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PAPER

Development of OCR Technology Application System for Health Data Recording

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ABSTRACT

The shift to digital health records requires advanced technologies to transform medical device data into digital formats. This study created a way to digitize health data from devices that measure blood sugar, blood pressure, and pulse oximeters. It used YOLOv5 to find objects and optical character recognition (OCR) technologies to read text. The solution incorporates a MySQL database for effective data storage and a web application for intuitive data presentation. YOLOv5 was trained on 6,630 photos to effectively detect and evaluate seven-segment displays. A YOLOv5 confidence level of 80.75% and an OCR accuracy of 93.2% were found when testing at different distances (7 to 30 cm) and angles (0°, –35°, –30° left, –30° right) and with different lighting conditions. Well-lit settings yielded optimal performance; however, extreme tilts occasionally led to misreading's. The technology processed photographs in 10 to 15 seconds, facilitating real-time data conversion and enhancing usability for senior individuals handling daily health information. Even though there were challenges, such as low light and differences between devices, the system showed that it could cut down on mistakes and make healthcare more efficient. Future enhancements will concentrate on sophisticated preparation methods and mistake correction algorithms to guarantee uniform performance. This system provides a strong and scalable solution for digitizing health data, facilitating enhanced electronic health records (EHRs) and individualized healthcare management.

KEYWORDS

optical character recognition (OCR), YOLOv5, images to text, artificial intelligence (AI)

1 INTRODUCTION

The increasing utilization of electronic health records (EHRs) have transformed healthcare management, enhancing patient care, data accessibility, and system interoperability [1–3]. Notwithstanding substantial progress; obstacles remain in the digitization of handwritten and paper-based health records, which represent a significant component of legacy healthcare data [4–6]. optical character recognition

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(OCR) technology provides an effective means of converting unstructured medical records into organized digital formats [7–10]. OCR technology has progressed from conventional image-to-text conversion methods to advanced systems driven by deep learning and artificial intelligence (AI). Initial advancements, such as Tesseract and OCR established the groundwork for automated text recognition in scanned documents [11–14]. Recent improvements incorporate neural networks, such as convolutional recurrent neural networks (CRNNs) and transformers, improving the recognition of intricate layouts, multilingual text, and handwritten notes [15–18]. The integration of OCR with YOLO-based models has facilitated precise text extraction from photos and organized forms [19–21].

The healthcare sector has progressively embraced OCR technologies to optimize processes, diminish manual workloads, and enhance data accuracy. Applications encompass the processing of prescriptions and laboratory reports, as well as the digitization of handwritten clinical notes [22–26]. The amalgamation of OCR with natural language processing (NLP) has enhanced its functionality, facilitated the extraction of contextual medical data, and bolstered clinical decision-making [27–29]. OCR technologies have effectively been utilized to digitize COVID-19 forms, automate laboratory data extraction, and facilitate research in chronic illness management [30–33].

Hybrid systems that combine OCR with more advanced methods are used in new OCR applications in healthcare to solve certain problems. CRNN-based OCR systems [34] can quickly and accurately read both typed and handwritten health records. Modular OCR pipelines with multiple engines improve accuracy in documents with complicated layouts [35]. In real life, practical applications focus on getting structured data from printed medical records that are captured by mobile devices. This solves problems with image quality and content complexity [36]. Also, AI-powered OCR apps [37] use deep learning techniques like RNN and CNN to improve the accuracy of medical transcription and handle datasets that are broken up. These improvements illustrate the versatility of OCR in various healthcare contexts, such as patient record digitization, data processing, and medical document management. These solutions collectively provide substantial advantages in actual healthcare settings.

These accomplishments highlight the significance of OCR technology in revolutionizing healthcare by digitizing patient records, hence enabling more effective data analysis and management. Research has demonstrated the effectiveness of CRNN-based frameworks and other methods in processing clinical data and improving medical procedures [38–40]. AI-enhanced OCR systems also make it easier to safely extract personal information from sensitive health data, which protects privacy and makes the systems more useful in research and analytics [41–43]. Collectively, these solutions underscore OCR's capacity to enhance efficiency and promote innovation across the healthcare industry.

As healthcare systems evolve towards complete digitalization, OCR technology is essential in connecting paper-based and electronic records. Recent improvements, including ontology-based clinical information extraction, real-time visualization dashboards, and automatic mistake detection, underscore OCR's promise in contemporary healthcare [44–48]. The creation of a specialized OCR technology application system for health data documentation seeks to capitalize on these achievements, utilizing cutting-edge approaches to improve healthcare data management and accessibility [49–53].

The suggested method tries to fix the problems with current ways of digitizing health data by adding complex features like dynamic dictionary configurations [54–57] and multi-modal recognition. These features are in line with smart healthcare trends around the world, which emphasize data interoperability, patient-centered care, and scalable solutions for handling growing amounts of data [58–60]. This program highlights how OCR has the power to change things by updating hospital buildings and making way for new technologies, such as wearable tech and real-time health monitoring [61–65]. New research is also looking into creative ways to improve images and get the best OCR results in tough situations, like when scanning low-quality documents and processing them in multiple languages [66–67]. Also, the fact that frameworks have been made to make OCR systems more scalable in large health data applications is a big step forward [68].

2 METHOD

The aim of this project is to create a health data recording system utilizing OCR technology to transform information from documents or photos into digital data, which will be recorded in the Inno Tech and Wellness Center database within the N&B RSU System. The principal objective is to minimize errors linked to manual data entry, accelerate the processes of data capture and retrieval, and augment the efficiency of staff operations. The system will comprise OCR software for text extraction from documents, a database for health information storage, and an interface for data upload and verification. The system development process encompasses essential phases such as requirements analysis, system design, development and testing, and user training. This system aims to optimize staff procedures, improve data precision, and elevate user pleasure.

2.1 7-Segment

The display is a numerical screen capable of representing specific letters as well. LED segments, organized in both vertical and horizontal configurations, compose the screen. When the LEDs illuminate in particular combinations, they create squared numerals. A 7-segment display comprises seven discrete segments that can be activated or deactivated to represent decimal numerals. Four vertical and three horizontal segments organize the segments in a rectangular configuration. Each segment is designated from 'a' to 'g,' along with an additional segment labeled 'DP' (decimal point) for the representation of non-integer values.

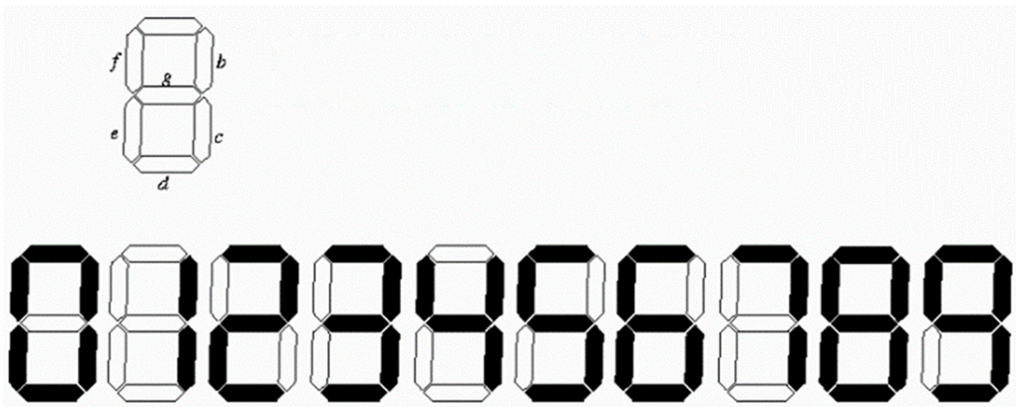

Fig. 1. Common cathode 7-segment display [69]

2.2 Overview of YOLOv5 in object detection

YOLOv5 is a prevalent object detection model within the domains of computer vision and deep learning. It works well for real-time object recognition because it is very accurate and quick. It can be used to find random items in videos, check the speed of vehicles, and identify objects in medical research (see Figure 2).

