Enhancing Hand Hygiene Training: Integrating Machine Learning with Glo Germ Visualization

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ABSTRACT
Objective: This study investigates the potential of integrating an efficient, automated, no-code machine learning classification model with Glo Germ fluorescent visualization to enhance hand hygiene training for nurse educators and infection preventionists. This approach aims to streamline training processes, eliminating biases stemming from human error during direct observation under ultraviolet light, and ultimately contributes to reducing healthcare-associated infections through effective hand hygiene training. **Methods:** This study utilized Google's Teachable Machine - a web-based graphical user interface tool designed for developing custom machine learning classification models without requiring specialized coding skills. Simulated contamination of hands was achieved using Glo Germ. A diverse training dataset was created with images of germ-contaminated and germ-free hands. The model was trained and evaluated using varying Glo Germ quantities. **Results:** The trained model exhibited a 100% confidence rating in classifying germ-contaminated hand surfaces and an average confidence rating of 94% for germ-free hands. Overall, the model achieved a 97% average confidence rating across the test dataset. **Conclusions:** This study illustrates the feasibility of using machine learning classification alongside Glo Germ fluorescent visualization for the real-time detection of germs on hand surfaces. The integration of these techniques presents an efficient and accessible approach to enhance hand hygiene training methodologies for nurse educators and infection preventionists by: (i) providing automated and immediate visual feedback on handwashing effectiveness, (ii) addressing inherent limitations associated with in-person monitoring such as bias, and (iii) providing no-code machine learning tool to healthcare educators and practitioners who may lack coding experience.

General Terms
Artificial intelligence, infection prevention, hand hygiene compliance, nurse education

Keywords
hand hygiene, glogerm, machine learning, teachable machine

1. INTRODUCTION
Hand hygiene is critical for healthcare providers to reduce the risk of transmitting infections within healthcare settings [1, 2]. Contrasted with the significant financial costs associated with healthcare-associated infections, maintaining hand hygiene compliance proves to be a cost-effective approach to improving quality with minimal added expenses [3]. Despite its significance, maintaining hand hygiene compliance remains a challenge, with healthcare workers often exhibiting inadequate adherence [4]. Nurses, with their frequent patient interactions, play a pivotal role in preventing disease transmission [5]. Furthermore, nursing students, who dedicate considerable time to patient care during their training, need to undergo effective hand hygiene training as they progress into their professional roles [6, 7]. However, effective hand hygiene training methods are critical but may face limitations due to human monitoring.

Currently, advancements in hand hygiene training include the use of fluorescent solutions like Glo Germ™, which highlight contaminated areas of hands under ultraviolet (UV) light, emphasizing the importance of thorough handwashing [8-12]. While these methods show promise, direct observation under UV light, either by a nursing student undergoing hand hygiene training, or by a nurse educator monitor, is constrained by the possibility of bias stemming from human error [13, 14].

Combining fluorescent visualization techniques using Glo Germ with an automated machine learning monitoring system under UV light presents a potent tool to augment hand hygiene training by removing human observation from the loop. This approach has direct application in educational settings, particularly benefiting nursing educators and infection preventionists. It offers a more efficient alternative to current practices, providing instant, automated visual feedback on handwashing effectiveness, while mitigating the limitations of subjective human observation.

However, implementing hand hygiene compliance models using machine learning poses challenges for healthcare professionals lacking expertise in data science or programming. Fortunately, user-friendly, web-based, no-code machine learning platforms like Google Teachable Machine® offer accessible solutions, enabling healthcare educators and practitioners to utilize advanced technologies without coding knowledge [15-18].

This study's objective is to assess the feasibility of utilizing no-code machine learning classification to detect germs on hand surfaces, providing an efficient and direct application in hand hygiene training settings. Specifically, it explores the integration of fluorescent visualization techniques using Glo Germ, and Google Teachable Machine® (GTM) - a web-based graphical user interface tool designed for developing custom machine learning classification models without requiring specialized coding skills. By introducing an automated, accurate, and efficient machine-monitoring approach that eliminates bias arising from human error associated with direct observation, this study addresses the need for a practical hand hygiene monitoring methodology for nurse educators and infection preventionists.

2. MATERIALS AND METHODS

2.1 Teachable Machine

GTM (version 2.0) interface includes data input, learning, and preview sections, with the ability to train models for video, audio, and posture projects. Training and test data are input through webcams/built-in camera of a computer, or via file uploads, adjusting variables for video type and quality during learning [19]. GTM constructs a pre-training model by leveraging a significant volume of training data with MobileNet. The transfer learning process involves modifying specific layers at the end of the model using an uploaded image dataset [15]. For this study, all images were input in real-time using the built-in camera of a MacBook Air M2 at a capture speed of 12 frames per second. The general schema of GTM is presented in Figure 1.

