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A Novel Deep Learning, Camera, and Sensorbased System for Enforcing Hand Hygiene Compliance in Healthcare Facilities

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A Novel Deep Learning, Camera, and Sensor-based System for Enforcing Hand Hygiene Compliance in Healthcare Facilities

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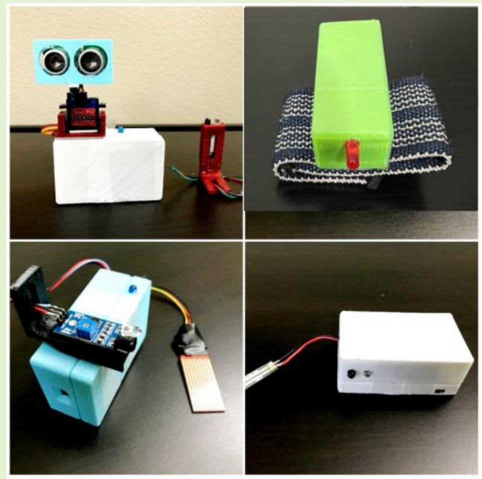
***Abstract*— Hospital-acquired infections are a major cause of death worldwide, and poor hand hygiene compliance is a primary reason for their spread. This paper proposes an artificial intelligence, microcontroller, and sensor-based system that monitors and improves staff hand hygiene compliance at various critical points in a hospital. The system uses a Convolutional Neural Network (CNN) to detect and track if staff have followed the WHO hand rub/hand wash guidelines at alcohol dispensers, hospital sinks, and patient beds. The system also uses RFID tags, vibration motors, LEDs, and a central server to identify staff, alert them of their cleaning requirements, monitor their cleaning activity, and report compliance data. We obtain an accuracy of 90.6% in classifying all steps of the WHO-stipulated hand wash/hand rub guidelines and a testing accuracy of 89.8% on Ivanovs et al.'s dataset. The system ensures that hospital staff stay compliant to all WHO hand hygiene guidelines, saving countless lives.**



***Index Terms*—Hand Hygiene Compliance Monitoring, Hospital-Acquired Infections, IOT, Sensors, Microcontroller System Design, Infection Prevention, Smart Hospital, Convolutional Neural Networks, Artificial Intelligence**

I. Problem Statement

HOSPITALS are meant to be treatment facilities to help the sick recover, but today rates of Hospital-Acquired Infections (HAI) have increased significantly making them a very threatening place to visit. According to the World Health Organization (WHO), every year, HAIs account for an estimated 99,000 deaths and 1.7 million cases just in the United States, and these tolls are continuously rising [1][2]. Furthermore, this problem is significantly worse in developing and underdeveloped countries. Hospital-acquired infections are infections that are acquired in a hospital by a visitor, staff, or patient during their visit, treatment, or stay. These infections are also known as nosocomial infections or HAIs [3][4]. WHO states that the primary reason for these infections is poor staff hand hygiene compliance, and it has stipulated very strict hand hygiene guidelines to be followed in hospitals to reduce the rates of hospital-acquired infections. These guidelines suggest exactly how to conduct proper hand washes and rubs [5][6][7][8].

According to several studies [9][10][11], conducting hand hygiene using alcohol dispensers and sinks located around the hospital is one of the most effective and efficient ways to reduce HAIs. But currently, practices employed in hospitals to track and enforce staff hand hygiene compliance at these critical points are substandard. Most hospitals conduct manual and random compliance checks. They typically attach poster-based hand hygiene guidelines similar to the ones in [8] throughout the hospital and trust that the staff will follow them [12][13][14]. A few hospitals use technological tools like video camera monitoring, robot usage, and electronic monitoring but these tools are limited in scope, ineffective, or too expensive [15]. Some examples of these existing tools are - Xenex LightStike robotic system, which focuses on disinfecting hospital surroundings using UV rays rather than focusing on the individual staff [16], and electronic monitoring solutions like from Debmed [17], Biovigil [18], Purehold [19] whose compliance checks are limited to alcohol dispenser usage at entry and exit of the room, not covering hand hygiene checks at the patient bed or sink area which are also very important for prevention of HAIs [20]. All existing methods and tools are only focused on some parts of the problem and therefore achieve moderate results. They also do not ensure that all steps stipulated in the WHO hand cleaning guidelines are followed. In most cases, their hand hygiene compliance monitoring is done only at the hospital level, not at the individual staff level.

The medical industry would benefit from a solution that addresses the shortcomings in current tools and research and solves all aspects of the problem instead of focusing on only a part of it. This proposed tool should track staff hand hygiene compliance at various critical points throughout a hospital, conduct detailed and highly accurate hand cleaning checks, send

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real-time compliance pass/fail alerts to staff, and record compliance data on a central server for management usage. A system like this will significantly help reduce rates of hospital-acquired infections by ensuring that all staff follow the hand hygiene measures required by WHO and can save countless lives in the future.

The major contributions of this paper are as follows:

- We propose and evaluate the performance of an automated deep learning, microcontroller, and sensor-based system that can track and enforce hand hygiene compliance throughout all critical points in healthcare facilities.
- We design robust hardware modules for staff, patient beds, alcohol dispensers, and sinks using microcontrollers and various sensors.
- We develop thorough software algorithms for each of the hardware modules that allow them to conduct detailed hand hygiene compliance checks, transmit hand hygiene data in real-time, and alert staff when hand hygiene is not maintained.
- We utilize state-of-the-art deep learning image classification techniques to develop an algorithm that accurately track hand movements of a staff during a hand rub/wash and ensure their hands are as clean as possible and hand hygiene is maintained as per WHO.

The remainder of this paper is organized in four different sections: Section II compares different industry research in hand hygiene compliance monitoring systems and hand wash/rub motion compliance tracking algorithms. Section III introduces the architecture of the proposed system, its different modules, and the hand motion compliance tracking deep learning algorithm. Section IV presents a detailed evaluation of the system performance considering different algorithms, modules, and complete system-level testing, and comparison to different related research and implemented industry tools. Section V summarizes this work and its contribution to this industry, and discusses some shortcoming and future plans.

II. Literature Review

A. Hand Hygiene Compliance Monitoring Systems

Sharma et al. [21] designed and implemented a video system for hand hygiene compliance monitoring of hospital staff. The video system recorded all movement of staff and their hand hygiene activity which could later be reviewed by hospital management to provide feedback to staff on compliance improvement. It utilized security cameras and was compared to real-time direct observation methodologies currently implemented in hospitals. Their results showcased that video monitoring improved the overall long-term staff hand hygiene compliance rates. However, a system like this is not viable in a hospital setting as it raises privacy concerns and still requires manual assessments from hospital management which can be subject to human error.

Asai et al. [22] proposed a multimedia system that utilizes speakers, screens, and augmented reality to motivate users to follow hand hygiene compliance through alcohol rub dispenser usage. While there was no primary implementation setting for this system, they stated that it could be used in hospitals, educational institutions, and other public areas. Their testing results showcased an increase in hand hygiene compliance. But their system does not track hand hygiene, it only provided a reminder to users in the area and cannot track individual users' rub completion rates.

