID-19 to the rest of the population. others. Therefore, reducing this kind of stress by providing health treatments at home for noncritical infected patients experiencing isolation is an important goal. This method is also quite helpful for keeping tabs on how at-home seniors are doing when it comes to their health. Home health monitoring is one such area of care provided in the comfort of one's own home that does not intrude on the patient's or senior's privacy. This paper proposes a home health monitoring system that uses edge computing and transfer learning. In particular, a model based on a pre-trained convolution neural network may take use of edge devices by using a minimal quantity of ground-labeled data and a fine-tuning technique. This suggests that inexpensive on-site processing of visual data recorded by an RGB, depth, or temperature sensor is feasible. Thus, there is no need to transmit the raw data collected by these sensors to an external source. As a result, concerns about confidentiality, safety, and inadequate bandwidth will be moot. The aforementioned uses for real-time computing must also be feasible on a budget.

INTRODUCTION:

Out of a total population of about 1.35 billion, only 1.9 million hospital beds across all hospital types are available in India. This equates to just 1.4 beds per 1000 persons. As a corollary to this, the scenario is not much better elsewhere. In addition, even the nations at the top of the list may be unprepared to deal with the consequences of a pandemic. As a result, in the face of a pandemic or epidemic like COVID-19, improvements to home health care are necessary. Moreover, given the rising

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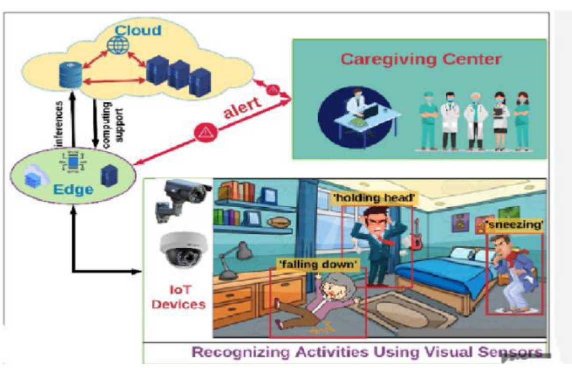
number of elderly persons, home health services are becoming increasingly important for independent seniors. Since AI is helping humans in numerous ways , it is clear that AI is enhancing human skills in many areas where humans play a central role. As a result, AI might help home health care in various ways. One such non-intrusive and cost-effective sub-area of these services is automated patient or elder monitoring (shortly we are calling it "Home Health Monitoring"); this sub-area may include activity monitoring, sleep monitoring, respiration monitoring, fall detection, facial expression understanding, speech recognition, hand hygienic practise monitoring, etc. Research shows that deep learning (DL) and computer vision (CV) are particularly useful for these kinds of tasks. But DL, particularly for CV activities, necessitated GPU-enabled computer equipment, which may not be commonplace in all households. One way to solve this problem is by using the cloud computing method, which entails transferring data to a distant cloud server for processing at a location different from the user's usual environment. However, real-time computing may not be viable due to concerns about privacy, security, and bandwidth limitations. These drawbacks encourage use of Edge Computing (EC) . Computing data from in-house health monitors might be done using EC.However, there are obstacles to overcome, since edge devices(ED) are often compact and have limited computational capabilities . Another major difficulty for the healthcare industry is the vast quantity of data required for DL-based models .We propose a deep transfer learning-based edge computing approach for in-house health monitoring in this research (TL-ECHM). Here, we use a transfer learning strategy, whereby a model based on a previously trained Convolutional Neural Network (CNN [19]) and its existing dataset may be fine-tuned for use in ED with a very modest amount of ground-label data. This manner, less processing power would be needed, and EDs would be able to do the necessary visual computing locally. As a result, it should be feasible to lessen the impact of the aforementioned problems. In Fig. 1, we see a potential implementation of TL-EC-HM, complete with a caregiver hub, cloud server, ED, and Internet of Things device (sensor) all interconnected. Some of the article's most salient points are as follows:

We provide a research on health and activity monitoring for patients and the elderly in the home as a means of preventing medical emergencies.

• We suggest a DTL and EC-based approach (TL-EC-HM) for health monitoring in the home.

•We present some suggestions on where future research may go in order to build upon the foundation laid by our analysis of the proposed privacy-preserving TL-EC-HM for localised visual computing.



RELATED WORK

Beds, ICU beds, and ventilators in Indian hospitals as of Covid19, by state

Policymakers all across the world have been forced by the fast spread of COVID-19 to assess the sufficiency of their local health care infrastructure. Numerous hard-hit areas have seen an inflow of severe cases, putting a pressure on medical facilities. Considering the rapid spread of COVID19 in India, it is crucial to assess the country's ability to manage particularly severe cases.

To estimate the number of hospital beds, intensive care unit beds, and mechanical ventilators in each Indian state, we pooled information from both the public and private healthcare sectors. We assessed capacity in each Indian state and union territory by using data from the 75th wave of the National Sample Survey (2017-2018) and the number of hospitals in the public sector from the 2019 National Health Profile (NHP) of India (UT). We assumed that half of all intensive care unit beds had ventilators installed in them, and that 5% of all hospital beds were ICU beds.

From our research, we determined that there are around 1.9 million hospital beds, 95,000 intensive care unit beds, and 48,000 ventilators in India. There are more private than public beds, intensive care unit beds, and ventilators on a national scale (1,185,242 vs. 713,986), and more private than public ICU beds and ventilators. Our research indicates that there is a significant disparity in available resources between the 50 states and the UTs.