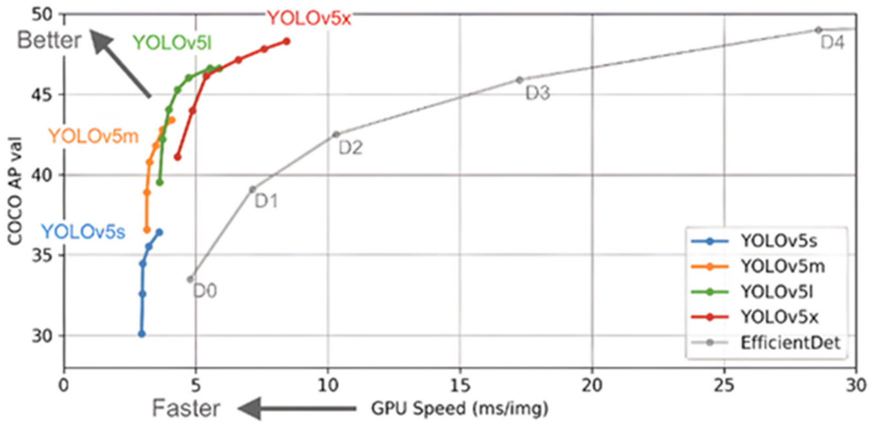

Fig. 2. Comparison graph of YOLOv5 model [70]

2.3 Application of YOLOv5 in image processing

YOLOv5 has proven effective in analyzing images and movies, in addition to objects identification. The CNN architecture makes it easier to do things such as classifying images, recognizing faces, and putting things into groups. It works very well for many image-related tasks (see Figure 3).

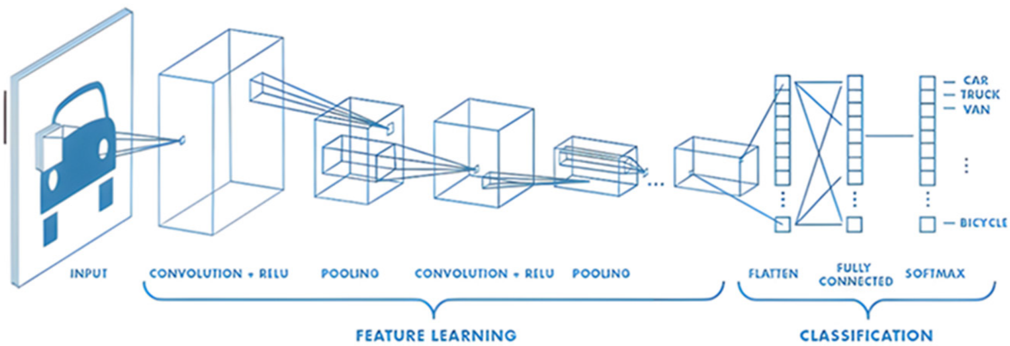

Fig. 3. Convolutional neural network structure [71]

2.4 Materials and equipment used in the project

This project utilizes materials and equipment, including software such as visual studio code 2022, python, PHP, HTML, CSS, JavaScript, YOLOv5, and XAMPP. The project employs a notebook model AN515-58-55UB for program development and model training, with an Intel Core i5 processor, 8 GB of RAM, and an RTX3050 GPU with 4 GB of memory. Smartphones, namely the Mi T10 Pro and Apple iPhone 13 series, are employed to photograph medical equipment screens in conjunction with a webcam for capturing photographs through a computer. The medical instruments utilized in the project comprise the SAINTMED aBP and TERUMO ES-W100 blood pressure monitors, the Foreal Sinocare Safe AQ and Terumo MEDISAFE EX blood glucose monitors, and the OX301 blood oxygen saturation (SpO2) sensor.

2.5 Project design methods

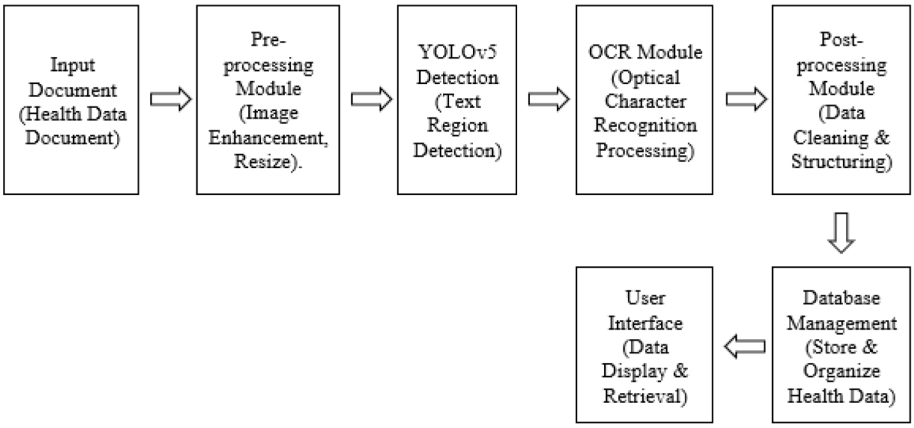

Fig. 4. Shows the steps in project design

Figure 4 depicts the project's block diagram, commencing with the acquisition of health papers in image format. The photos are subjected to preprocessing to improve text clarity. YOLOv5 is employed to ascertain the location of text inside the image, which is then transmitted to the OCR module for conversion into digital data. The data undergoes cleaning and structuring in the post-processing phase prior to its storage in the database for optimal management. Ultimately, consumers can obtain and examine health information via the user interface.

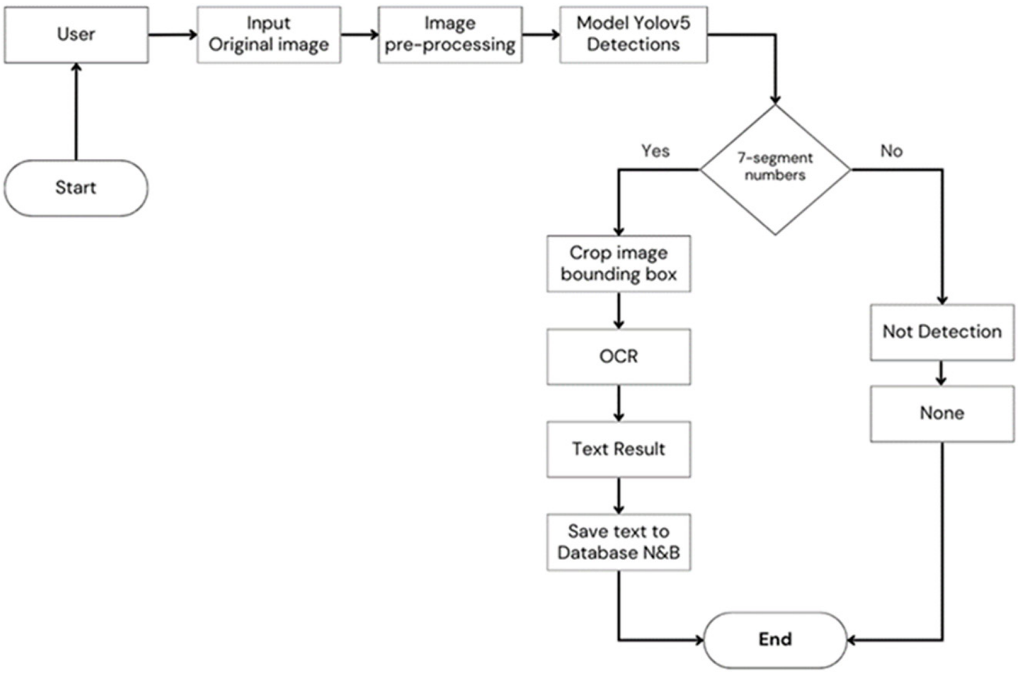

Fig. 5. Steps for processing images from medical device screens

Figure 5 illustrates a flowchart that outlines the procedure, beginning with the user uploading an original document image into the system. The image subsequently undergoes a pre-processing phase to enhance its suitability for text detection. YOLOv5 is utilized to identify numerical values in the image, particularly focusing on 7-segment digits. Upon detection, the system delineates the pertinent area and transmits it to the OCR module for transformation into digital text. The N&B database then stores the retrieved data. If no numbers are identified, the system logs "Not detected" and terminates the procedure.