Kinsella et al. [23] built a system using a microcontroller and pressure detection resistor to identify staff usage of alcohol dispensers in hospitals. This system is attached to walls near alcohol rub stations and as staff used the dispensers, this system took in account each handwashing account and compared it to the total number of patient procedures conducted which provided insight into the hand hygiene compliance of hospital staff as a whole. The testing results of this system showcased that it had the potential to boost compliance rates. But this system has clear disadvantages as it has no way to ensure specific staff hand hygiene compliance, quality of hand hygiene compliance, and cleaning episodes at locations other than dispensers such as hospital sinks.

Kanan et al. [24] developed a system using transmitters of 868 MHz radio frequency and 40 KHz ultrasound waves that are located throughout a hospital setting. The radio frequency waves were used to users near dispensers in a hospital setting and the ultrasound waves were used to detect their distance. Their had limited results as only initial testing was conducted. A system like this only focuses on a specific point in a hospital and the algorithm proposed for the staff-distance detection using ultrasound waves has many limitations, for example, beds or other objects can fall between the staff and the sensors.

Ellen et al. [25] created a system that formed a "smart hospital room" using RFID communication protocol and staff movement around the hospital. The "smart hospital room" detected staff, displayed patient medical records, gave lighting cues for hand hygiene compliance, and allowed staff with easy access to pocket cleaning gel. This system had no way to ensuring staff's hands were fully clean, did not record hand hygiene compliance data for management usage, and as per experimental results only slightly increased staff hand hygiene compliance and efficiency in conducting patient procedure.

Bal et al. [26] designed a system that utilizes RFIDs and the ZigBee communication protocol to identify hospital staff at soap dispensers and, transmit and store time/location data. While the RFID usage in their system was very promising as it allows for direct identification of hospital staff and can be integrated with existing staff badges, the rest of the system was elementary and did not conduct detailed checks for hand hygiene compliance. Instead, it only identified user, established their presence at rub stations throughout a hospital, and stored this data.

Karimpour et al. [27] proposed a system based on BLE RSSI values to reduce manual surveillance of hand hygiene requirements in hospitals. Using BLE beacons from staff's phones and ESP devices, they were able to form a trilateration algorithm that used proximity scanning for identification of staff and establish their hand hygiene compliance status. Based on their experimentation, they achieved a high accuracy but had limitations in their algorithms as it could easily be exploited by staff.

Haque et al. [28] developed a convolutional neural network-based vision system for hand hygiene monitoring. Their tool utilized depth sensor modality for privacy and only focused on general hand hygiene compliance (staff detection and dispenser push), not the identification of the specific WHO hand cleaning motion steps. They also had no way to identify staff throughout the hospital and alert them for corrective action.

Shrimali [29] previously worked on an elementary microcontroller and sensor-based system to track and monitor hand hygiene at alcohol dispensers and sinks. But only preliminary tests were conducted so evaluation data is unavailable, and the system had no way of ensuring hands were clean, it only identified staff and established their presence at critical points in a hospital.

Wang et al. [42] conducted a systematic review of electronic hand hygiene monitoring systems and summarized the latest technologies adopted in these systems. They identified 89 studies that evaluated various types of electronic monitoring systems for hand hygiene compliance and quality, such as application-assisted, camera-assisted, sensor-assisted, and real-time locating systems. They discussed the capabilities and limitations of these systems and highlighted the issues of accuracy, data integration, privacy and confidentiality, usability, associated costs, and infrastructure improvements. They also suggested that more research is needed to establish standardized metrics to measure system performance and to implement new sensing technologies and algorithms to improve system performance and address other hand hygiene-related issues.

McCalla et al. [43] evaluated the impact of an automated hand hygiene compliance system on HAI rates in a community hospital in the United States. The system used a badge worn by healthcare workers to detect hand hygiene events and provide real-time feedback. The system also collected data on hand hygiene compliance and provided reports and dashboards for quality improvement. The authors compared HAI rates before and after implementation of the system and found a significant reduction in catheter-associated urinary tract infections (IRR 0.55; 95% CI 0.35-0.87) and central line-associated bloodstream infections (IRR 0.45; 95% CI 0.23-0.89). They concluded that monitoring hand hygiene practices with an automated system, in addition to other infection control measures, may be an effective means of reducing HAIs.

B. Hand Wash/Rub Hand Motion Compliance Tracking Algorithms

Hoey et al. [30] were one of the first to approach the problem of hand wash/rub motion compliance tracking. They developed a handwashing assistant for patients with dementia using a particle filter-based classification approach. However, their research did not work to identify specific WHO hand cleaning motion steps.

Fernández-Llorca et al. [31] also attempted at developing a vision-based hand motion classifier. They utilized Support Vector Machine (SVM), a widely known machine learning algorithm to segment hands and filter their pixels for prediction. Their accuracy was 86.6% based on their dataset with 4 test subjects but their model's applicability for the real world is questioned as they conducted all their testing in one environment with skin color bias.

Prakasa and Sugiarto [44] presented a video analysis method for evaluating the completeness of hand washing movements based on the WHO guidelines. They used a webcam to record hand washing videos and applied image processing techniques to segment and track the hands. They then used a rule-based approach to classify the hand movements into different steps of hand washing and calculated a completeness score for each step. They tested their method on 20 videos of hand washing and reported an average completeness score of 86%. Limitations of their method including discrepancies in occlusion, illumination, and camera angles.

Bakshi et al. [45] proposed a method for tracking hand hygiene gestures with Leap Motion Controller, a device that can capture the motion of hands and fingers in 3D space. They segmented and analyzed videos of hand washing experts and extracted their corresponding features using machine learning techniques. They aimed to develop an automated tool that can ensure compliance with the WHO hand washing guidelines. Although their proposed methodology achieved a fair accuracy in feature extraction and segmentation, their model was not viable for healthcare settings as it had poor generalization and demonstrated mediocre performance on complex lab-based datasets.

Most recently, Ivanovs et al. [32] used a variation of MobileNETV2 and Xception transfer learning CNNs for WHO hand cleaning motion detection. Their work aimed to utilize a self-collected dataset of 2,000 hand motion videos to construct a mobile application for hand cleaning quality alerting. The highest accuracy they got was only 64% for the MobileNETV2 and 67% for the Xception and their dataset was from one sink, only conveying low practicality for real-world applications.

III. System Architecture

This paper presents CareHAI, a deep learning and microcontroller-based system that can track and enforce hand hygiene compliance throughout healthcare facilities. CareHAI is based on 4 modules that work together as a connected system to track hand hygiene compliance through a hospital. A Wi-Fi-based central server aids all modules in sending/receiving information. Figure 1 showcases a top-level overview of the system and each module's internal components.

CareHAI has various practical use cases. It can aid in monitoring hand hygiene compliance rates of individual healthcare workers, teams, departments, or wards, identifying high-risk areas or situations where hand hygiene compliance is low or insufficient, and educating healthcare workers on proper hand hygiene procedures.