2.2 Training Dataset, Annotation and Training of Model

This study aimed to classify hand surface images into two categories: (i) germ-contaminated and (ii) germ-free. However, it is unsafe and impractical to use actual germs to generate contamination dataset. To address this, germ-contaminated hand surfaces were simulated using Glo Germ™.

To create the simulated training dataset for hands contaminated with germs, three volunteers (including the author) meticulously washed their hands with soap and water, adhering to the World Health Organization (WHO) handwashing procedure for a duration of 45 seconds [20] as illustrated in Figure 2. Following that and after hand drying, 5 mL of Glo Germ lotion was applied to dried hands, simulating a handwashing motion for 10 seconds to ensure the even distribution of the Glo Germ.

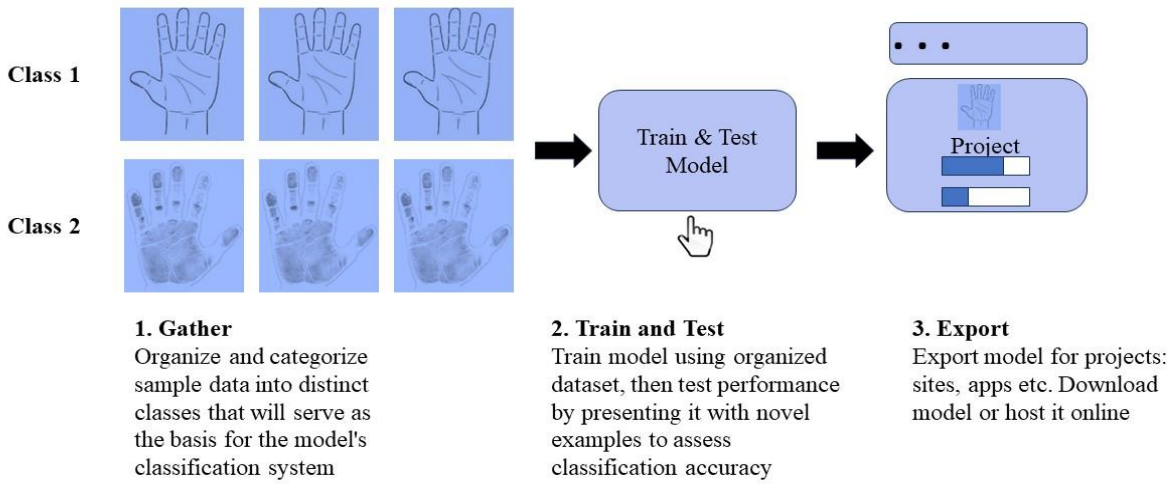

Figure 1: General schema of GTM

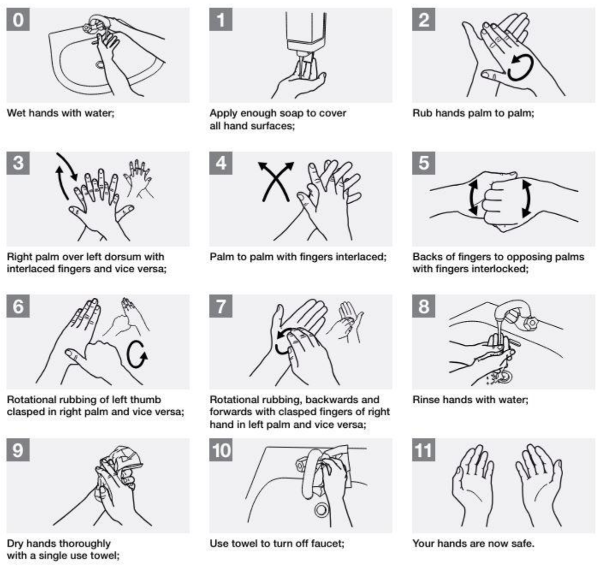

Figure 2: WHO hand washing procedure [20]

Conversely, the training dataset for germ-free hand surfaces was generated by the same individuals. They washed their hands with soap and water, following the WHO handwashing procedure. The handwashing process was performed in the presence of a volunteer monitor to ensure consistent adherence to the WHO handwashing procedure.

Images of simulated germ-contaminated hand surfaces and germ-free hand surfaces were captured using the computer's built-in camera interfaced to GTM. Illumination was provided by a commercial UV flashlight equipped with 128 light-emitting diodes emitting a wavelength of 395 nanometers. For consistency, all images were obtained by placing hands at 0.3 meters from the camera in a dimmed environment.

Each of the three volunteers presented hands of distinct sizes. Moreover, they intentionally varied the positions of both hands during each image capture to ensure a diverse set of images. In the end, the training dataset comprised 799 images of germ-contaminated hands and 678 images of germ-free hands. A partial screenshot of these two classes of training images is shown in Figure 3. The author manually annotated germ-contaminated and germ-free hands as "germ-detected" and "germ-free," respectively during training the GTM.

