Contactless Hand Sanitizer System with Machine Learning Verification in Reducing Healthcare-Associated Infection (HAIs) - An Initial Study

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ABSTRACT

Healthcare-associated infections (HAIs) remain a huge concern in most healthcare facilities, mainly caused by the inability to perform proper hand hygiene and poor compliance with established hand hygiene practices. Behavioural lapses in hand hygiene significantly contribute to the transmission of pathogens and the persistence of Healthcare-associated infections (HAIs) within clinical environments. HAIs is a a huge concern in most healthcare facilities, mainly caused by the inability to perform proper hand hygiene. This study proposes a contactless hand sanitizer that incorporates an automated access control for ensuring proper hygiene and limiting cross-contamination in areas that require high sterility, such as the Intensive Care Unit (ICU). The system, built using Raspberry Pi 4 and components like ultrasonic sensors, IR sensors, a UV light, and the OV5647 camera, dispenses sanitizer and verifies compliance before unlocking the door. A Convolutional Neural Network (CNN), MobileNetV2, was trained on ultraviolet (UV)-lit images of sanitized and unsanitized hands to detect the presence of fluorescent residue. It analyses the presence of fluorescent liquid in hand sanitizer for compliance before granting access. While the model demonstrated high accuracy during training, hardware limitations, especially the camera's low sensitivity under UV light, affected its real-time performance. Nevertheless, the system provides an initial basis that exemplifies the potential of machine learning-integrated sanitary enforcement as an initial point of further development in the direction of more comprehensive approaches to reducing HAIs.

INTRODUCTION

Healthcare-associated infections (HAIs) are infections that can be transmitted while patients are receiving healthcare, whether in a hospital, healthcare facility, or home care. HAIs can appear within the first 48 hours of hospitalisation and within 30 days of receiving treatment [1] . According to the US Centers for Disease Control and Prevention, one in 31 hospital patients in the United States has at least one HAI, with an estimated 1.7 million patients acquiring HAIs each year. This leads to approximately 99,000 deaths annually due to these infections[2]. HAIs have been a significant global burden, with estimates indicating that for every 100 patients admitted to acute-care, approximately 7 patients in high-income countries and up to 15 patients in low- and middle-income countries acquire at least one HAI during their hospitalisation. The risk becomes even more critical in intensive care units (ICUs), where up to 30% of patients may develop HAIs due to invasive procedures, immunocompromised conditions, and frequent contact with healthcare personnel and equipment. It is noticeable that the incidence of HAIs in ICUs is two to twenty times higher in low- and middle-income countries than in

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high-income countries, with neonates being the most vulnerable [3]

HAIs can spread via droplet, airborne, or contact transmission, with contact both direct and indirect being the primary route. They can be transmitted through the hands of healthcare workers, other patients, or hospital visitors. Recent qualitative research in ICU settings has identified multiple determinants of hand hygiene compliance spanning individual knowledge, team norms, workload pressures, and organizational support highlighting that hand hygiene behaviour is shaped by complex social and contextual factors rather than availability of resources alone [4]. Contaminated hands are able to transfer pathogens to patients or surfaces, leading to infections. Studies conducted in 2019 and 2022 indicate that approximately 50% of HAIs occur due to inadequate hand hygiene practices among healthcare workers [5], [6]. The transmission chain can be effectively disrupted by implementing proper hand hygiene protocols. In order to combat HAIs, healthcare facilities implemented various strategy to focus on prevention, education and surveillance. One of the ways is by promoting hand hygiene among healthcare workers and visitors. A study indicates that proper hand hygiene practice can reduce infection by 40% to 70% [2] This includes handwashing with soap and water or alcohol-based hand sanitizers. Despite knowing the importance of hand hygiene, healthcare workers and visitor fail to perform them correctly or frequently. The compliance rate among healthcare workers falls 40% on average, in countries with limited resources, this figure can drop as low as 12.8% [7]. This indicates a gap that requires continuous monitoring and standardisation.