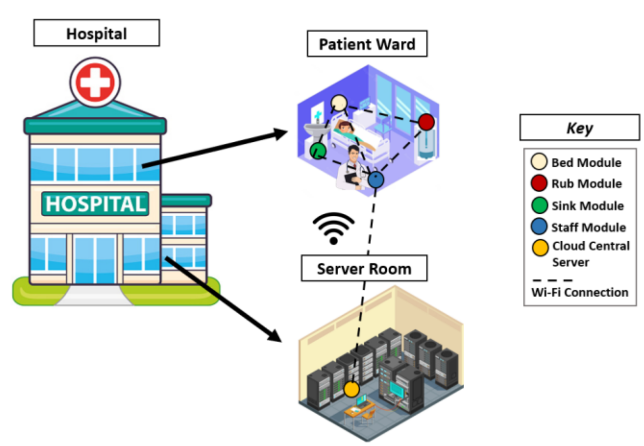

Fig. 1. CareHAI overview diagram. The entire system is based on a Wi-Fi-based central sever and individual modules that contain various input sensors.

A. Staff Module

The Staff Module uses a ESP8266 Wi-Fi Microcontroller, RFID Tag, vibration motor, and LED. This module is worn by staff on their wrist or bicep. The RFID tag on this module provides each staff member with a unique ID. It is detected by other modules placed at various compliance checkpoints across the hospital to identify staff. This module receives real-time compliance updates from the server and alerts staff through real-time vibration and LED indications. To power the module, a LIPO (Lithium Ion Battery) was chosen as a cost-effective option that can last for 48 hours with moderate use. The power consumption of the module depends on the ESP8266 Wi-Fi Microcontroller which has different power modes. In an idle state with powered Wi-Fi, the ESP8266 consumes about 70mA, which translates to about 231mW at 3.3V supply voltage. In deep sleep mode, the ESP8266 consumes only about 10µA, which translates to about 33µW at 3.3V supply voltage. The power consumption of the other components (RFID Tag, vibration motor, and LED) is negligible compared to the ESP8266.

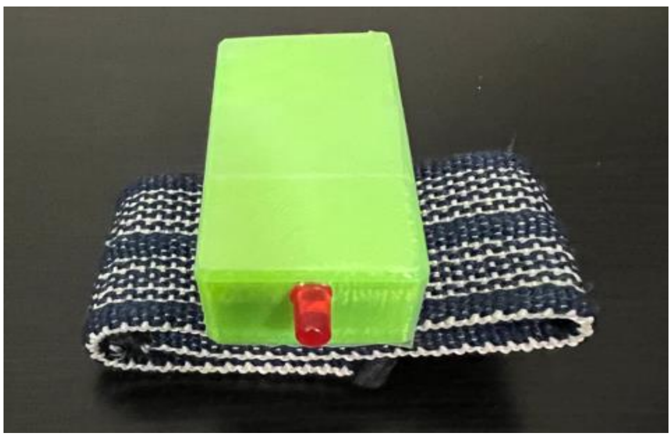

Fig. 2. The Staff Module can be worn on one's wrist or bicep. The prototype is shown with a custom 3D-printed enclosure.

B. Sink Module

The Sink Module uses a ESP8266 Wi-Fi Microcontroller, RFID reader, water detection sensor, Camera Microcontroller, Camera Wi-Fi Shield, and two InfraRed (IR) sensors. This module is attached to the sinks throughout the hospital. It conducts a detailed check for proper hand cleaning by staff as recommended in the WHO guidelines. The RFID reader on this module reads the staff's unique tag and starts the compliance check. The IR sensor detects the presence of staff's hand, the water detection sensor detects the water flow for an initial rinse, the IR sensor on the soap dispenser checks for soap usage, and the IR sensor on the water tap checks for the final hand wash completion. When a staff member puts their hand underneath the sink/soap dispenser it breaks the infrared beam, which triggers the IR sensor to detect staff hand presence. For the hand wash quality check, the camera takes continuous real-time images during the hand wash process and sends them through a CNN, which checks if all required hand cleaning motions are performed. When all the compliance checks are satisfied, a successful event is reported to the server, otherwise a fail event. The server then sends an immediate pass/fail alert to the staff module.

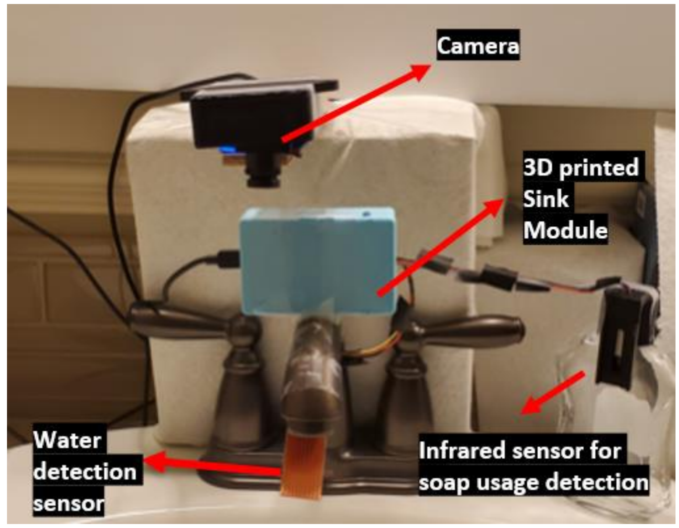

Fig. 3. The Sink Module prototype. The module can easily be deployed to hospital sinks.

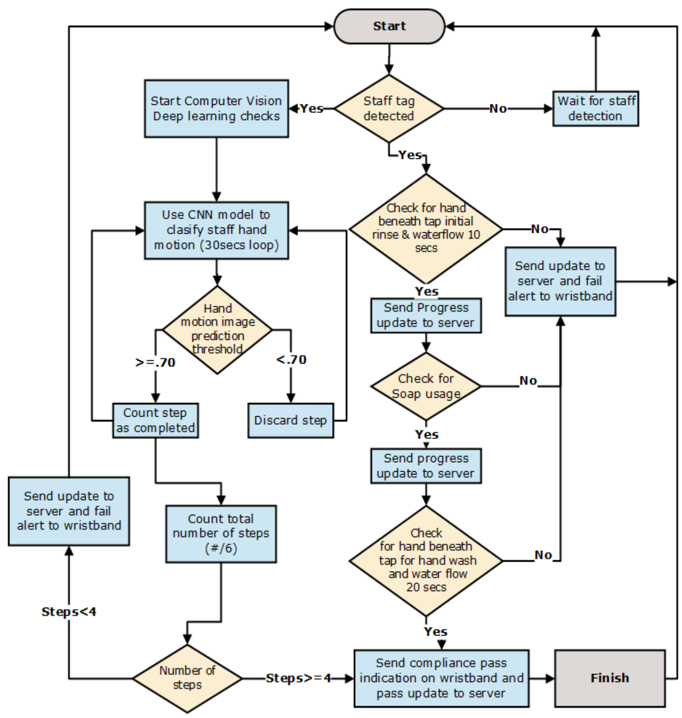

Fig. 4. Flow chart of the Sink Module Compliance Check Algorithm. Diamond block represents a decision point where the flow of the algorithm splits into different paths based on a specified condition. Rectangle block represents an operation, or a task, where the algorithm performs some action or computation.