Acute care hospitals are ready for covid-19

Hospitals are an integral aspect of the healthcare system because they provide urgently needed medical attention to the public. Hospitals and the healthcare system as a whole might be overwhelmed by the steady spread of illness and the rapidly rising demand for services brought on by prolonged and coupled outbreaks. In order to better prepare hospitals for emergencies such as an epidemic, pandemic, or natural catastrophe, hospital administrators must oversee the implementation of appropriate general priority action. The purpose of this paper is to serve as a checklist for the most important things to accomplish as part of an ongoing hospital emergency preparation strategy.

We hope that this checklist will be useful to hospital administrators and emergency planners in identifying and implementing the steps necessary to guarantee a swift response to the COVID-19 epidemic, as outlined above. The checklist is broken down into eleven sections, and inside each section, there is a set of questions to ask about the current state of a suggested activity. Healthcare facilities that may see an uptick in patient demand should be ready to swiftly execute each measure. In the "Recommended reading" section, we've compiled a list of resources that we think are particularly useful for learning more about each component.

METHODOLOGY

Adjusting the Settings of a Fully-Trained CNN: This is the initial stage of computation in ED. To begin, a small sample of actual data gathered by installed sensors with ground truth label is prepared for train and test as:

dataT rain0 = {(x 0 i , y0 i) : i = 1 to n}

dataT est0 = {(x 0 i , y0 i) : i = 1 to n 0 }

Later, this dataset is used to fine-tune the trained CNN, preparing the ED to carry out the necessary EC. It's the same deal here; you choose a series of actions from 1 to C 0. The last few layers of the trained CNN-based model undergo the same set of operations as in (1), (2), and (3) (again, this varies by task and ED). Once they are completed, EDs will be able to detect and react to a live video's frames in real time.

Running activity recognition involves creating a CNN-based activity detecting model and then extracting overlapping frames from a live video feed using a windowing technique. The CNN is used on each window to get a probability score at

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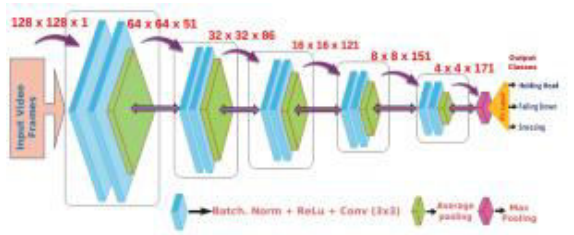
that level. After that, a mean is calculated at the frame level. Let's say the window size is [t1 to t2], and we take K overlapping frames to compute the probability score for each frame.

$$\hat{y_i}' = \frac{1}{K} \sum_{\forall j \in K} \hat{y_j}$$

where the mean and individual frames of the window [t1, t2] are assigned probability ratings denoted by ybi 0 and ybi, respectively. The softmax score, which represents the likelihood of an event occurring in a given frame, is used to identify motion in individual frames. With them, we may determine how accurate our judgments and inferences typically are across all frames. After that, the data is sent to a caregiver hub, where it is processed, and then to a cloud server, where it is stored.

Achieving Results: The CDC gets a generalisation about the kind of caregiver needed. Categories might include "severe alarm," "service necessary," etc. The care facility acts in accordance with these classifications. These steps may include providing a service, consulting with medical professionals, etc. Data may be kept in the cloud and retrieved as needed for long-term monitoring of the sick or the elderly person.

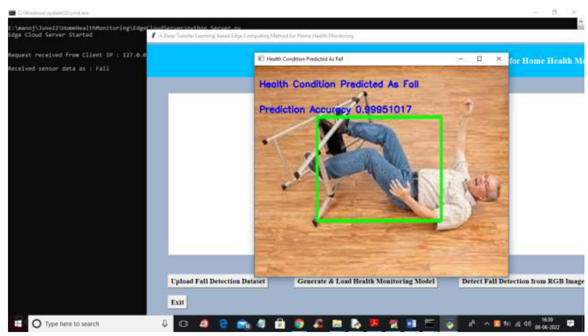
The patient or senior citizen will be more likely to employ home health monitoring services if they know that only conclusions (not raw data) leave the house.



Architecture and number of parameters of our CNN.

RESULT AND DISCUSSION

Health monitoring models may be generated and loaded when the uploaded Fall Detection Dataset has been opened in Dataset open. Use a jpeg picture to detect whether or not a person has fallen using a red-green-blue image.



Similarly, the above picture was likewise predicted by AI to be a FALL; now it is being tested with other photographs.

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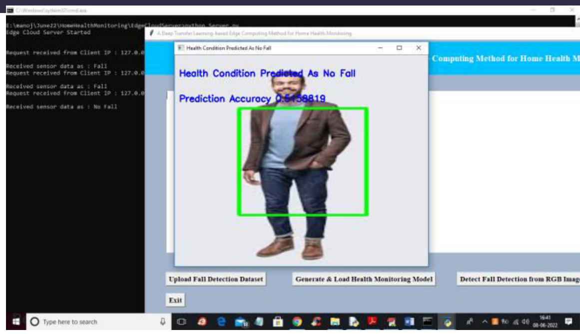

Above, the patient's status is shown to be NO FALL.

CONCLUSION

In the event of a pandemic or to provide cost-effective care for the elderly, home health monitoring would be an invaluable tool. An essay proposing a computer system was written here.edge computing relies on a vision-based strategy using deep transfer learning in edge devices. The method relies on internal processing and does not need the transmission of the raw visual data continually captured by visual sensor(s). As a result, latency, lack of privacy, and security of data are not major concerns.

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