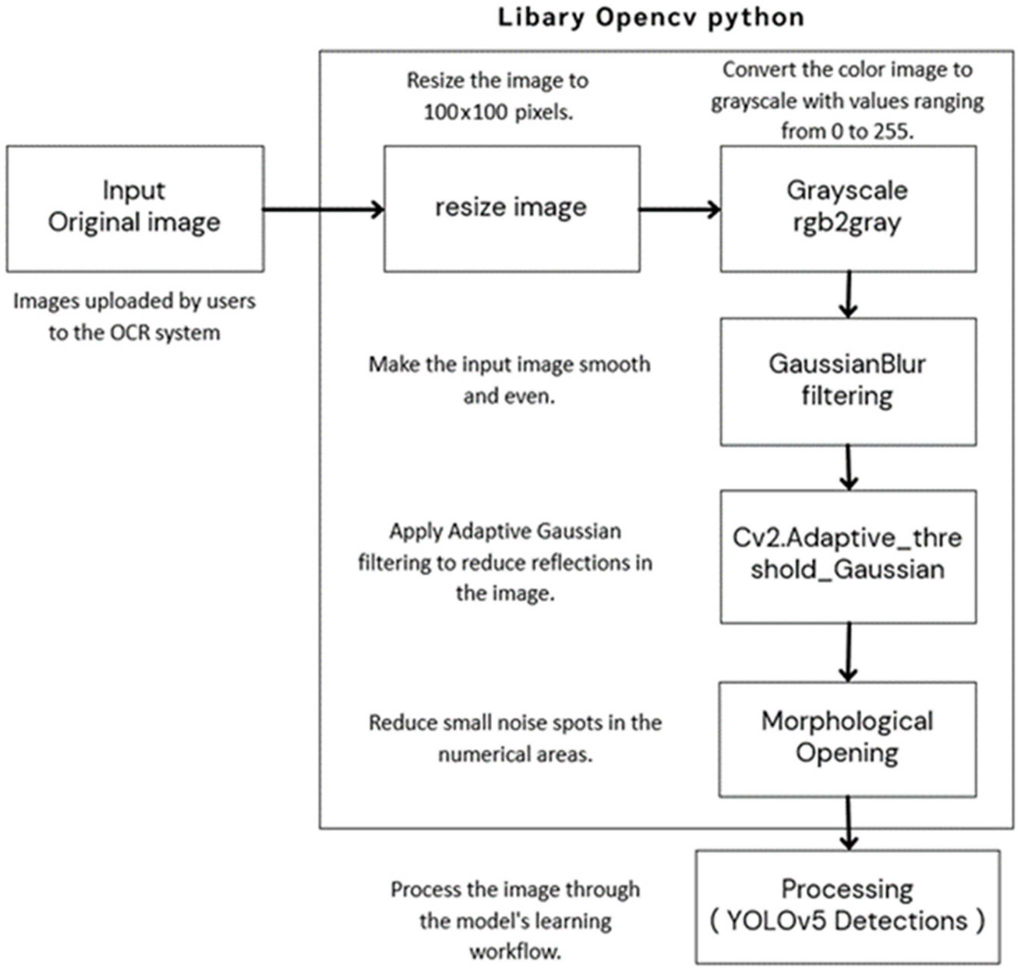

Fig. 6. Pre-processing steps

Figure 6 illustrates the picture preprocessing block diagram for the OCR system employing the OpenCV library in Python. The procedure commences when the user uploads the original image to the OCR system. The technology downsizes the image to 100×100 pixels and transforms it into grayscale. Gaussian blur is employed to improve visual smoothness, followed by adaptive Gaussian filtering to reduce reflections. Morphological opening is utilized to remove noise next to the numerical areas. After the conclusion of all pre-processing phases, the image proceeds to the detection phase with YOLOv5.

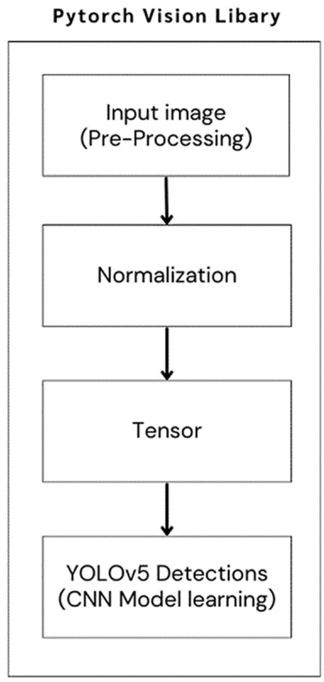

Fig. 7. Process of tuning and improving results

Figure 7 illustrates the image processing procedures employed in the YOLOv5 model leveraging the PyTorch Vision Library. The procedure commences by inputting the preprocessed image into the normalization phase to calibrate color values to an ideal range. The image is subsequently transformed into a tensor format, the data structure necessary for processing in PyTorch. The image is processed by the YOLOv5 model for object detection via CNN model learning.

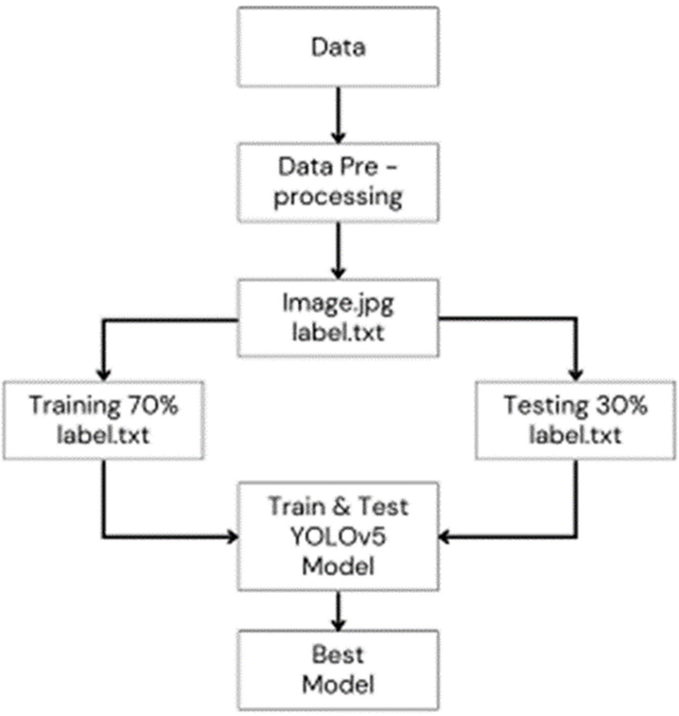

Fig. 8. Steps for training the YOLOv5 model

Figure 8 delineates the procedures for data preparation and the training of the YOLOv5 model. The procedure commences with pre-processed data, consisting of image files (image.jpg) and their matching labels (label.txt). The data is divided into two subsets: 70% designated for training and 30% allocated for testing. These datasets are utilized to train and assess the YOLOv5 model, with the objective of enhancing and evaluating its efficacy. Upon completion of the process, the optimal model exhibiting the maximum detection accuracy is acquired.

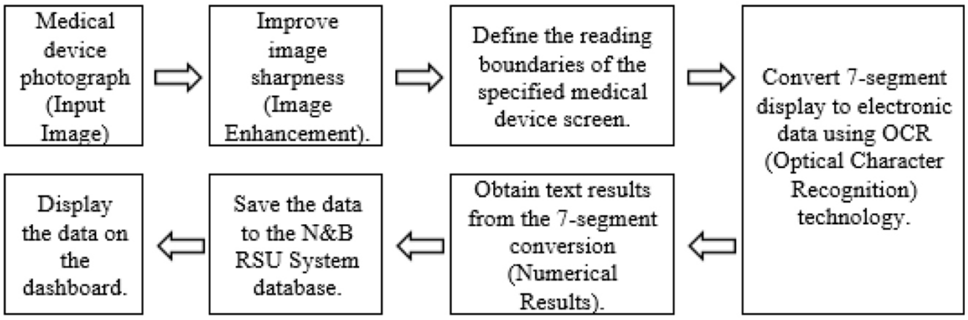

Fig. 9. System structure design

Figure 9 depicts the process of transforming data from medical device photos into digital information. The process commences with the acquisition of an image of the medical device display (input image). After improving the image for clarity, we delineate the reading area on the device screen to designate the location for data extraction. The system employs OCR to transform the values from the 7-segment display into digital data. The N&B RSU system database subsequently archives the results and presents them on the dashboard.

