Remote Reading of ICU Monitor`s Physiological Readings: An Image Processing Approach.

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Abstract

As a result of the global effect of infectious diseases like COVID-19, remote patient monitoring has become a vital need. Surgical ICU monitors are attached around the clock for patients in critical care. Most ICU monitor systems, on the other hand, lack an out port for transferring data to an auxiliary device for post-processing. Similarly, strapping a slew of wearables to a patient for remote monitoring creates a great deal of discomfort and limits the patient's mobility. Hence, an unique remote monitoring technique for the ICU monitor's physiological vital readings has been presented, recognizing this need as a research gap. This mechanism has been put to the test in a variety of modes, yielding an overall accuracy of close to 90%.

Keywords - *Detectron; ICU Monitor; Object Detection; Perspective Transformation; YOLO*

Introduction

With the recent COVID pandemic repercussions, remote patient monitoring has been highlighted as a pressing necessity around the world [1]. The significance of remote patient monitoring becomes especially important when dealing with infectious health concerns [2]. Blood pressure, blood oxygen level, pulse rate, and several other health-related critical decisive parameters must be monitored frequently, especially for bedridden patients in critical care [3]. However, due to the shortage of health professionals and the risk of spreading contagious diseases, healthcare personnel are unable to maintain a tight watch on key parameters displayed on surgical monitors located besides the patients' beds [1,4-5]. This necessitates remote monitoring of the patient's critical parameters, which are presented on the surgical monitor. However, there is no alternative for remote monitoring of the patient's health indicators projected on surgical monitors. As a result, this has been identified as a research gap that needs to be addressed.

Literature Review

In this section, several latest remote patient monitoring systems have been assessed to identify the shortcomings. The systems assessed have been tabulated as in Table 1 depicted below.

Table 1 Existing System analysis

System Name	Features	Deficiencies
VitalPatch [6]	Attached wearable device to the chest to monitor vital cardiac signs	• Costly solution, as device per person is needed and communication complexities. • Restricted mobility for the patient.
IoT based vital signal monitoring [7]	IoT sensor attachments to monitor heart rate, oxygen level, glucose level, temperature and etc.	• Restricted mobility for the patient with too many attachments • Complex communication network management
PRISMS [8]	Questionnaire based remote patient information capturing and intelligent assessment.	• Symptoms capturing and doctor alerting only. • No real-time patient specific parameter capturing.
Wearable ECG monitor [9]	Wearable belt for ECG monitoring	• Restricted mobility for the patient. • Complex communication with IoT server for data transmission to the user interfaces
IoHT Remote monitor [10]	Wearable sensors for heartbeat and body temperature monitoring	• Restricted mobility for the patient. • Complex communication with IoT server for data transmission to the user interfaces

ICU patient monitoring at home [11]	Wearable sensors for heartbeat, blood oxygen level and body temperature monitoring	• Restricted mobility for the patient. • Complex networked communication hurdles.
IoT based COVID-19 patient monitoring [12]	Wearable sensors for heartbeat, blood oxygen level and body temperature monitoring	• Restricted mobility for the patient. • Complex networked communication hurdles.

The bulk of existing systems, as shown in Table 1, require a physically attached wearable device to obtain bodily parameters from the patient. Usually, an ICU monitor is attached around the clock for a patient in the ICU. However, in addition to the ICU monitor cuff and sensors, an extra wearable device must be attached externally to the patient in order to gather the aforementioned bodily parameters for the purpose of remote monitoring. This can be viewed as a burden to the patient, as it limits the patient's mobility in the bed [13-14]. Other disadvantage is the complex configurations to be done manually to synch the system to the network. This could escalate the work burden of the hospital `s technical staff as well.

Consequently, this study intends to reduce the requirement for additional wearable attachments other than the typical ICU cuff and sensors for remote monitoring of the bedridden patient's body vitals. Furthermore, to relieve hospital IT officers from the configuration burdens associated with synchronizing wearable outputs with the remote monitoring systems.

Methodology

This research utilizes Object Detection and Optical Character Recognition technologies. The functional prototype has been developed using Detectron2 [15], PyTorch [16] and YoloV4 [17] frameworks. Figure 1 depicts the high-level flow of the system in form of a bird's-eye view.