Visitor compliance is notably lower than healthcare workers with the baseline as low as 0.4%. However, by relocating and making the hand sanitizer more visible, it can increase the visitor compliance by 19.7%. Due to COVID-19, people have more awareness, hence higher rates have been observed[8]. Cross- contaminations, the transfer of microorganisms between different surfaces or individuals, may lead to HAIs. This often happens in healthcare environments, where pathogens spread via contaminated hands, surfaces or medical equipment. The results of transmission of pathogens includes increased incidence of HAIs, spread of Multidrug-Resistant Organisms (MDROs) and reduced patient safety and trust to the healthcare provider and facilities as a whole. While current infection prevention strategies in hospitals heavily rely on handwashing and alcohol-based hand rub dispensers, staff education and compliance audits, there are still remain a significant gap where there is no practical, automated system to verify whether hand sanitization has been performed properly before entering high-risks areas like ICUs and NICUs[9]. The existing systems depend largely on manual observation and trust-based compliance, which can be risk in errors. This project proposes developing a contactless device that uses verification and machine learning to check for proper hand sanitization before granting access. By automating this verification process, the device aims to reduce the risk of cross-contamination.

METHODOLOGY

The research was categorized into four successive steps: requirement, development, implementation, and testing. Each stage flows from the previous one, from defining system needs, developing hardware and software, integrating the prototype, and finally evaluating system performance and verification of hand hygiene. In this way, the particular approach was technically sound to guarantee functionality and also supported proper compliance with hand hygiene in health institutions.

Fig 1. The four phases involved in this project

The study was conducted in four sequential phases, as depicted in the project flowchart in Fig. 1. The requirement phase involved problem identification and a literature review to establish the significance of developing a device that promotes proper hand hygiene, examines existing technologies, and informs component and model selection, including the Convolutional Neural Network (CNN) MobileNetV2[9]. In the development phase, hardware components such as Raspberry Pi 4, ultrasonic and infrared sensors, UV light, and OV5647 camera were integrated with software, and the CNN model was trained on UV-illuminated images to detect fluorescent residues, with each module developed and verified independently[10]. During the implementation phase, these modules were assembled into a functional prototype, programmed to automate sanitizer dispensing and verify hand hygiene compliance before granting access to restricted areas such as ICUs, ensuring seamless operation between hardware and software[11]. The testing phase assessed system performance under real-time conditions, including detection accuracy, response time, and overall functionality, while identifying limitations such as UV camera sensitivity. Collectively, these phases provide an initial-stage foundation for further refinement and development of a comprehensive machine learning assisted hygiene enforcement system[12]

Dataset Collection and Preparation

This step involved the collection of hand images under UV light to create a custom dataset for model training. Images were captured under UV light using an iPhone XS Max for dataset collection purposes. The images were categorized into fluorescent (properly sanitized hands) and non-fluorescent (unsanitized hands). A total of 124 fluorescent and 149 non-fluorescent images were collected. Both datasets are uploaded into Google Drive as shown in Fig.2 and Fig.3 for the machine learning training that will be continued in Google Colab.