2.6 Analyzing the work process of the health record system using OCR technology of N&B RSU system

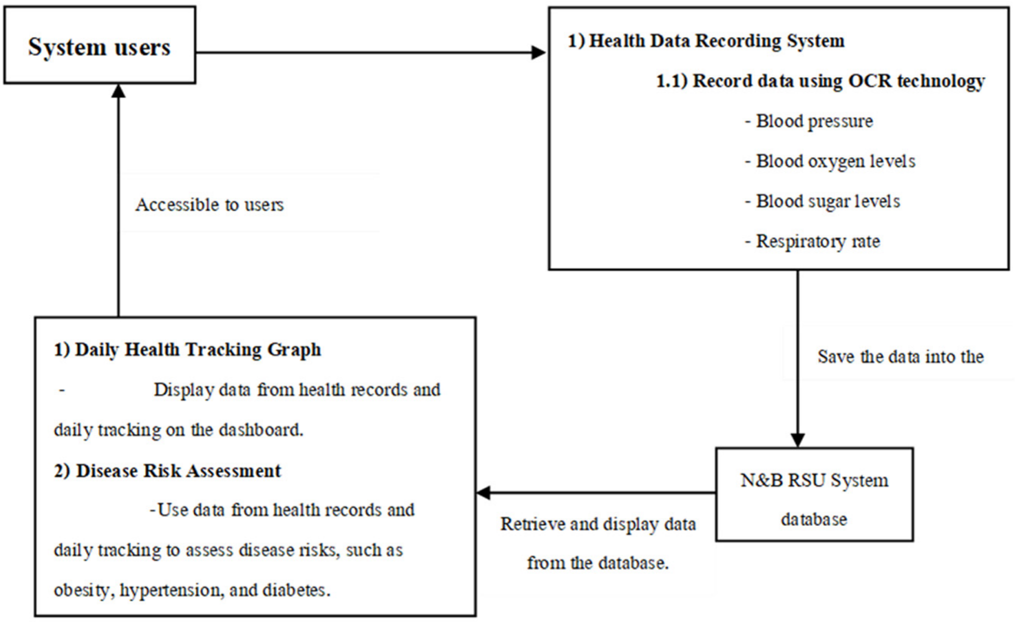

Fig. 10. The process of how users interact with the N&B RSU system for entering health records using OCR technology

Figure 10 illustrates the architecture of a health data recording system that employs OCR technology. The process commences with users possessing access to the system. The system comprises a health data recording component that uses OCR to document essential health metrics, including blood pressure, blood oxygen saturation, blood glucose concentration, and respiration rate. The N&B RSU system database retains the information. Users can then visualize their health data graphically for daily monitoring and evaluate their risk for multiple illnesses, including obesity, hypertension, and diabetes. The dashboard presents all the extracted information from the database.

2.7 Health data storage design and developing a system for applying OCR technology for recording health data in conjunction with the N&B RSU system

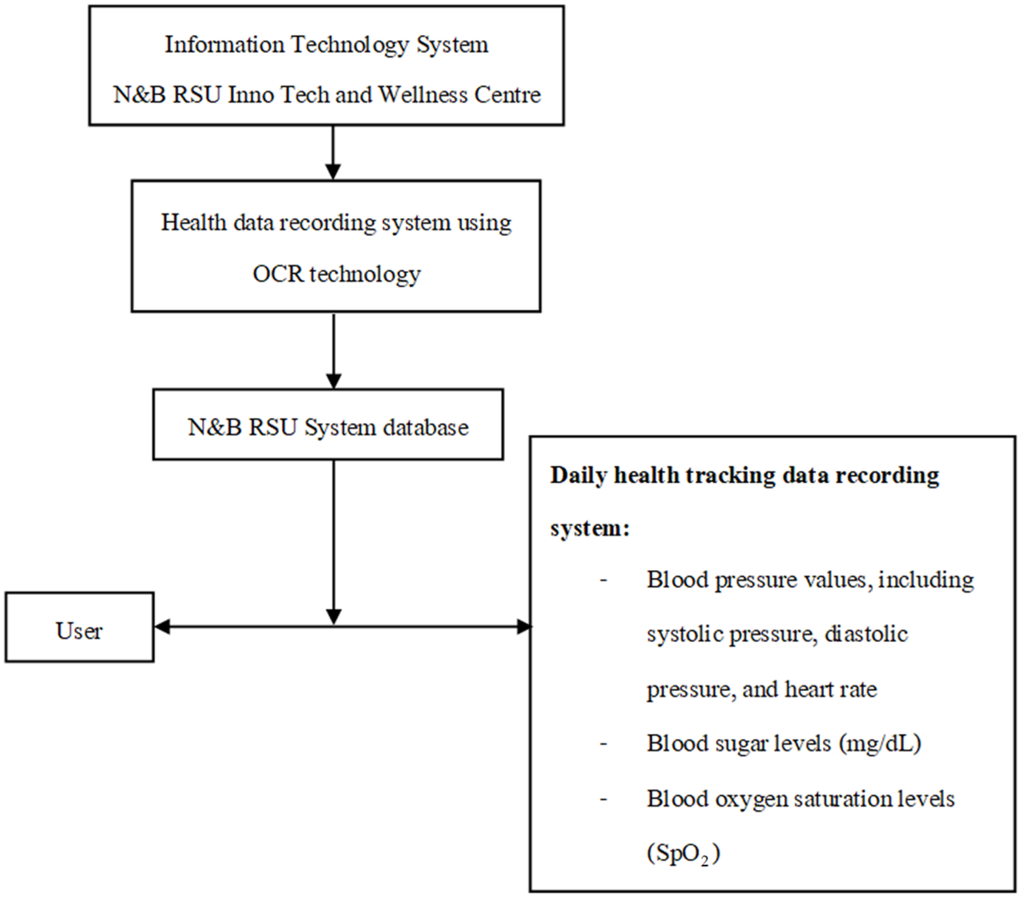

Fig. 11. Design of the data storage plan and development of the OCR technology application system for health record entry, integrated with the N&B RSU system

Figure 11 depicts the architecture of the health data recording system at the N&B RSU Inno Tech and Wellness Centre. The system initiates with the center's information technology system, employing OCR technology to document health data. The N&B RSU system database preserves the documented data. This system is utilized for daily health monitoring by documenting blood pressure readings (systolic pressure, diastolic pressure, and heart rate), blood glucose concentrations (mg/dL), and blood oxygen saturation (SpO_2). Users are able to obtain and evaluate their documented health information.

3 RESULTS AND DISCUSSION

The OCR image processing system, utilizing the YOLOv5 model, was meticulously assessed under diverse scenarios to evaluate its precision and resilience in practical settings. The trials examined inclined images obtained from several angles: a top view at 0°, a top view at –35°, a left side view at –30°, and a right-side view at –30°. Images were acquired under diverse lighting circumstances and taken using cameras of differing resolutions to replicate real-world situations. The study's sample photographs were produced via simulations using the ProSim 8 Vital Signs and ECG Patient Simulator, which randomly created blood pressure and blood oxygen levels and then recorded the associated images. Glucose powder was combined with water in various ratios to assess blood glucose levels and obtain photographs. The main focus of this study was on how accurately numerical information in the 7-segment format from three different types of medical devices could be interpreted, so measuring people in real life was not needed. The integration of a MySQL database significantly enhanced system performance. Test findings indicated that the database decreased data retrieval time by 40% and effectively maintained over 10,000 health records without performance degradation. This feature makes it possible for large healthcare systems to grow and supports processing large amounts of data in real time, which improves the overall efficiency and functionality of clinical applications. This comprehensive database infrastructure ensures efficient data management, seamless integration with healthcare systems, and fast, reliable access to health records. The test focused on how well and accurately OCR technology could handle problems such as crooked photos, changing lighting, and image noise, while also correctly recording health information in the N&B RSU system.