C. Rub Module

The Rub Module uses a ESP8266 Wi-Fi Microcontroller, RFID reader, Force Sensitive Resistor (FSR), Camera Microcontroller, Camera Wi-Fi Shield, and InfraRed (IR) sensor. This module is attached to alcohol dispensers throughout the hospital. When staff comes near the alcohol dispenser, the RFID reader on this module reads the staff's tag, the IR sensor detects the presence of their hand underneath the automatic alcohol dispenser for its usage, in a case of a non-automatic alcohol dispenser FSR sensor will detect pushing of the dispenser button. Similar to the sink module, this module also uses a CNN-based algorithm to check if all motions of the WHO stipulated hand rub process are properly performed. When the above checks are satisfied, a successful event is reported to the server, otherwise a fail event is reported, and staff will receive an immediate alert.

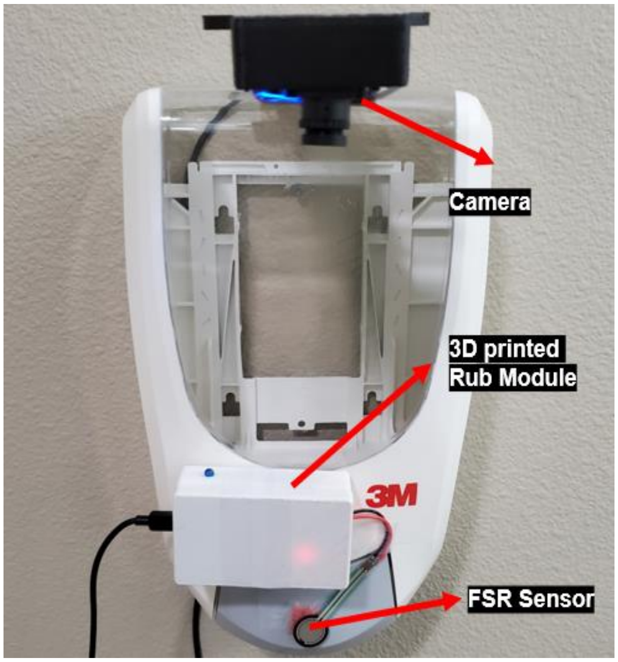

Fig. 5. The Rub Module prototype. The module can easily be deployed to hospital alcohol dispensers.

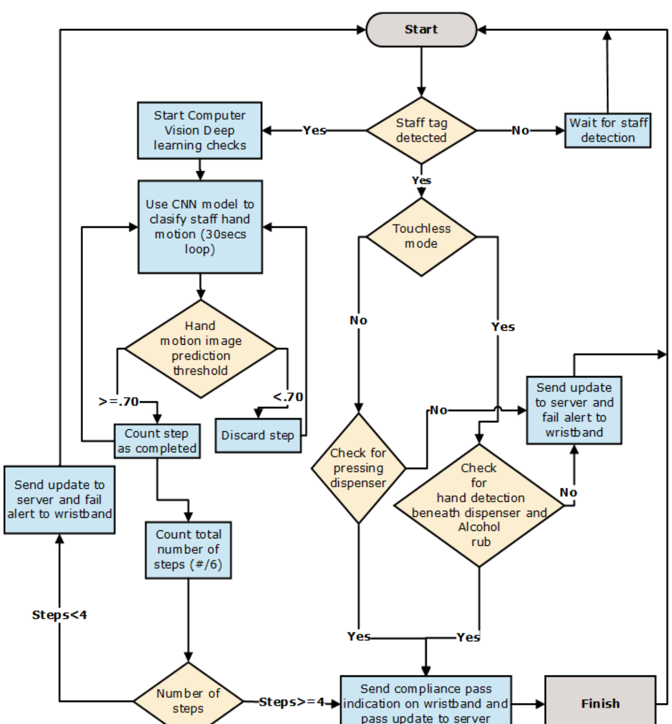

Fig. 6. Flow chart of the Rub Module Compliance Check Algorithm. Diamond block represents a decision point where the flow of the algorithm splits into different paths based on a specified condition. Rectangle block represents an operation, or a task, where the algorithm performs some action or computation.

D. Bed Module

The Bed Module uses a ESP8266 Wi-Fi Microcontroller, RFID reader, ultrasonic sensor, InfraRed (IR) sensor, Force Sensitive Resistor (FSR) and servo motor. WHO recommends that healthcare staff should conduct an alcohol rub when they enter the patient bed area and when they leave the patient bed area. This module is attached to each patient's bed and enforces the compliance of this guideline. The ultrasonic sensor on this module detects the staff's entry within the 1-meter range of a patient bed, the RFID reader on the module reads the staff's unique tag and provides staff with an alert to conduct an alcohol rub. This module then checks for a proper alcohol rub completion and once done sends a compliance alert to staff. When staff leaves the 1-meter range, this module provides another alert to staff to conduct an alcohol rub, before attending any other patients.

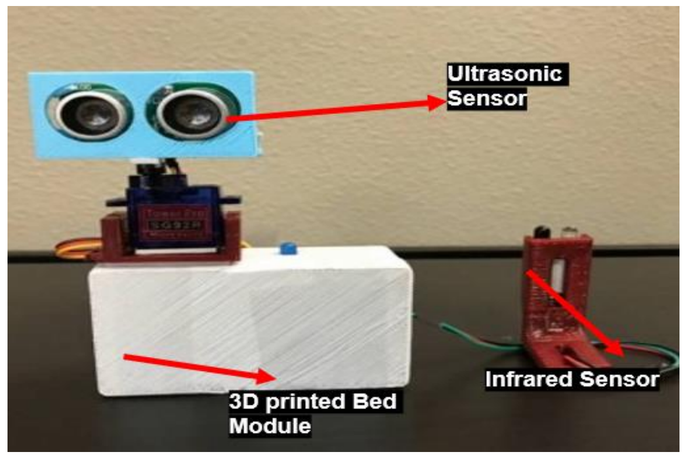

Fig. 7. The Bed Module can be easily deployed to patient beds in a hospital (electronic circuit within custom 3D-printed enclosures).

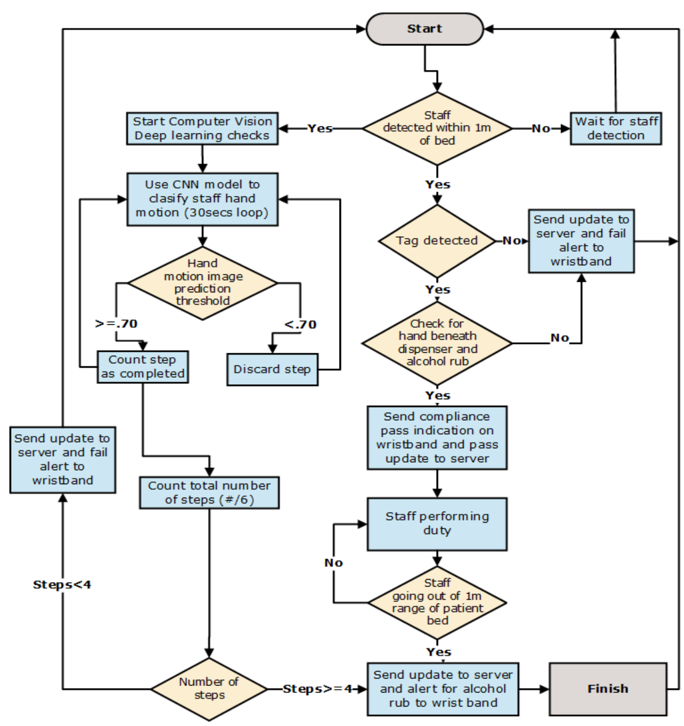

Fig. 8. Flow chart of the Bed Module Compliance Check Algorithm. Diamond block represents a decision point where the flow of the algorithm splits into different paths based on a specified condition.