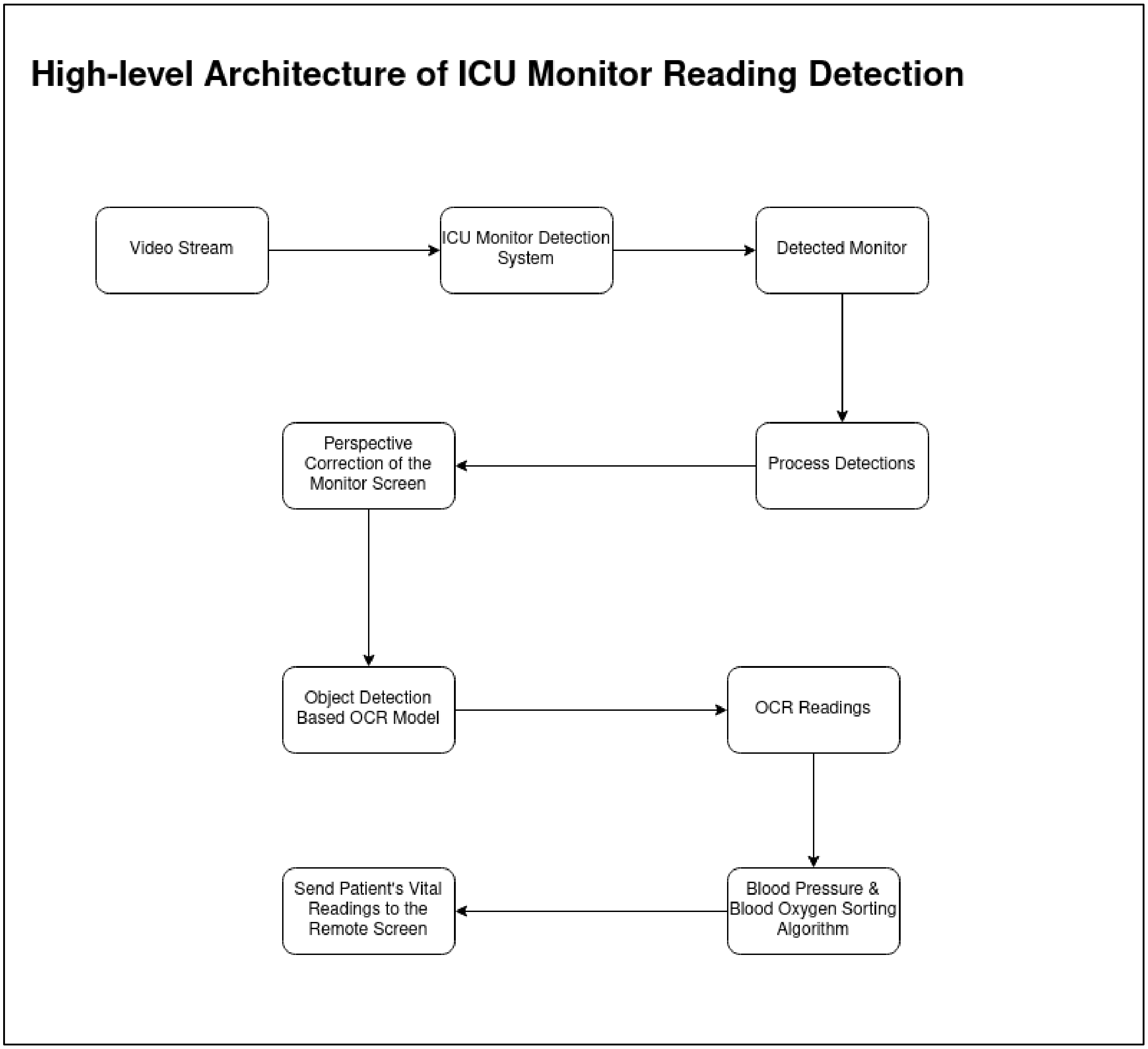

Figure 1. High Level Architecture of ICU Monitor Reading Detection

The methodological flow used to develop the prototype in accordance with the research findings is detailed as visualized in Figure 2. `