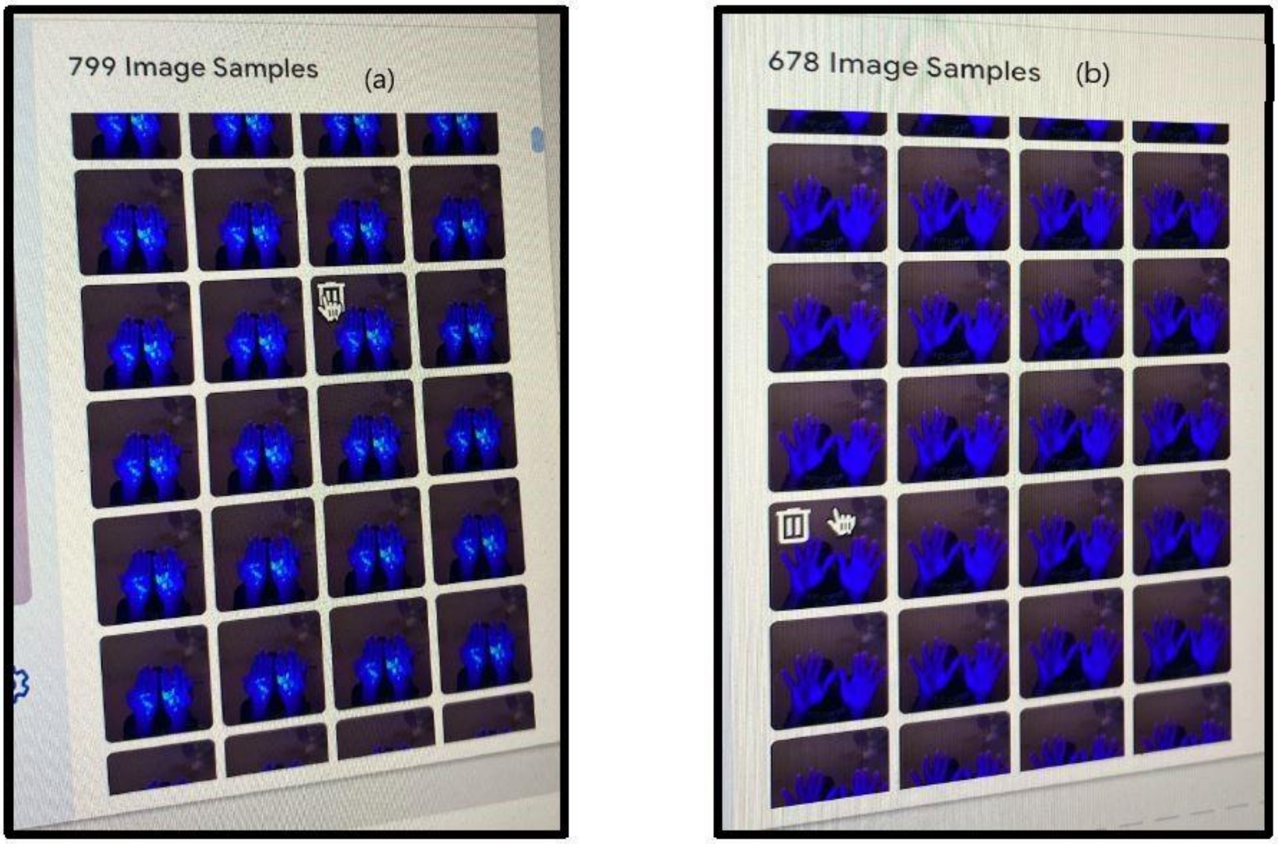

Figure 1: Partial screenshots of (a) germ-contaminated and (b) germ-free training images

The GTM uses three key learning parameters during training: (i) epoch, (ii) batch size, and (iii) learning rate. Epoch denotes the number of samples in the training dataset that are fed into the training model at least once. A batch represents the set of samples utilized in a single iteration of training. The learning rate serves as a variable determining the step size for computing the loss function [16, 17, 21]. To train the model in this study, GTM default values were applied to epoch, batch size, and learning rate as summarized in Table 1.

Table 1. GTM default values

Epoch	Batch Size	Learning Rate
50	16	0.001

2.3 Test Dataset and Binary Classification of Data

New images of germ-contaminated hands were presented in two sub-groups to the trained GTM: (i) 50 images with 5 mL of Glo Germ smeared on the hand surface, and (ii) 50 images with 1.3 mL of Glo Germ applied to the hand surface. (i) and (ii) together resulted in a test dataset comprising 100 images of germ-contaminated hand surfaces. The choice of two different Glo Germ quantities was made for variation in the dataset. Additionally, 100 new images of germ-free hand surfaces were presented to the trained GTM. The same set of three volunteers followed an identical procedure as outlined in the "Training Dataset, Annotation, and Training of Model" section above to generate the germ-contaminated and germ-free hand surface test data. The number of training and test images used in this study are summarized in Table 2.