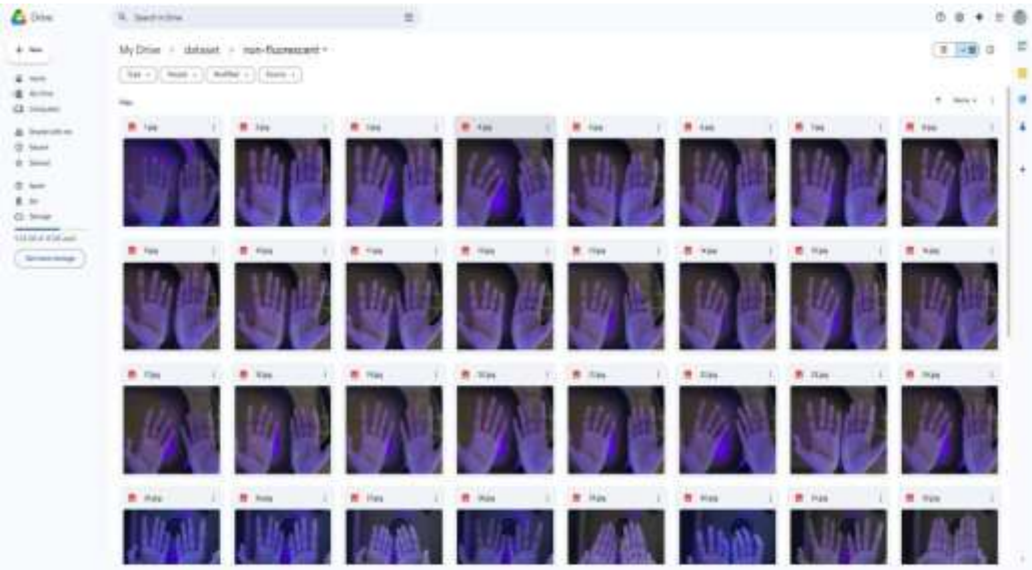

Fig.2. Non-fluorescent dataset samples

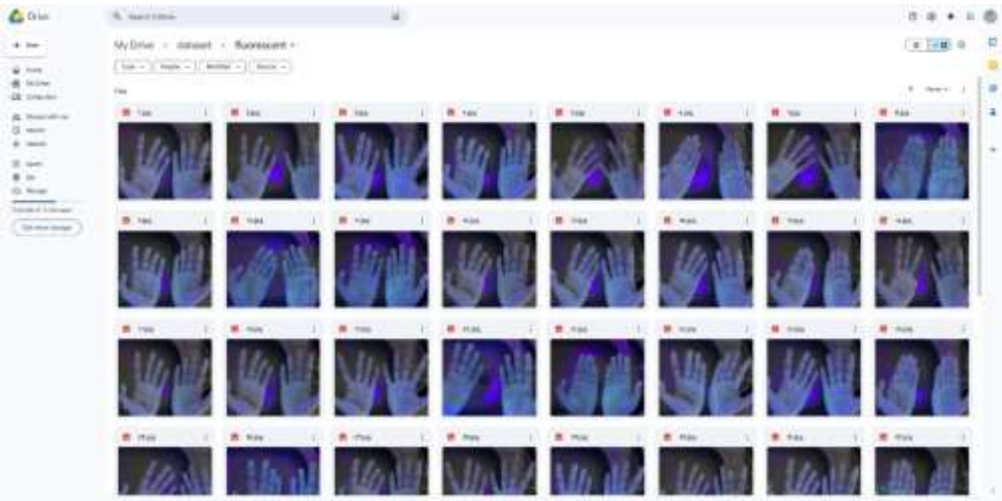

Fig.3. Fluorescent Dataset samples

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Model Architecture

A transfer learning approach was used by employing MobileNetV2. The top classification layers were removed, and a custom classifier was added to reduce spatial dimensions, learn deeper features of the images, and help in output binary prediction. . The base model layers were initially frozen to preserve pretrained weights and prevent overfitting during early training, a strategy commonly adopted in CNN-based transfer learning frameworks [13]

Training Configuration

The model was compiled using Adam as an optimizer. The binary cross-entropy loss function was selected for the binary nature of the classification task, and in order to evaluate the model's performance during training and validation, accuracy was chosen as the primary metric. To prevent overfitting, EarlyStopping was implemented to monitor validation loss and restore the best weights if no improvement was seen after 3 epochs. The training was conducted up to 10 epochs, with a batch size of 32, with training and validation generators flowing from the directory.

Flow of Device

The proposed device is designed to ensure strict cleanliness and hygiene compliance before entry into the ICU. The device integrates hand-sanitizing detection, image analysis for compliance verification, and a door locking mechanism. The proposed device follows an operational flow, as detailed in Fig.4.