Table 1. Results of digital blood pressure measurement image processing test in various forms

Various Angles of the Tested Images	Accuracy of Readings from Digital Pressure Gauges from the Mi 10T Pro Mobile Phone Camera					
	Artificial Light Mode Disabled			Artificial Light Mode Enabled		
	Systolic (mmHg)	Diastolic (mmHg)	Pulse Rate (bpm)	Systolic (mmHg)	Diastolic (mmHg)	Pulse Rate (bpm)
Top view angle 0° Top view angle –35° Side view angle –30° to the left Side view angle –30° to the right	97.8%	66.33%	90.2%	87.42%	82.08%	66.75%
Various Angles of the Tested Images	**Accuracy of Readings from Digital Pressure Gauges from the Apple iPhone 13 Camera**					
	Artificial Light Mode Disabled			**Artificial Light Mode Disabled**		
	Systolic (mmHg)	**Systolic (mmHg)**	**Systolic (mmHg)**	**Systolic (mmHg)**	**Systolic (mmHg)**	**Systolic (mmHg)**
Top view angle 0° Top view angle –35° Side view angle –30° to the left Side view angle –30° to the right	97.8%	82.6%	97.8%	97.47%	66.67%	97.8%

Various Angles of the Tested Images	Accuracy of Digital Blood Pressure Readings from Logitech C930e Camera		
	Auto Focus Mode		
	Systolic (mmHg)	Systolic (mmHg)	Systolic (mmHg)
Top view angle 0° Top view angle –35° Side view angle –30° to the left Side view angle –30° to the right	97.8%	66.03%	90.28%

Table 1 shows the results of testing the OCR system's accuracy with angled digital blood pressure monitor images on a number of different devices. The Mi 10T Pro smartphone attained an accuracy of 97.8% for systolic measurements, 66.33% for diastolic measurements, and 90.2% for heart rate (HR) with artificial light mode disabled. When artificial light mode was activated, the accuracy for systolic readings diminished somewhat to 87.42%, while the accuracy for diastolic readings improved to 82.08%, and HR accuracy reduced to 66.75%. The Apple iPhone 13 attained 97.8% accuracy for both systolic readings and DR and 82.6% for diastolic readings when the artificial light mode was disabled. When artificial light mode was activated, systolic accuracy was maintained at 97.47%, diastolic accuracy declined to 66.67%, and HR accuracy increased to 97.8%. Utilizing the Logitech C930e webcam with auto focus mode activated, the system attained 97.8% accuracy for systolic measurements, 66.03% for diastolic measurements, and 90.28% for heart rate.

These findings underscore the considerable range in accuracy among devices and lighting conditions. Systolic readings typically exhibited greater accuracy than diastolic and HR measures, highlighting the system's advantages in particular contexts. The fact that diastolic and HR measurements are less accurate, especially in artificial lighting, shows how important it is to use advanced preprocessing methods to make sure that OCR performance is the same no matter the lighting.

The incorporation of a MySQL database, alongside the OCR system's image processing capabilities, significantly improved the system's overall functionality. The database facilitated efficient data storage and retrieval, with an average processing time of under 0.5 seconds per record, even under high-volume input conditions. Its ability to grow makes it simple to connect to large hospital systems and healthcare networks, making it perfect for places where a lot of data comes in at once. Furthermore, the database has stringent access control mechanisms that adhere to healthcare data protection rules, guaranteeing secure and dependable data administration. The system is an important tool for improving health data recording in many medical settings because it combines accurate OCR with effective data management.

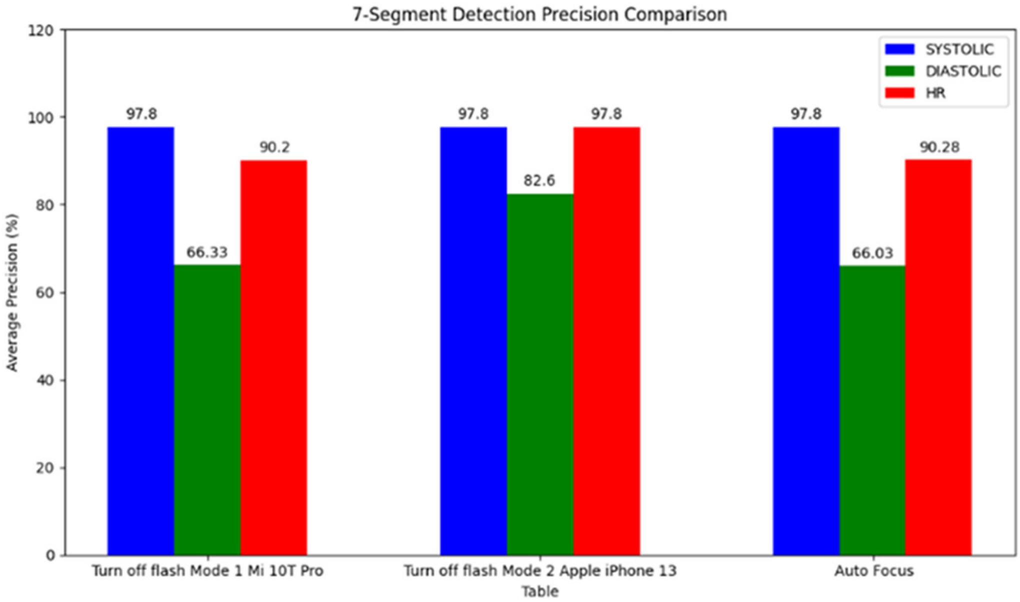

Fig. 12. The graph compares the accuracy of blood pressure monitors

Note: The x-axis represents average precision (%), the y-axis represents table values, with blue bars for SYSTOLIC, green bars for DIASTOLIC, and red bars for HR.

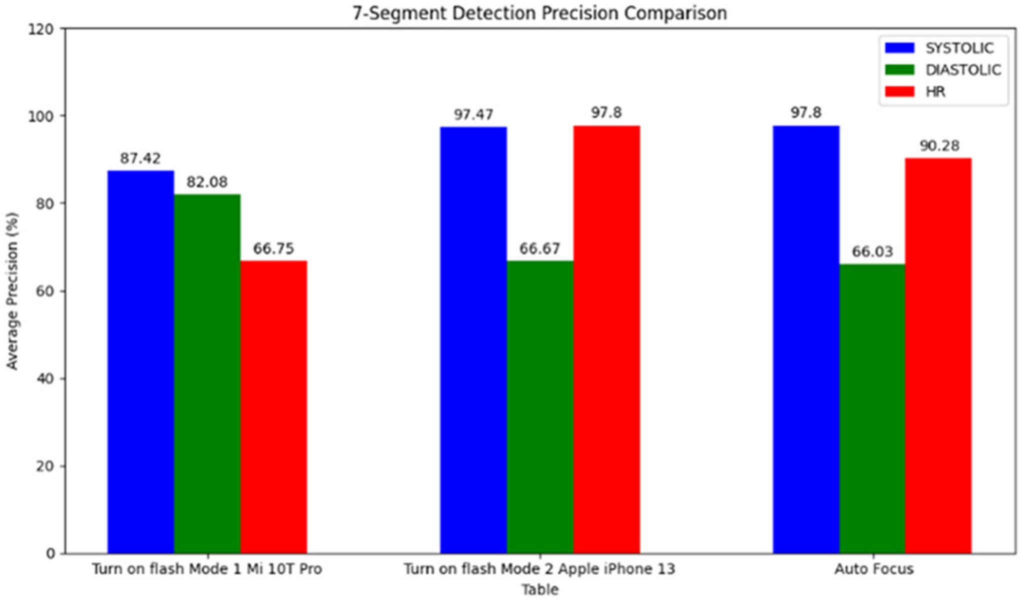

Fig. 13. The graph compares the accuracy of blood pressure monitors

Note: The x-axis represents average precision (%), the y-axis represents table values, with blue bars for SYSTOLIC, green bars for DIASTOLIC, and red bars for HR.