Rectangle block represents an operation, or a task, where the algorithm performs some action or computation.

E. Hand Motion Compliance Checks

CareHAI's Sink and Rub Modules utilize deep learning camera checks that are based on a Convolutional Neural Network (CNN). These checks examine a staff's hand cleaning process and ensure all required hand motions of the WHO stipulated hand wash/rub are followed.

To develop an optimal CNN for the module camera checks, first a dataset was self-collected and preprocessed. This dataset was carefully designed to include a range of images taken in various lightings, backgrounds, and angles to ensure a controlled dataset with minimal bias. The OpenMV cam was used to take images while the subject was performing the hand motions without any time constraints. The dataset is publicly available and can be accessed at https://drive.google.com/drive/folders/1NRZ5Na5N3b-B6bk261bnRnYTmO8PCMlr?usp=sharing. It contains 5,500 images divided into 7 classes: no hand, step 1, step 2, step 3, step 4, step 5, and step 6. Figure 9 shows samples images from the self-collected handwash/rub dataset.

Fig. 9. Sample images from the handwash/rub self-collected dataset (steps 1-6 of the WHO handwash/rub). Images were taken in various lightings, backgrounds, and angles to ensure a controlled dataset.

The image dataset was split into an 85:10:5 ratio for training, validation, and testing respectively. 10 CNN transfer learning models were selected for an initial comparative training and validation analysis on the dataset: VGG16 [33], VGG19 [33], ResNet152 [34], Xception [35], InceptionV3 [36], InceptionResNetV2 [37], MobileNetV2 [38], EfficientNetB5 [39], EfficientNetB7 [39], and DenseNet201 [40]. A custom Keras Library Model was also developed for comparison. Each neural network varied in size and efficiency.

To aid the CNNs in feature extraction, 3 image filters were used on the dataset during the training and validation process. These image filters were: Laplacian Filter Sharpening, Canny Edge Detection, and Gaussian Blur [41]. Additionally, no image filter was also used as a control group to ensure that if the image filters had a negative impact on a model's accuracy, it could be easily identified.

In this analysis 44 different neural networks were trained, validated, and tested, each based on a unique model architecture and image filter. For each neural network, hyperparameters such as learning rate, momentum, and epoch were constantly modified using hyperparameter optimizers during the training and validation process to ensure the highest possible validation accuracy was achieved and validation loss was minimized.

Based on this analysis, MobileNetV2 and EfficientNetB7 were found to be the two neural network transfer learning architectures with the most optimal performance and inference times, and the Laplacian Sharpening Filter was determined most optimal image filter for effective feature extraction on the dataset. Therefore, using the architectural characteristics of these CNNs and image filter, a modified hybrid transfer learning CNN that uses feature fusion was developed, trained, validated, and tested on the dataset. This hybrid model had the highest validation accuracy of 91.2% and F1 score of 90.3. When run on new images from the testing dataset, this model had an accuracy of 90.5% showcasing peak performance out of all of the models from the comparative analysis and therefore was chosen for the Rub and Sink Module hand cleaning checks.

TABLE I
CNN PERFORMANCE EVALUATION METRICS

Model Architecture	Parameters (M)	Image Filter	Validation Accuracy (%)	Precision	Recall	F1 Score
VGG16	138.4	Gaussian Blur	66.4	63.2	67.2	65.1
		Canny Edge Detection	74.1	75.6	73.9	74.7
		Laplacian Sharpening	79.6	81.2	77.4	79.3
		N/A	70.5	67.1	71.6	69.3
VGG19	143.7	Gaussian Blur	77.5	73.6	78.3	75.9
		Canny Edge Detection	70.9	70.4	71.3	70.8
		Laplacian Sharpening	74.9	74.2	75.2	74.7
		N/A	71.6	72.6	71.9	72.2
ResNet152	60.4	Gaussian Blur	64.0	62.8	65.7	64.2
		Canny Edge Detection	67.3	67.8	70.4	69.1
		Laplacian Sharpening	72.5	74.5	73.7	74.1
		N/A	59.8	62.5	64.9	63.7
Xception	22.9	Gaussian Blur	77.8	78.5	77.2	77.8
		Canny Edge Detection	76.0	75.3	76.2	75.7
		Laplacian Sharpening	80.9	81.7	78.5	80.1
		N/A	73.9	71.5	74.4	72.9
InceptionV3	23.9	Gaussian Blur	72.2	71.6	73.2	72.4
		Canny Edge Detection	73.5	70.7	75.3	72.9
		Laplacian Sharpening	74.3	72.6	78.2	75.3
		N/A	72.9	71.8	74.6	73.2
InceptionResNetV2	55.9	Gaussian Blur	66.0	64.2	66.4	65.3
		Canny Edge Detection	68.7	70.7	67.5	69.1
		Laplacian Sharpening	77.5	75.7	78.8	77.2
		N/A	76.9	77.2	76.8	77.0
MobileNetV2	3.5	Gaussian Blur	70.2	70.5	70.2	70.3
		Canny Edge Detection	74.8	75.8	73.2	74.5
		Laplacian Sharpening	88.2	90.3	83.1	86.6
		N/A	66.0	65.8	68.5	67.1
EfficientNetB5	30.6	Gaussian Blur	76.5	75.3	77.9	76.6
		Canny Edge Detection	74.9	72.9	76.2	74.5
		Laplacian Sharpening	82.2	81.4	81.9	81.6
		N/A	74.6	74.4	75.2	74.8
EfficientNetB7	66.7	Gaussian Blur	80.9	82.7	78.3	80.4
		Canny Edge Detection	79.1	82.2	79.0	80.6
		Laplacian Sharpening	87.4	88.6	85.1	86.8
		N/A	82.1	80.2	83.7	81.9
DenseNet201	20.2	Gaussian Blur	67.9	65.5	68.1	66.8
		Canny Edge Detection	68.2	68.8	68.1	68.4
		Laplacian Sharpening	71.4	68.2	73.9	70.9
		N/A	67.9	66.8	70.5	68.6
Custom Keras Configuration	1.3	Gaussian Blur	57.5	58.4	59.7	59.0
		Canny Edge Detection	75.8	74.3	72.7	73.5
		Laplacian Sharpening	81.4	79.5	82.6	81.0
		N/A	70.9	69.5	75.6	72.4

The hand cleaning checks use this hybrid CNN's classification confidence values to distinguish between proper versus improper hand cleaning. In a 30-second time loop, if the model predicts that a hand motion has been classified with a confidence of 70+%, then the hand motion step is counted as completed, if probability of the model's confidence is lower than the 70% threshold, then the hand motion step is not counted as completed. At the end of the loop, depending on how many steps the CNN has detected as completed, the staff is sent an immediate compliance pass/fail alert and results are reported to the central server (if staff has completed 4+ steps out of 6, they would receive a pass alert as a proper handwash/rub has been completed, else a fail alert to redo their low-quality hand cleaning).