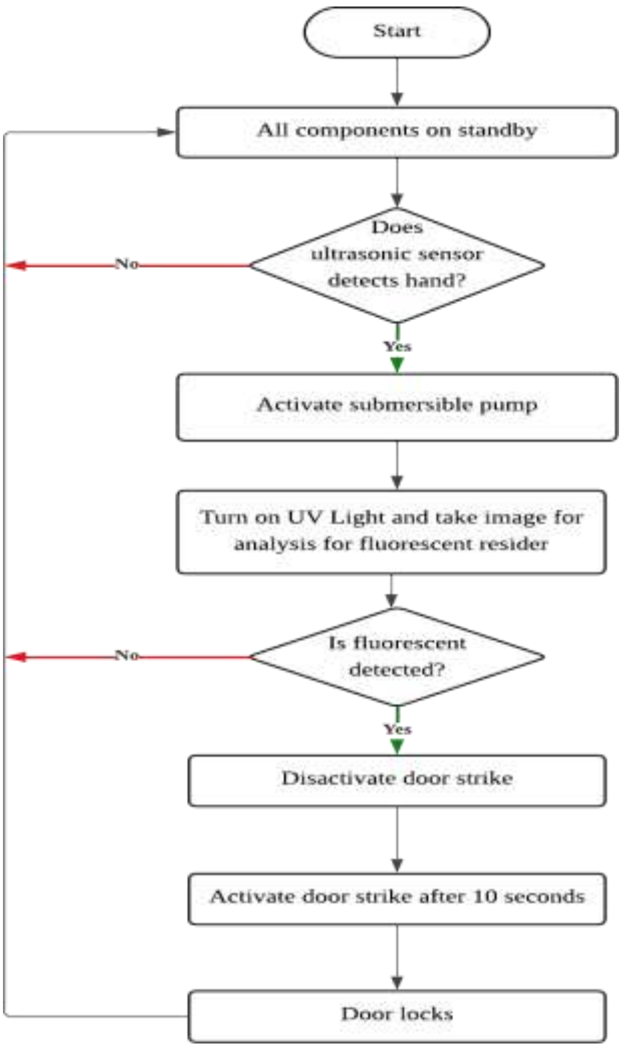
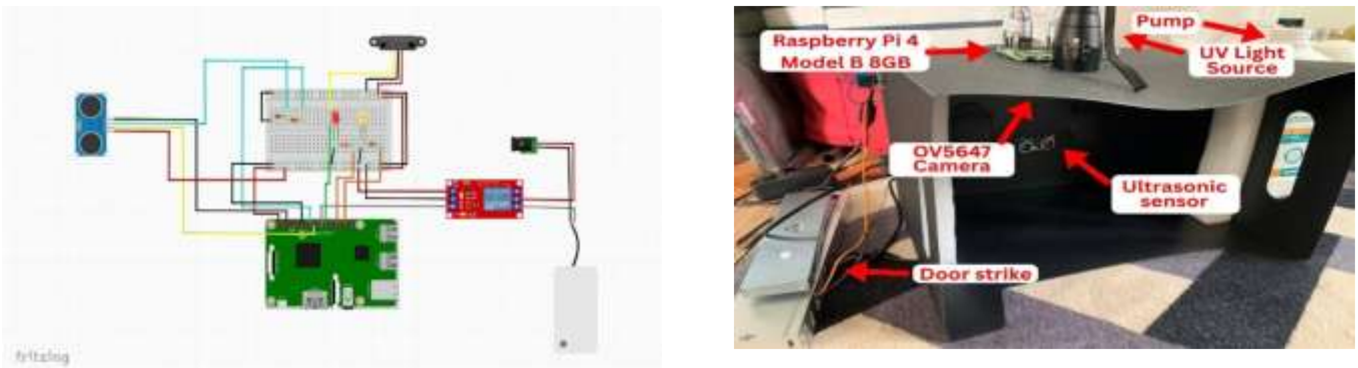


Fig. 4 Flow of Device

Initially, all components remain on standby until activated. The system first monitors the sanitizer liquid level, indicating low or critical levels, which shall be warned through LED alerts. Upon detecting a hand using an ultrasonic sensor, the submersible pump activates and dispenses sanitizer. This is followed by the illumination of UV light, and the OV5647 camera captures an image to analyze for fluorescent presence. If fluorescent residue is detected, the door unlocks for 10 seconds to allow access. After 10 seconds, the door automatically locks, and the device resets for the next user. Meanwhile, if fluorescent is not detected, access is denied, and the device resets and returns to standby. This operational flow is consistent with prior automated hand hygiene enforcement systems that combine proximity sensors for sanitizer dispensing, UV-fluorescent imaging for hygiene verification, and vision-based decision logic to control access to restricted areas such as healthcare facilities [14].