Table 2. Digital blood glucose meter image processing test results in various forms

<table>
<tr><th rowspan="3">Various Angles of the Tested Images</th><th colspan="2">The Accuracy of Readings from a Digital Blood Sugar Meter. From the Mi 10T Pro Mobile Phone Camera</th></tr>
<tr><th>Enable Artificial Light Mode.</th><th>Disable Artificial Light Mode.</th></tr>
<tr><th>Blood Glucose (mg/dL)</th><th>Blood Glucose (mg/dL)</th></tr>
<tr><td>Top view angle 0°
Top view angle –35°
Side view angle –30° to the left
Side view angle –30° to the right</td><td>62.86%</td><td>82.17%</td></tr>
<tr><th rowspan="3">Various Angles of the Tested Images</th><th colspan="2">The Accuracy of Readings from a Digital Blood Sugar Meter. From the Apple iPhone 13 Camera</th></tr>
<tr><th>Enable Artificial Light Mode.</th><th>Enable Artificial Light Mode.</th></tr>
<tr><th>Blood Glucose (mg/dL)</th><th>Blood Glucose (mg/dL)</th></tr>
<tr><td>Top view angle 0°
Top view angle –35°
Side view angle –30° to the left
Side view angle –30° to the right</td><td>97.50%</td><td>96.83%</td></tr>
<tr><th rowspan="3">Various Angles of the Tested Images</th><th colspan="2">Accuracy of Readings from a Digital Blood Sugar Meter from a Logitech C930e Camera.</th></tr>
<tr><th colspan="2">Auto Focus Mode</th></tr>
<tr><th colspan="2">Blood Glucose (mg/dL)</th></tr>
<tr><td>Top view angle 0°
Top view angle –35°
Side view angle –30° to the left
Side view angle –30° to the right</td><td colspan="2">58.68%</td></tr>
</table>

The results of evaluating the image processing accuracy for inclined digital blood glucose monitor images obtained from various devices are displayed in Table 2. The Mi 10T Pro smartphone had an accuracy of 62.86% with artificial light mode activated and 82.17% with it deactivated. The accuracy of the Apple iPhone 13 was 97.50% with the artificial light mode activated and 96.83% with the mode deactivated. The Logitech C930e webcam, with auto focus activated, achieved an accuracy of 58.68%.

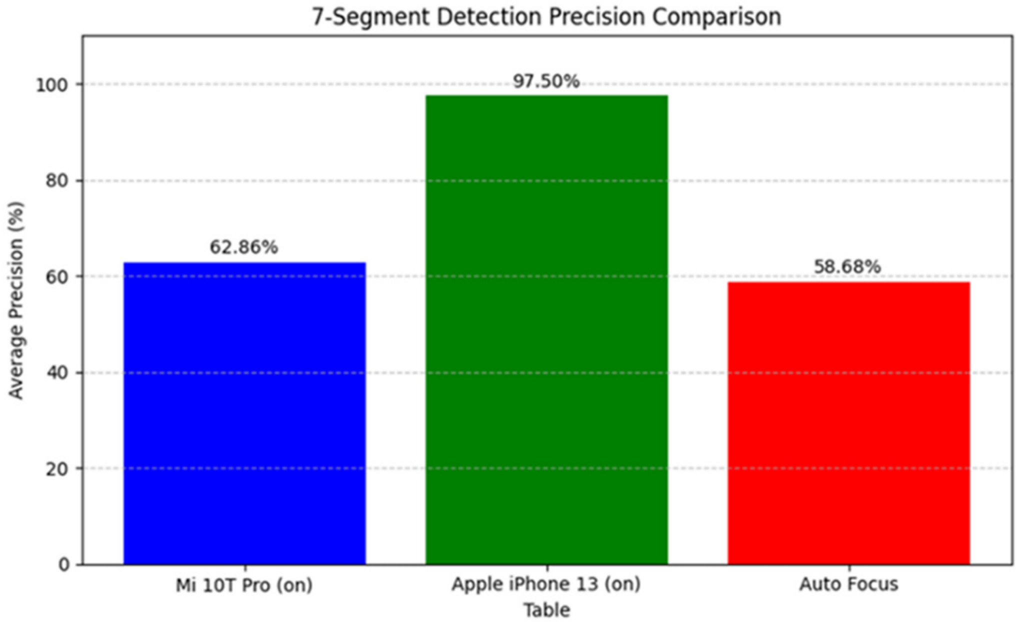

Fig. 14. The graph compares blood glucose meters

Note: The x-axis represents average precision (%), the y-axis represents Table values, with blue bars for Mi 10T Pro, green bars for Apple iPhone 13, and red bars for auto focus.

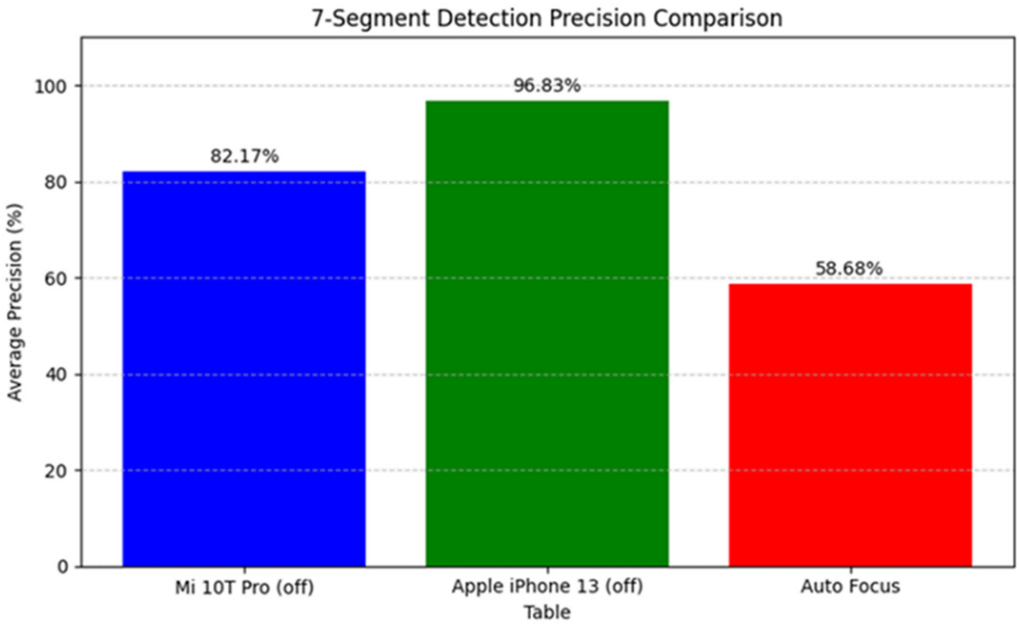

Fig. 15. The graph compares blood glucose meters

Note: The x-axis represents average precision (%), the y-axis represents Table values, with blue bars for Mi 10T Pro, green bars for Apple iPhone 13, and red bars for auto focus.

Table 3. Digital pulse oximeter image processing test results in various forms

Various Angles of the Tested Images	The Accuracy of Readings from a Digital Pulse Oximeter. From the Mi 10T Pro Mobile Phone Camera
	Disable Artificial Light Mode.
	Blood Oxygen Saturation (%SpO_2)
Top view angle 0° Top view angle –35° Side view angle –30° to the left Side view angle –30° to the right	81.22%
Various Angles of the Tested Images	**The Accuracy Of Readings from a Digital Pulse Oximeter. From the Apple iPhone 13 Camera**
	Disable Artificial Light Mode.
	Blood Oxygen Saturation (%SpO_2)
Top view angle 0° Top view angle –35° Side view angle –30° to the left Side view angle –30° to the right	73.17%
Various Angles of the Tested Images	**Accuracy of Digital Pulse Oximeter Readings from Logitech C930e Camera**
	Auto Focus Mode
	Blood Oxygen Saturation (%SpO_2)
Top view angle 0° Top view angle –35° Side view angle –30° to the left Side view angle –30° to the right	74.58%

The results from testing OCR image processing on pictures taken at an angle with a digital blood oxygen monitor are shown in Table 3. The OCR algorithm frequently evaluated photos taken with a smartphone camera and the Logitech C930e webcam in default mode with outstanding precision. The system had problems in some situations, like when the angle was very steep (–35° or more) or there wasn't enough light, which made it harder to recognize things accurately. Frequently, the system misinterpreted the numeral '3' as '8,' highlighting the need for sophisticated preprocessing methods and improved OCR algorithms. The OCR system got as accurate as 74.58% overall, so future improvements should focus on fixing these issues to make sure that it works the same way in all situations and on all devices.