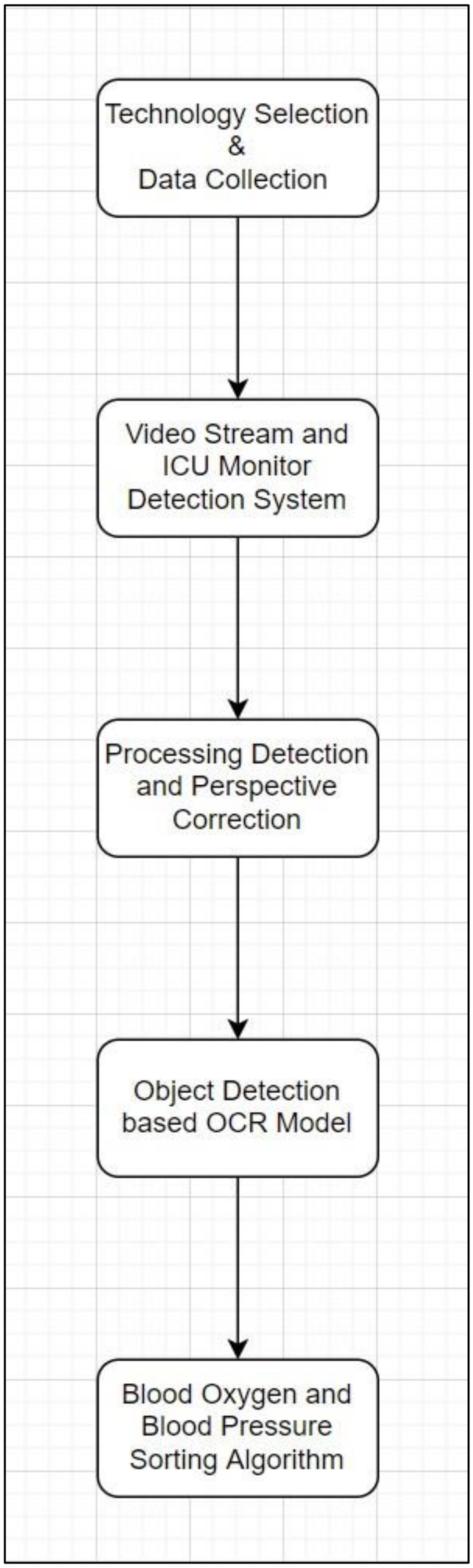

Figure 2. Methodology

A. Technology Selection and Data Collection

Data collection for this research is bilateral. ICU surgical monitor system`s image data has been collected for the ICU surgical monitor detection purposes. Approximately, close to 50 images produced from the ICU surgical monitors have been collected and monitor regions have been annotated using the CVAT tool. Since the ICU monitor detection is a crucial component with less amount of available data, it` decided to use Detectron 2 framework for the object detection purposes. Detectron 2 is a powerful object detection framework developed by Meta AI research [15], which is capable to provide optimal results, even with limited data elements. Detectron 2 comprises of pre-trained Mask R-CNN models allowing to extend its functionality for the custom purposes.

Subsequently, about 200 CCTV image footages are recorded in order to train a model that can perform ICU monitor`s vital readings. This dataset has been annotated with values ranging from 0 to 9 to aid in the accurate detection of ICU monitor readings. This was done adhering to the ethical standards by obtaining the legit approvals from the hospital administration. CCTV footages of patients` rooms were captured and cropped those images to emphasize the clarity of the vital readings displayed on the ICU monitor screens. YOLOV4 framework was utilized for the 0-9 digits recognition and easy OCR library was used for ICU screen understanding. Since this project requires an edge device to be connected to the CCTV, NVIDIA Jetson Nano [18] was used for that purpose.

B. Video Stream and ICU Monitor Detection System

The ICU Monitor can be detected from anywhere in the patient's room due to the power of Detectron2, as long as it isn't in opposing to the CCTV. This eliminates the ICU monitor's need for stationery and allows it to move with the patient as needed. The WEBRTC protocol has been used to send the video stream from the CCTV to the Jetson Nano system.

C. Processing Detection and Perspective Correction

Initially, the system provided low accuracy because the screen detected by Detectron2 could be slightly tilted depending on the position and angle of the ICU Monitor. To address this issue, perspective transformation technique has been used. This technology is capable of correctly adjusting the detected region of the ICU display, allowing the digits recognition system to run more efficiently. Figure 3 depicts the pseudocode associated with the pipeline, already elaborated.