Hardware Development and Verifications

Simultaneously, the physical system was developed to enable the sanitization and access control. Since the design was based on a modular approach, it allows each component to be developed and tested independently before integrating it with the ML model. The system architecture was centered around the Raspberry Pi 4, which is the main controller of this system. Fig. 5(a) shows the basic circuit designed in Fritzing software, illustrating the connections of components used for the proposed device. Raspberry Pi 4, which acts as the main controller, interfaces with several components to manage the device operations. A relay module is included to control the submersible pump. The OV5647, UV light, and electronic door strike are not included in the circuit as the components are not available in Fritzing. While these components are not included, they would be connected to the Raspberry Pi 4 for image analysis and door lock control. Circuit design, writing, and GPIO pin mapping were carefully planned to ensure safe operation without having any burnt components. Component connections were all connected on a breadboard for easy assembly and disassembly. All components, such as the ultrasonic sensor, submersible pump, and door strike, were tested independently to ensure functionality as in Fig. 5(b). Once the software (fluorescent detection model) and hardware (sanitizer dispenser and access control) were verified independently, they were integrated into one working system. For integrating the hardware and for the components to work with the Raspberry Pi OS, Python scripts were used, as well as for the camera input, model inference, and logic controls. A functionality test is performed to evaluate the device's overall performance. This involves testing the device under real-life conditions and scenarios to ensure smooth operations and that the device functions optimally. If no issue arises until this point in the project, the project concludes. This modular design and testing approach is consistent with previous IoT and embedded system frameworks, where sensors and actuators are verified independently before integration with machine learning models on Raspberry Pi controllers for real-time applications [[15], [16]



(a) (b)

Fig. 5(a). Circuit designed on Fritzing Software; (b) Hardware and prototype

RESULTS AND DISCUSSION

Machine Learning Data Accuracy

The MobileNetV2 model was trained for 10 epochs using the custom-collected dataset of fluorescent and non-fluorescent hand images. Fig. 6 shows the training and validation accuracy and loss values across each epoch.

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Initially, the model had an accuracy of 58.96%, but the accuracy improved rapidly as the training progressed. By epoch 10, the training accuracy reached 94.01%, and the validation accuracy reached 98.11%, indicating strong generalization. This high validation accuracy should be interpreted cautiously due to dataset size. As for validation loss, it started from 0.4978 in epoch 1 to 0.1094 in epoch 10. The steady improvement in both training and validation accuracy, alongside the declining loss, indicates that the model did not overfit and was able to learn the distinguishing features effectively, which is consistent with previous studies reporting similar convergence behavior for MobileNetV2 trained on custom image datasets [17].

```
/usr/local/lib/python3.11/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121: UserWarning: Your `PyD
  self._warn_if_super_not_called()
Epoch 1/10
/usr/local/lib/python3.11/dist-packages/keras/src/models/functional.py:237: UserWarning: The structure of `inputs` doesn't
Expected: ['keras_tensor_1250']
Received: inputs=Tensor(shape=(None, 128, 128, 3))
  warnings.warn(msg)
7/7 ━━━━━━━━━━━━━━━━━━━━ 36s 4s/step - accuracy: 0.5896 - loss: 0.8337 - val_accuracy: 0.7358 - val_loss: 0.4978
Epoch 2/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 5s 668ms/step - accuracy: 0.7814 - loss: 0.4588 - val_accuracy: 0.8868 - val_loss: 0.3043
Epoch 3/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 7s 949ms/step - accuracy: 0.8467 - loss: 0.3519 - val_accuracy: 0.9245 - val_loss: 0.2359
Epoch 4/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 5s 662ms/step - accuracy: 0.9656 - loss: 0.1935 - val_accuracy: 0.9245 - val_loss: 0.1966
Epoch 5/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 5s 701ms/step - accuracy: 0.9116 - loss: 0.2111 - val_accuracy: 0.9434 - val_loss: 0.1409
Epoch 6/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 6s 827ms/step - accuracy: 0.9332 - loss: 0.2009 - val_accuracy: 0.9057 - val_loss: 0.1668
Epoch 7/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 5s 653ms/step - accuracy: 0.9657 - loss: 0.1042 - val_accuracy: 0.9434 - val_loss: 0.1129
Epoch 8/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 7s 1s/step - accuracy: 0.9753 - loss: 0.1086 - val_accuracy: 0.9434 - val_loss: 0.1134
Epoch 9/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 5s 681ms/step - accuracy: 0.9301 - loss: 0.1576 - val_accuracy: 0.9811 - val_loss: 0.0794
Epoch 10/10
7/7 ━━━━━━━━━━━━━━━━━━━━ 5s 728ms/step - accuracy: 0.9401 - loss: 0.1702 - val_accuracy: 0.9811 - val_loss: 0.1094
<keras.src.callbacks.history.History at 0x7d2a9dede610>
```