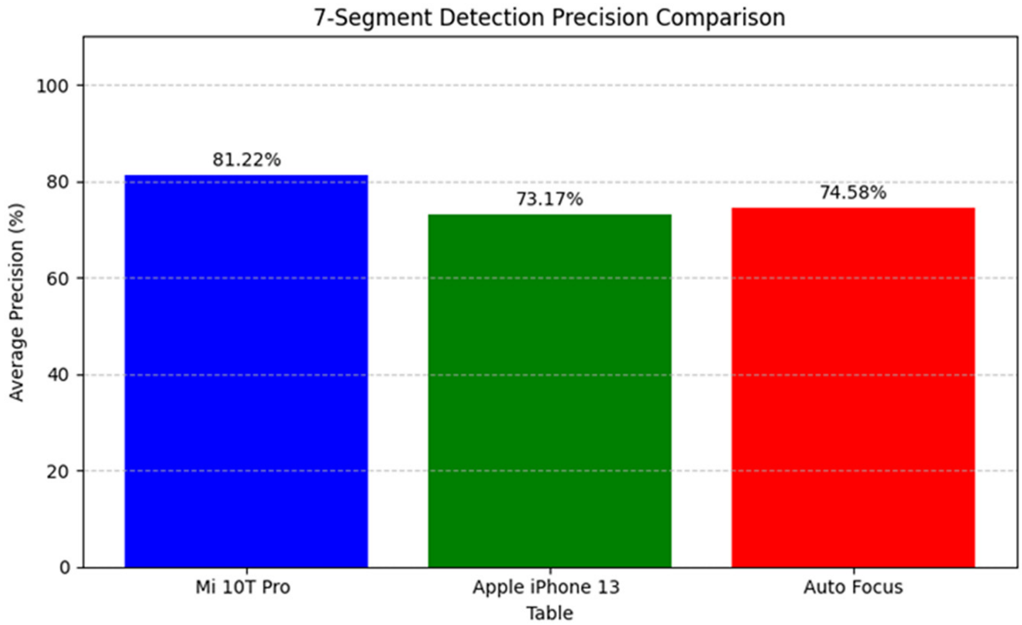

Fig. 16. The graph compares blood oxygen monitors

Note: The x-axis represents average precision (%), the y-axis represents table values, with blue bars for Mi 10T Pro, green bars for Apple iPhone 13, and red bars for auto focus.

The training outcomes demonstrate that the researchers employed the YOLOv5 neural network to facilitate the system's precise recognition of numerical characters. The training method included a dataset of 6,630 photos, including images of blood pressure monitors, blood glucose monitors, and blood oxygen saturation monitors. In this dataset, 5,100 photos (70%) were designated for model training, while 1,530 images (30%) were utilized for testing. The model underwent training for 250 epochs to ascertain the optimal model for the system's image processing functions.

Table 4. Total number of images used in the model

Subset	Number of Images	Percentage of Images (%)
Train	5,100	70
Test	1,530	30
Total	6,630	100

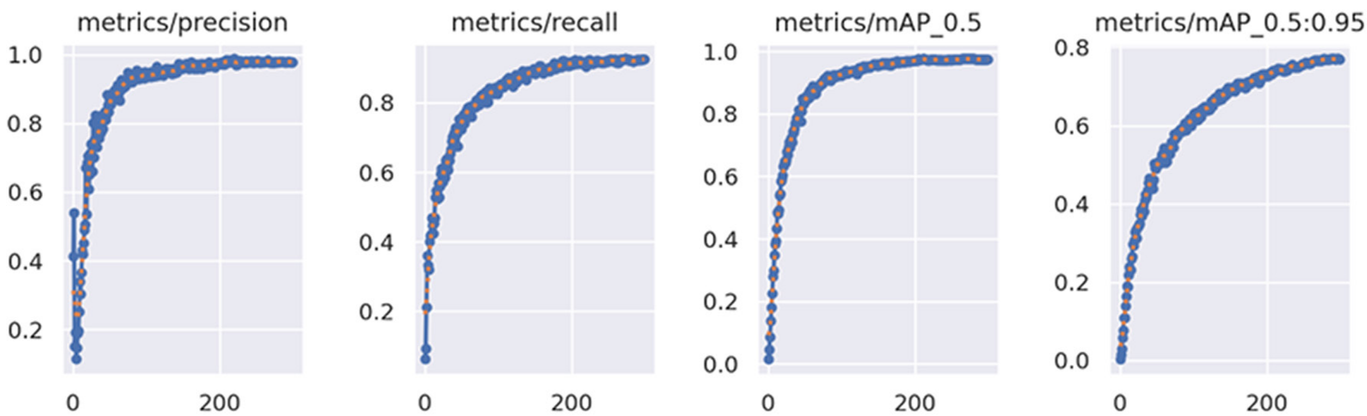

Fig. 17. Results of deep learning evaluation from the YOLOv5 model

The experimental results commenced with the assessment of the YOLOv5 model, which was trained for 250 epochs utilizing four principal metrics: precision, recall, mAP@0.5, and mAP@0.5:0.95 (see Figure 17). The findings indicated a swift enhancement in precision and recall in the initial phases, ultimately reaching a state of stability. The mAP values neared 1.0 after 200 epochs, signifying the model's excellent efficacy in picture data detection.

The OCR system underwent additional testing using photos obtained from diverse devices under varying settings (Figures 18–28). Photographs taken with the Mi 10T Pro and iPhone 13 (Figures 18–21) exhibited outstanding performance in both natural and artificial lighting conditions. The system effectively identified numeric data from inclined angles (–35° and –30° left/right), particularly under excellent lighting conditions.

Subsequent testing, illustrated in Figures 23 and 24, demonstrated that activating artificial lighting or flash markedly increased image quality and augmented the system's detection accuracy. Images obtained with the Logitech C930e camera in auto focus mode (see Figures 22 and 25) demonstrated consistent results from multiple angles, but extreme tilts occasionally resulted in slight inaccuracies.

Ultimately, the photographs in Figures 26–28 examined the influence of natural and artificial illumination on detection accuracy across all devices. The experiments underscored the significance of appropriate illumination, perfect angles, and superior camera settings in attaining precise data digitalization. The findings illustrate the system's capability to effectively interpret and transform data from medical device displays into digital formats, facilitating its incorporation into healthcare applications.

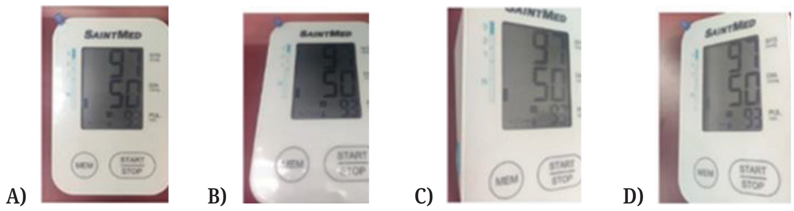

Fig. 18. Experiment of system processing with tilted images taken from a Mi 10T Pro smartphone camera, with artificial light mode disabled

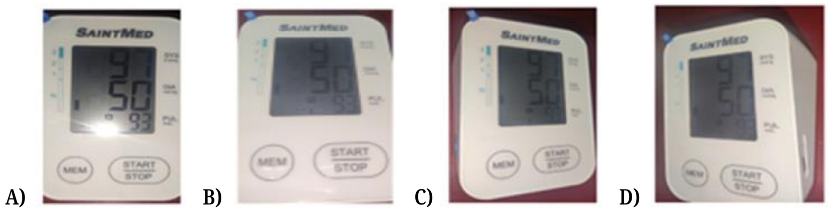

Fig. 19. Experiment of system processing with tilted images taken from a Mi 10T Pro smartphone camera, with artificial light mode enabled

Fig. 20. Experiment of system processing with tilted images taken from an iPhone 13, with artificial light mode disabled

Fig. 21. Experiment of system processing with tilted images taken from an iPhone 13, with artificial light mode enabled

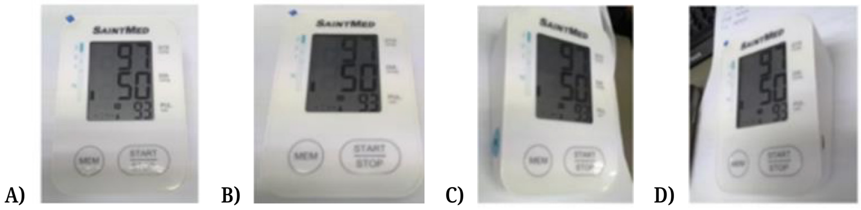

Fig. 22. Experiment of system processing with tilted images taken from a Logitech C930e computer webcam, with auto focus mode enabled