F. Cloud Central Server

Staff hand hygiene compliance data from each of modules is sent to a cloud central server using Wi-Fi-protocol where it is securely stored through 2FA. Specifically, this data consists of the room where the module is located, staff ID, compliance messages, and compliance pass/fail status. The data is organized into a table where it can be used by the hospital management to take corrective action towards a staff or be visualized or analyzed. Figure 10 (a-b) shows sample images of the server user interface.

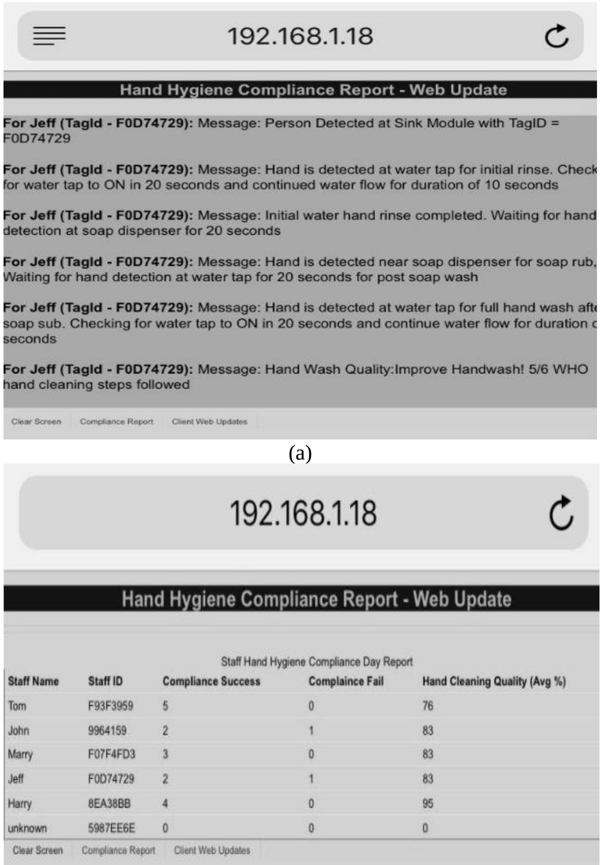

Fig. 10. Screenshots of the (a) real-time staff hand hygiene web updates generated for sample staff with ID=F0D74729 at the Sink Module on the central sever and (b) "staff hand hygiene compliance day report" page on the central server which tracks each staff member's daily compliance pass/fail count and average hand cleaning quality.

IV. System Performance and Evaluation

Multi-level testing and data analysis was conducted for CareHAI. First each sensor was independently calibrated and tested to ensure their proper operation. Next, each module was tested for its individual functionality by stipulating hospital-like events.

A. CNN-based Compliance Checks

For the deep learning checks, 44 different CNNs were initially designed, trained, and validated to classify each WHO handwash/rub step. Validation Accuracy, precision, recall, and F1-score were the evaluation metrics used to determine optimal model performance. Accuracy is the ratio of total correct predictions to overall predictions on the validation dataset. Precision (or Positive Predictive Value) is the number of correct positive results divided by the total number of positive results predicted by the classifier. This measure describes the accuracy of the network in differentiating between positive and negative results. Recall (or True Positive Rate) is defined as the ratio of true positives to false negatives plus true positives. This measure describes the proportion of correctly classified positive data points to all actual positive data points. F1-Score represents the balance between precision and recall rate. In network classification, it is crucial that there is a high precision rate because that is necessary for accurate classification. But there should also be a high recall rate as that determines how well the network can "remember" its training and continue to identify the images correctly. This measure helps to describes the rate of this balance (harmonic mean of precision and recall). Table I shows each neural network's performance based on the described evaluation metrics. Figure 11 shows a visualization of the table.

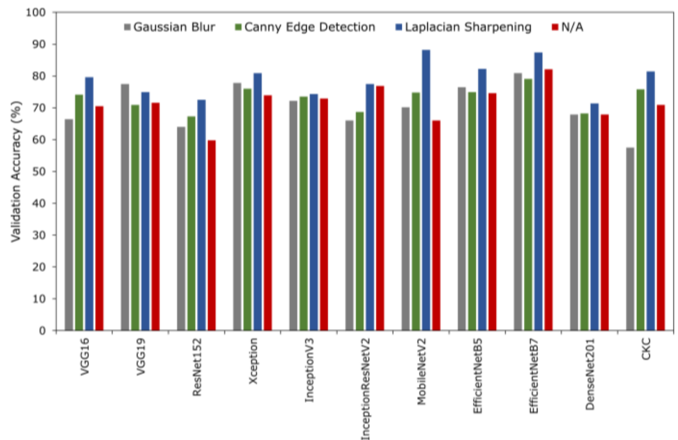

Fig. 11. Validation Accuracy of CNN architectures using No Filter, Laplacian Sharpening, Gaussian Blur, and Canny Edge Detection. Overall, for each CNN architecture the Laplacian Sharpening filter was most effective in feature extraction and led to the highest accuracies. The best performing model architectures were MobileNetV2 and EfficientNetB7 using the Laplacian Sharpening Filter with validation accuracies of 88.2% and 87.4% respectively.

Based on the comparative analysis, MobileNetV2 and EfficientNetB7 using the Laplacian Sharpening Filter were found to be the two neural network architectures with the most optimal performance. Therefore, based on their architectural characteristics, using transfer learning, a hybrid model was developed, trained, and validated on the dataset. This hybrid model had a validation accuracy of 91.2% and F1 score of 90.3 on the training and validation dataset which was significantly higher than the initial 44 comparative analysis models. This CNN model also surpassed the design criteria of an 80%+ validation accuracy and size under 70,000,000 model parameters. To further test this hybrid model, it was evaluated on the testing dataset (5% of the total dataset) on which it had an accuracy of 90.5% and was able to successfully classify 249 images out of 275 while showcasing minimal bias towards each of the 6 hand motion classes as seen from its precision score of 90.2, recall score of 91.0, and F1-score of 90.6. Based on this optimal performance, the hybrid model was chosen for the Rub and Sink Module hand cleaning compliance checks.

B. System Updates/Alerts

Lastly, complete system-level testing was conducted. All the modules were connected with the central server and data was collected and analyzed to see if all the modules work cohesively. Figure 12 (a-b) and Tables II and III show the system-level testing results. As per the results, CareHAI showed a high accuracy of 94% in reporting compliance updates to the server and 95% accuracy in receiving alerts from the server out of 100 trials conducted for each event.