Fig. 6 MobileNetV2 Model Training and Validation Accuracy/Loss Over 10 Epochs

Image Classification Model

To illustrate the visual difference between sanitized and unsansitized hands under UV light, refer Fig. 7. These images provide a clear contrast between the presence and absence of fluorescent residue, which acts as an indicator for proper hand hygiene. In Fig 7 (a), the hands have been thoroughly sanitized with a fluorescent-mixed hand sanitizer, resulting in a visible glow under UV light illumination. This bright green fluorescent is noticeable on the palm's creases, fingers, and in between the fingers. The even distribution of glow indicates proper coverage and application, aligning with effective hygiene practices. In contrast to Fig.7 (b) displays that there is no visible fluorescent residue under the same UV lighting conditions. The absence of glow highlights how areas remain unsanitized and potentially contaminated. This comparison highlights the system's ability to distinguish between sanitized and unsanitized hands. This observation is consistent with previous studies that used UV-fluorescent tracers to objectively assess hand hygiene quality, where visible fluorescence under UV illumination indicated areas with sanitizer coverage, while the absence of fluorescence highlighted missed or unsanitized regions [9], [18], [19].

(a) (b)

Fig. 7 (a) Fluorescent Residue Under UV Light; (b) Non-Fluorescent Residue Under UV Light

Performance Limitations

Despite the successful integration of the machine learning model and the hardware components, certain hardware limitations were encountered during prototyping and testing, particularly in the image capture process. The OV5647 camera module was not able to capture the fluorescent residue on the hand under UV light. This affected the accuracy of the model to represent the training data. While the conceptual design is practical, its implementation lacks key components such as the camera module, UV lighting, and the physical enclosure. One of the critical hardware limitations was the underperformance of the Raspberry Pi Camera Module (OV5647) in detecting fluorescent residue under UV light. Although OV5647 was a cost-effective choice, its image quality was insufficient to capture low-intensity fluorescence. The high exposure levels and lack of detail in low-light settings resulted in poor contrast between sanitized and non-sanitized areas, leading to misclassification by MobileNetV2. As shown in Fig. 8(a) and Fig. 8(b), there are noticeable differences between images captured using an iPhone XS Max and OV5647 camera module. As a result, the model could not operate optimally in real-world conditions due to poor image input. This highlights a crucial hardware bottleneck that needs to be addressed to ensure system reliability. The limitations observed with the OV5647 camera module align with previous studies showing that low-resolution or low-light images significantly degrade CNN performance, especially when detecting subtle features such as fluorescent residues [[20], [21], [22]

(a) (b)

Fig. 8(a) Image Taken by iPhone XS Max; (b) Image Taken by Raspberry Pi OV5647 Camera Module