Start

Get pretrained mask RCNN model from GitHub

Adjust number of classes

Set path to custom trained model weight file

Initiate predictor = DefaultPredictor()

Get the frame from the video as an image

Pass it to the predictor

Get the bounding boxes predictions

Convert it to a list

Cropped the ICU Monitor from the frame

Homography and Perspective warp

End

Figure 3. Perspective adjustment of the ICU Monitor reading

Figures 4 and 5 show the impact of the perspective correction before and after.

Figure 4. Before Perspective Correction

Figure 5. After Perspective Correction

D. Object Detection based OCR Model

When conventional optical character recognition models were combined, they did not perform accurately. Because most OCR models have not been trained to read digits captured on a digital display. To address this issue, Yolov4 was used to train a dedicated object detection model. The training was done for ten classes and covered all of the numerical combinations on an ICU Monitor. While doing the annotations, the class and the target were given the same name. The classes used were "0,1,2,3....9."

E. Blood Oxygen and Blood Pressure

After detecting the ICU monitor screen, the warped image is sent to the Optical Character Recognition Module, which is built with YoloV4. This module returns results as classes, confidence scores, and their respective bounding boxes. The coordinates of the boxes and classes are then merged and saved in a list called "mergedList." The detected digits' x coordinates were then taken and sorted across the x-axis. This allowed to get the detection in the order that it appeared on the screen. The digits were then sorted into blood pressure readings and blood oxygen readings based on these coordinates. Figure 6 depicts the pseudocode associated with process steps, D and E.

Figure 6. Object Detection and OCR Process

Start
Get the detections of Yolov4 OCR Model
classes, scores, boxes = detection _output
Use zip iterator for boxes and classes
Put them in mergedList and sort according to the x coordinates
result = sorted(mergedList, key= lambda x:x[0][0])
End

Results and Discussion

Results derived after the experimental observations have been segmented into three different clusters as A, B and C for the ease of comprehension. Initially, as depicted in Table 2, under the cluster- A, an overall accuracy of 94% has been derived for the ICU patient`s vital readings feature.

A. Testing Accuracy for Patient Vital Readings

Table 2. ICU Patient`s Vital Readings

Frame ID	Blood Pressure Ground Truth	Detected Blood Pressure	Blood Oxygen Ground Truth	Detected Blood Oxygen	Blood Pressure Correct Reading	Blood Oxygen Correct Reading	Accuracy
1	77	77	97	97	True	True	100
2	77	77	97	97	True	True	100
3	82	82	97	97	True	True	100
4	78	78	97	97	True	True	100
5	80	80	97	97	True	True	100
6	80	89	97	97	False	True	50
7	87	87	97	97	True	True	100
8	89	89	97	97	True	True	100
							(750/800) * 100
							94%

B. Testing Accuracy for Optical Character Recognition

Cluster – B, represents the accuracy confidence of the OCR predictions. As depicted in Table 3, it had yielded close to 90% accuracy level.

Table 2. OCR confidence levels

	Optical Character Recognition Confidence Levels
1	9(0.98) 7(0.82) 7(0.93) 7(0.95)
2	9 (0.98) 7 (0.91) 7 (0.96) 1 (0.96)
3	9 (0.98) 8 (0.99) 7 (0.96) 2 (0.91)

C. Testing Accuracy for ICU Monitor Detection

Cluster C represents the ICU monitor detection`s accuracy. According to the Detectron model trainings, it had yielded as overall of 96% accuracy. Figure 6 depicts the prediction accuracy of the surgical ICU monitor detection.

Figure 7. ICU Monitor detection

Conclusion

Remote patient monitoring has become a pressing need, as it may be an efficient solution to health-care staffing shortages, particularly in the case of infectious diseases. In addition to the ICU monitor cuff, the majority of existing systems, as determined by the literature analysis, need to be physically attached to the patient's body. This may cause to the patient's discomfort and limit his or her mobility. Furthermore, the vast majority of existing ICU monitor systems lack an out port for routing the data stream to a secondary source for post-processing.

As a result of these flaws, a novel approach has been developed that does not produce network traffic or necessitate any specific configuration. This suggested technique's pipeline consists of numerous modules, each of which has been thoroughly evaluated for correctness. As a result, the proposed technique's total accuracy can be estimated to be around 90%.

As future recommendations, it`s anticipated to improve this mechanism to detect specific gestures of the patients as well to convey more enriched information to the medical consultant.

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