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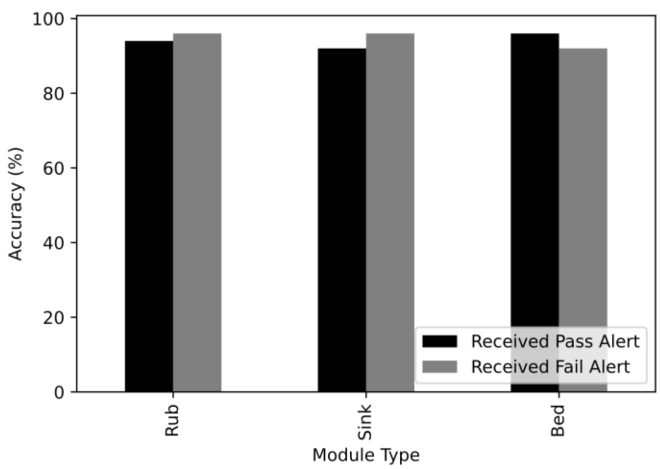
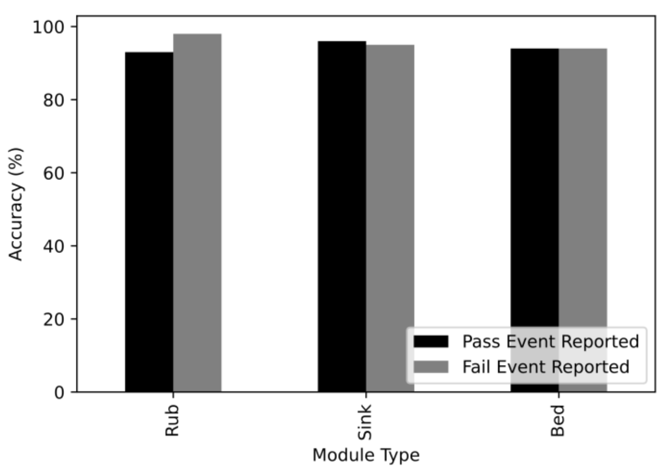
TABLE IV
COMPARISON OF CAREHAI'S HAND HYGIENE MOTION CHECK ALGORITHM TO OTHER ALGORITHMS

	[30]	[31]	[32]	CareHAI
Basis of Algorithm	Bayesian sequential and decision-theoretic framwork	Support Vector Machine	CNN (MobileNetV2 and Xception)	Hybrid CNN (Feature Fusion of MobileNetV2 and EfficientNetB7)
Hardware Used	Camera, Laptop with prcessor (2GB RAM)	High-Quality Camera, PC	AirLive IP Cameras, Raspberry Pi 4	OpenMV Camera and Wi-Fi Shield
Locations Covered	Sinks	Sinks	Sinks	Sinks, Alcohol Dispensers
Checks for the 6 WHO-required Hand Motions	No (focuses on general hand wash + soap and towel usage)	Yes	Yes	Yes
Sends Hand Hygiene Alerts	Yes (audio)	No	Yes (audio)	Yes (vibration, visual)
Overall Algorithm Evaluation Metric and Accuracy	Conducted 20 Simulations of Hand Washing and Actor Trials (not enough data to calculate accuracy)	Training/Testing Dataset Evaluation of Motion Detection Rate (86.6%)	Validation Dataset Evaluation of Both CNNs (MobileNetV2 – 64%, Xception – 67%)	Multi-Level Testing (90.5% on testing dataset, 89.8% on [24]'s dataset)



(a)



(b)

Fig. 12. (a.) Staff module's accuracy in receiving compliance pass/fail alerts from other modules (out of 100 trials) (b.) Modules' accuracy in sending compliance updates to the central server (out of 100 trails).

TABLE II
ACCURACY IN RECEIVING COMPLIANCE UPDATES AND ALERTS

Device	Received Pass Alert	Received Fail Alert
Rub Module	94	96
Bed Module	92	96
Sink Module	96	92
System-Level (Avg of Modules)	*95*	

TABLE III
ACCURACY IN SENDING COMPLIANCE UPDATES AND ALERTS

Device	Received Pass Alert	Received Fail Alert
Rub Module	93	98
Bed Module	96	95
Sink Module	94	94
System-Level (Avg of Modules)	*94*	

C. Comparison of CareHAI's CNN-based Compliance Checks to Previous Published Research

To compare this paper's work to previous research, CareHAI's hand cleaning motion check CNN model (hybrid transfer learning of MobileNetV2 and EfficientNetB7 using the Laplacian Sharpening Filter) was trained, validated, and tested using Ivanovs et al. [32] hand-washing video dataset that was annotated according to WHO's hand-washing guidelines.

TABLE V
COMPARISON OF CAREHAI TO OTHER HAND HYGIENE COMPLIANCE SYSTEMS

	[21]	[22]	[24]	[26]	[27]	[28]	CareHAI
Communication Protocol	N/A	Bluetooth	Wi-Fi	Wi-Fi, ZigBee	Bluetooth	N/A	Wi-Fi
Basis of System	Camera	Laptop/PC	N/A	Raspberry Pi	ESP Nodes, Smartphone	Camera and ResNet152 CNN	Camera and ESP8266 Microcontroller
Sensors Used	N/A	IR, Pressure, Nintendo Wii Balance Board	Wave Transmitters (868 MHz Radio Frequency and 40 KHz Ultrasound)	IR	N/A	N/A	RFID Tags/Readers, Ultrasonic, IR, Water Detection, FSR
Identifies Specific Staff	Yes (not real-time)	No	Yes	Yes	Yes	No	Yes
Alerts Staff	No	Yes (audio/visual)	Yes (audio)	No	No	No	Yes (visual/vibration)
Checks for Hand Cleaning Quality (All WHO Steps)	No	No	No	No	No	No	Yes
Logs Compliance Data	Yes (requires manual effort)	No	No	Yes	No	No	Yes
Locations Covered	ICU, HDU, ER Sinks and Alcohol Dispensers	Alcohol Dispensers	Alcohol Dispensers, Patient Beds	Alcohol Dispensers, Sinks	Alcohol Dispensers, Sinks	Alcohol Dispensers	Patient Beds, Sinks, Alcohol Dispensers
Overall System Evaluation Metric and Accuracy	Video Monitoring measured with Manual Observation (staff compliance rates of 67% and 81%)	N/A (not enough experimentation conducted)	N/A (not enough experimentation conducted)	N/A (not enough experimentation conducted)	Compared to proximity-based solution (12% more reliable)	Overall Detection of Staff/Push of Dispenser Button (95.5%)	Sending and Receiving Alerts/Messages (94 and 95%)

Based on the initial evaluation results, CareHAI's CNN model performed with a validation accuracy of 88.4% on their dataset, it proves to be better than current published work (67%) [32]. Furthermore, this trained and validated model was integrated with a camera apparatus for real-time hand motion classification testing where it was able to detect 97 out of 108 hand motions correctly, leading to a real-time performance testing accuracy of 89.8% when trained and validated using Ivanovs et al.'s dataset [32]. Figure 13 and 14 showcase a visualization of these results.