Enclosure Design, Component Positioning and Limitation Discussion

The structure of the enclosure had ergonomic and detection challenges that affected both usability and image quality. Figure 4.5 shows, there was an issue with the distance between the camera and the user's hand. Due to limited space, the Raspberry Pi camera was mounted very low and close to the target area, which resulted in images being captured only of the palm and parts of the fingers, instead of both hands. This might vary due to different people's hand sizes. This framing limitation had hindered the model's ability to analyze full hand sanitization, especially for those who did not apply sanitizer evenly. Moreover, the camera module had a fixed lens, making it impossible to adjust the field of view to accommodate larger hand areas. There was also an inconsistent hand placement, since there were no alignment guides on the enclosure, which caused partial and skewed image captures. This inconsistency affected the detection, since the model was not able to generalize the images.

On the hardware part, the wiring was based on jumper cables and a breadboard layout. While it is suitable for prototyping, it is more prone to disconnections, contact noise, and wear over time. As the jumper wires are not secure and easily break, there were multiple disconnections before testing. To address the limitations observed during the testing, several practical improvements are recommended for future versions of the device. One of the most critical upgrades would be to replace the camera module with a higher resolution camera, such as the Raspberry Pi HQ Camera, it is recommended for its suitability for low-light conditions. This could significantly improve the accuracy of fluorescent residue detection under UV light.

Another important recommendation involves standardizing the fluorescent solution. Since the chemical composition was not thoroughly studied in this study, it is recommended to analyze its compatibility with alcohol-based sanitizers and confirm that it is biocompatible for regular skin contact. As for the enclosure, it could benefit from a redesign, with guides that would help users consistently align their hands for image capture. As for the hardware, replacing the breadboard with a dot-board and soldering the wires would increase the system's durability and reduce the chances of disconnections. Lastly, add filters or the ability to auto-adjust for clearer contrast between fluorescent and non-fluorescent regions of the hand. These changes would possibly make the system readier for real-world deployment in hospitals. These limitations align with prior studies demonstrating that camera placement, field of view, and user alignment critically affect CNN-based hand hygiene detection [23] Prototype hardware using breadboards and jumper wires is prone to disconnections and wear, necessitating soldered connections for long-term reliability [16] Furthermore, standardization of fluorescent tracers and camera settings is essential to ensure accurate detection and user safety [21]

CONCLUSION

Developing the contactless hand sanitizer, integrated with image analysis and door lock control, is a significant step toward reducing HAIs and encouraging proper hand hygiene for healthcare providers, patients, and visitors. By combining a fluorescent-based detection approach with a machine learning classification model and an embedded control system, the prototype demonstrates the potential to improve compliance and reduce HAIs, offering immediate visual feedback to users. Unlike traditional systems that rely on manual observation or assumption-based compliance, this approach supports existing hospital SOPs and aligns with WHO and CDC hygiene guidelines.

Furthermore, the low-cost, modular design using Raspberry Pi and open-source frameworks makes the system scalable, adaptable to different clinical settings, and sustainable for hospitals with limited resources. The framework also serves as an educational and training tool, providing real-time visual feedback on hand hygiene technique. The technical knowledge gained through dataset preparation, image processing, and hardware-software integration provides a foundation for future research, enabling further innovations in smart infection-control systems and healthcare safety technologies.

Future Works

Several key areas require further development to enhance system performance and reliability. A critical improvement involves replacing the current camera module with a more suitable alternative that is capable of capturing clear fluorescent residue under UV light. Enhancing the image quality will allow the ML model to perform with greater accuracy in real-world conditions. In addition to hardware refinement, converting the MobileNetV2 model into a TensorFlow Lite version would be recommended. This would optimize the model for faster inference on devices like Raspberry Pi.

Expanding the dataset would also be necessary to improve model robustness and accuracy. Varying the images would also help, such as varied skin tones and hand sizes, to generalize better and reduce false predictions. From a broader perspective, future studies may also examine user interaction, acceptance, and behavioural response to automated hygiene verification systems, enabling further refinement of the system as a supportive tool for sustainable hand hygiene practices in healthcare social environments.

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