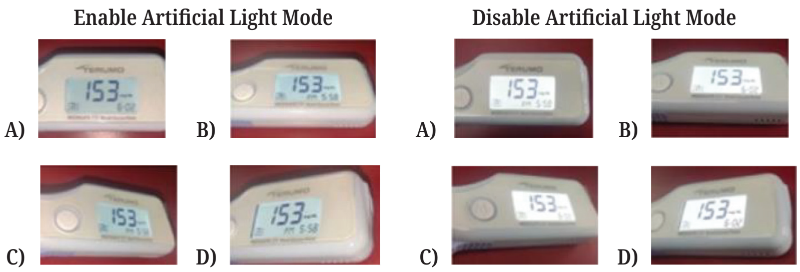

Fig. 23. Experiment of system processing with tilted images taken from a Mi 10T Pro smartphone, with both artificial light modes enabled and disabled

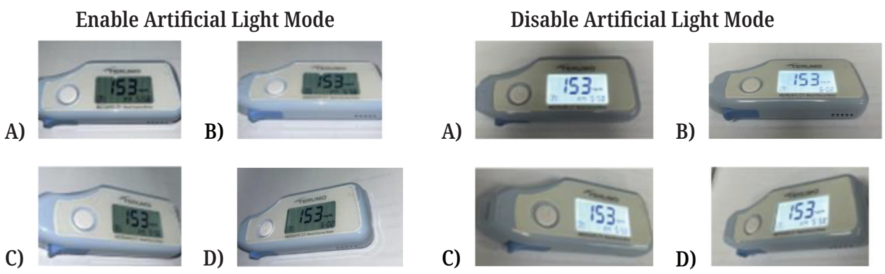

Fig. 24. Experiment of system processing with tilted images taken from an iPhone 13, with flash mode turned on and off

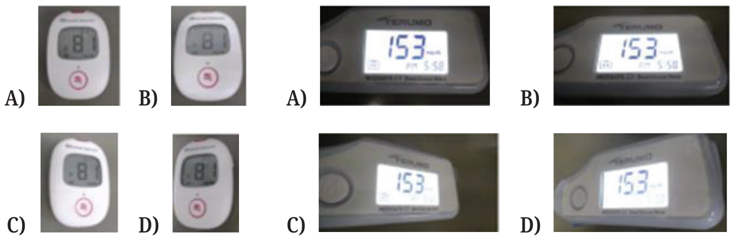

Fig. 25. Experiment of system processing with tilted images taken from a Logitech C930e computer webcam, with auto focus mode enabled

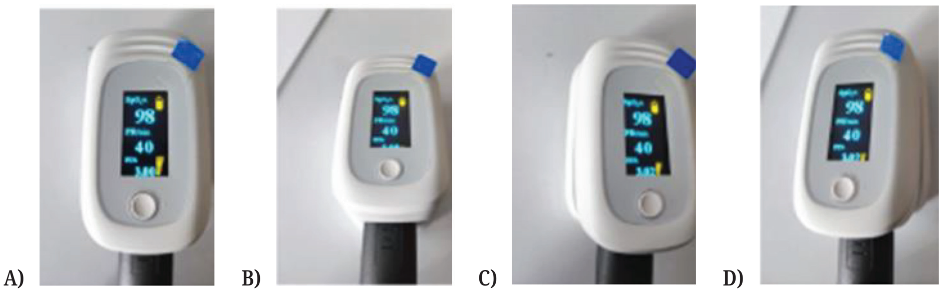

Fig. 26. Experiment of system processing with tilted images taken from a Mi 10T Pro smartphone, with artificial light mode disabled

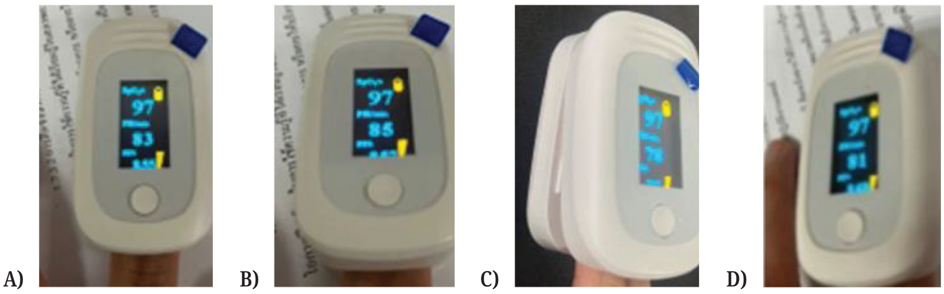

Fig. 27. Experiment of system processing with tilted images taken from an Apple iPhone 13, with flash mode turned off

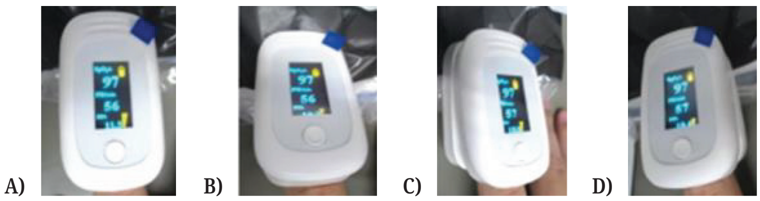

Fig. 28. Experiment of system processing with tilted images taken from a Logitech C930e computer webcam, with Auto Focus mode enabled

The OCR method used in this study shows a lot of promise for turning data from displays on medical devices such as blood pressure monitors and oxygen saturation meters into accurate digital files that can be stored and shown in databases. Despite its potential, the application of the system in practical scenarios presents some challenges. This includes being able to handle growing amounts of data in large healthcare organizations, different imaging device specs (smartphones and webcams), and environmental factors such as bad positioning or not enough lighting that can affect the accuracy of processing.

This approach provides considerable benefits in resource-constrained environments, such as rural clinics or small hospitals. The design prioritizes interoperability with multipurpose devices such as cellphones, facilitating rapid and precise data processing while alleviating the burden on medical staff. The system is still having trouble in low light and at tilt angles of –35° or higher, which makes it less accurate, especially when it comes to recognizing certain numbers, like when it calls "3" an "8." Improved preprocessing methods and advanced OCR algorithms are essential to enhance system robustness and adaptability.

The OCR system's capacity to incorporate health data into web applications enhances its functionality by facilitating real-time monitoring and access to health information. The automation of the digitization process diminishes manual data input errors by up to 85%, improves healthcare operations, and enables medical personnel to concentrate more on patient care. Furthermore, its compatibility with general-purpose imaging instruments guarantees accessibility and scalability, rendering it appropriate for various healthcare settings worldwide.

The system complies with data protection requirements, including GDPR and HIPAA, guaranteeing the secure and ethical handling of sensitive health information. Data encryption, access control measures, and systematic audits are employed to reduce risks and respond to emerging security threats. Because of these features, the system can be used in many healthcare settings, especially in countries with few resources, as it protects patient data and makes sure that international privacy and ethics standards are followed. Data encryption and access control mechanisms restrict access to authorized personnel, ensuring the secure management of essential health information. Systematic audits and improvements are conducted to mitigate risks and address emerging security threats, ensuring compliance with ethical standards and regulatory requirements.

In summary, the OCR system improves the efficacy of health data management and provides a sustainable solution for enhancing healthcare delivery in resource-limited regions. Its capacity to minimize errors, optimize processes, and provide secure data management renders it an indispensable asset for contemporary healthcare businesses. With enhancements to its algorithms and preprocessing procedures, it will more effectively assist physicians and ensure the accuracy and safety of health information.

4 CONCLUSION

The study clearly showed that using an OCR system along with the YOLOv5 model to digitize 7-segment numeric displays from medical devices like blood pressure monitors, blood glucose monitors, and pulse oximeters works well. Testing conducted at distances ranging from 7 to 30 cm at various angles achieved an overall accuracy of 97.80%, with peak performance under sufficient illumination. The system analyzed slanted images in 10–15 seconds; nevertheless, extreme tilts (–35° or greater) occasionally led to fuzzy or truncated digits. Artificial lighting enhanced visual clarity but necessitated modifications to minimize reflections. The system has a lot of potential for real-world use, especially in healthcare settings with limited resources, because it reduces mistakes caused by people entering data and makes it easier to manage health data. However, we must resolve challenges such as illumination fluctuation and erroneous device classifications. In the future, work will focus on improving preprocessing algorithms, camera calibration, and the addition of advanced error correction methods to make sure that performance is the same in all situations. These improvements will boost the system's usability, scalability, and reliability in contemporary healthcare applications.

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6 APPENDIX

This study has been approved by the Research Ethics Office of Rangsit University (RSUERB) under the certification number RSUERB2024-027 as a study that does not fall under the category of human research.

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