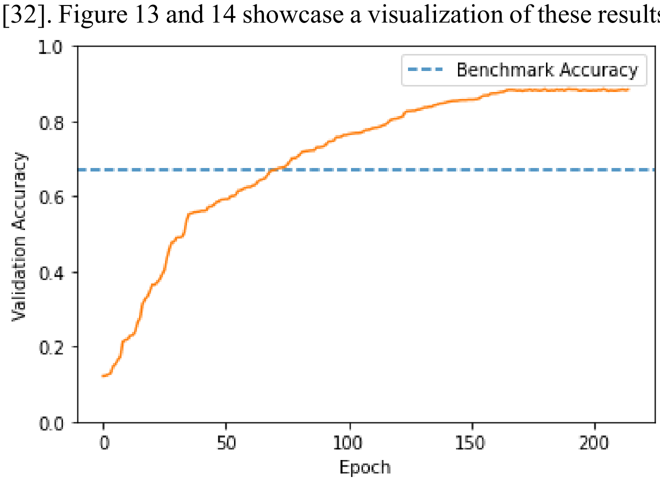


Fig. 13. Graph of the Validation Accuracy of CareHAI's hand cleaning motion check CNN model when trained on Ivanovs et al. [32] hand-washing video dataset. CareHAI's model performed well above the currently published benchmark of 67% as it had a validation accuracy of 88.4%.

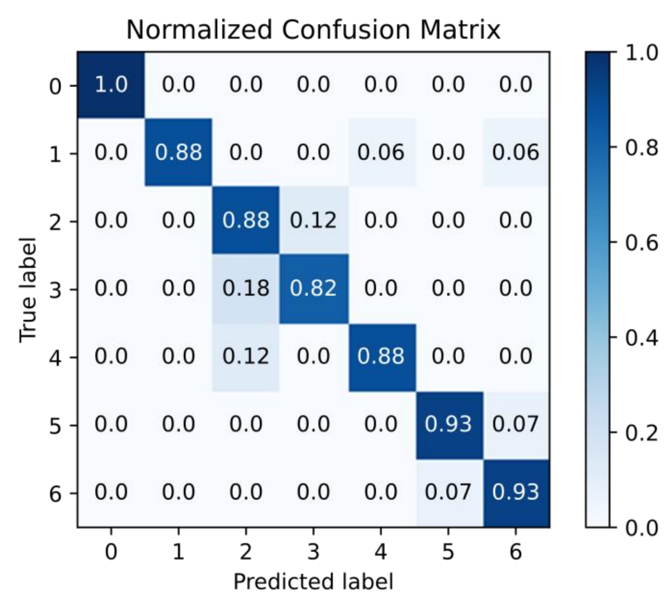


Fig. 14. Normalized confusion matrix showcases that CareHAI's hand cleaning motion check CNN model, when trained on Ivanovs et al. [32] hand-washing video dataset, had a real-time hand motion classification accuracy of 89.8%.

Table IV showcases a detailed comparison of CareHAI's CNN-based hand motion compliance checks to previously published research that was discussed in the Related Works section, in terms of their basis of algorithm, hardware usage, location coverage, algorithm ability, prediction time, and accuracy. CareHAI's checks are novel, accurate, efficient, thorough, and ensure that hospital staff complete all required hand cleaning motions of the WHO-stipulated handwash/rub, outperforming all previous work in every evaluation category.

D. Comparison of CareHAI to Other Proposed Hand Hygiene Compliance Systems

Table V showcases a detailed comparison of CareHAI to other previously published hand hygiene compliance systems were discussed in the Related Works section, in terms of their functionality, communication protocol, hardware usage, location coverage, and overall evaluation results. CareHAI is novel, automated, highly accurate, thorough, and scalable for a healthcare setting. It mitigates the problems of current implemented solutions and outperforms all previous work, providing an optimal tool for implementation.

V. Limitations and Future Work

This research focused on the development and technical evaluation of an artificial intelligence, microcontroller, and sensor-based system to track and monitor hand hygiene compliance among hospital staff. Our extensive dataset and rigorous evaluation criteria provide strong evidence of the effectiveness of our proposed system. However, we also acknowledge some limitations and directions for future work.

One limitation is that the performance of the deep learning model may be affected by the quantity and quality of the training data. Although we collected a large and diverse dataset of hand hygiene motions that included a range of images taken in various lightings, backgrounds, and angles, it is possible that some rare or complex cases were not captured correctly. Therefore, we plan to expand our dataset with more data and annotations in the future.

Another limitation is that while our approach achieves better performance than existing methods in terms of accuracy, speed, and scalability, there is still room for improvement in these aspects. For example, we could optimize the model architecture and hyperparameters to reduce the inference time and memory consumption. We could also explore domain adaptation to improve the generalization ability of the model to different environments and users.

The biggest limitation of this work is the absence of a clinical study to validate the effectiveness of the proposed system in a real-world hospital setting. A clinical study would be an important and valuable component of validating the system's efficacy in reducing hospital-acquired infections and improving patient outcomes. However, a clinical study would require significant resources and approvals from an Institutional Review Board (IRB), which is beyond the scope of this work.

One of our main future research steps is to test the system in real hospitals to collect on-field data and feedback from hospital staff and patients. This would allow us to evaluate the system's usability, reliability, acceptability, and impact on hand hygiene compliance and infection rates. Another potential avenue for improvement is to add more configurable options for the Staff Module such as integrating it with existing smartwatches and mobile devices. This would increase the convenience and flexibility of using the system for different staff members. Furthermore, we could explore online learning techniques, which would allow the deep learning model to be updated in real-time as new data becomes available. This could enhance the adaptability and accuracy of the system to different situations and patients.

VI. Conclusion

In this paper, CareHAI, a novel, automated, and scalable system for hand hygiene compliance monitoring in healthcare facilities was successfully designed and tested. This system conducts detailed, and thorough deep learning and sensor-based checks at various critical points throughout a hospital to enforce and monitor staff's hand hygiene compliance. This system provides immediate alerts to staff to inform them about their compliance and additionally stores all compliance events and results on a central server that can be used by hospital management. This system is designed in a robust way and can easily integrate into healthcare environments, it operates in real-time, and sends immediate updates to staff without hampering the normal medical staff activity. This system's deep learning-based hand cleaning quality checks are based on an optimal and efficient convolutional neural network that was chosen through comprehensive analysis and comparison of 44 different CNNs. The designed hybrid model (transfer learning of MobileNetV2 and EfficientNetB7 using the Laplacian Sharpening Filter) has a testing accuracy of 90.5% and F1 score of 90.6 which surpassed the design criteria goal. Through multi-level testing and data analysis, results show that this system has an accuracy of 94% in reporting compliance pass/fail/generic updates to the server and 95% accuracy in receiving pass/fail alerts from the server. Furthermore, CareHAI was also evaluated on Ivanovs et al. [32] hand-washing video dataset to ensure it is more optimal than the current industry best. When trained, validated, and tested on the dataset, CareHAI performed exceptionally well as it had a validation accuracy of 88.4% compared to the current industry benchmark of 67% [32] and a real-time performance testing accuracy of 89.8%.

CareHAI has the potential to significantly reduce rates of hospital-acquired infections around the world and save thousands of lives. With slight modifications, this system can be used in the food industry, schools, and even homes to track and monitor hand hygiene.

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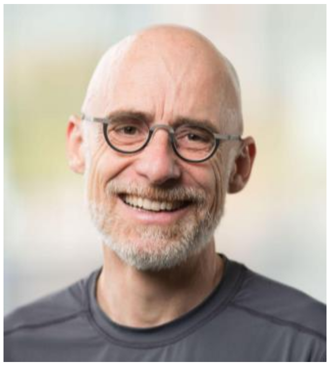

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