Table 2. Summary of number of training and test images in this study

Class of Image	No. of Training Images	No. Of Test Images	
Germ-Contaminated	799	w/ 5 mL Glo Germ	50
		w/ 1.3 mL Glo Germ	50
Germ-Free	678		100
Total	**1477**		**200**

When a test image is presented to the trained GTM, it conducts a real-time binary classification and calculates a percentage confidence rating. This rating indicates GTM's confidence in the extent to which the test image resembles one of the training classes. Illustrative screenshots of GTM classification rating of a germ-contaminated and germ-free hand surfaces are provided in Figure 4. If GTM calculates the percentage confidence rating of the presented test image as germ-contaminated as P, then the percentage confidence rating of the test image being germ-free is represented by 100 – P, in a binary classification model.

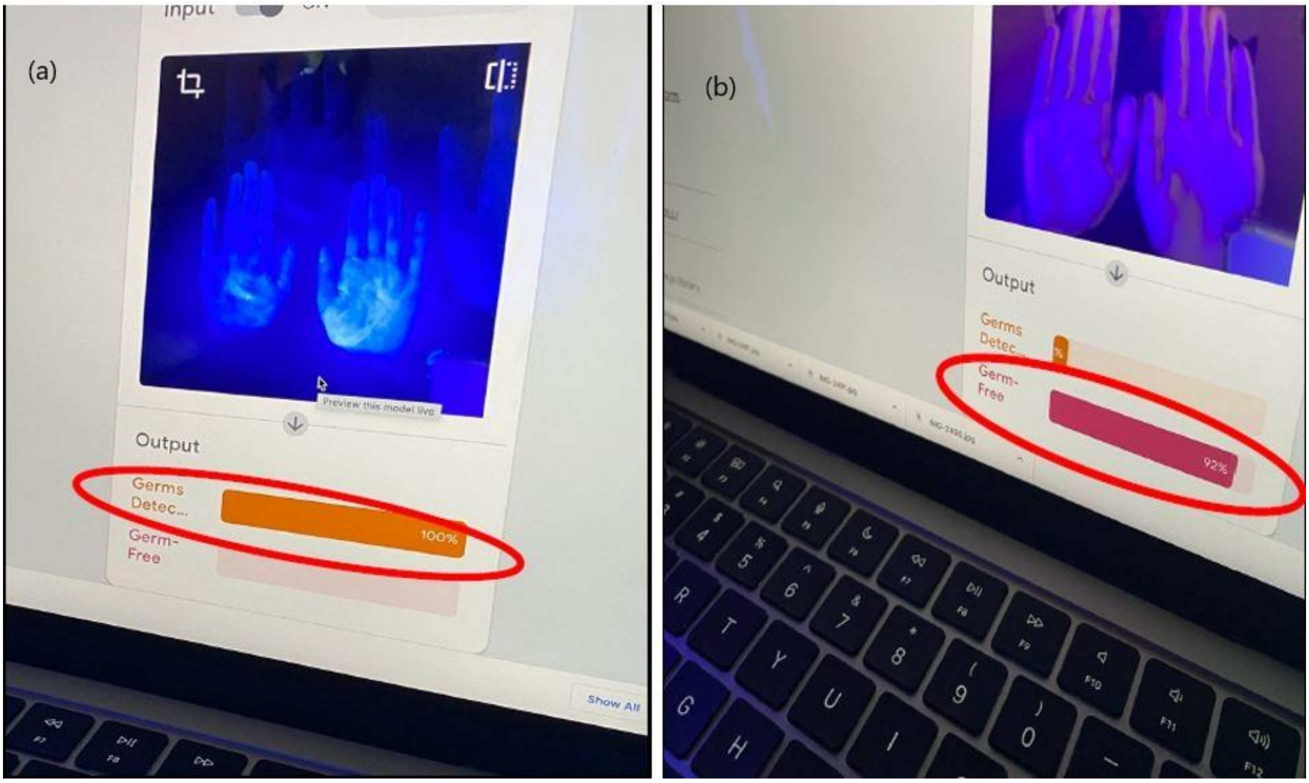

Figure 2: Classification confidence rating of (a) germ-contaminated and (b) germ-free hand test images

3. RESULTS

The trained GTM model classified germ-contaminated hand surface test data with a 100% confidence rating in both test sub-groups: hand surface images with 5 mL of Glo Germ smeared and images with 1.3 mL of Glo Germ applied. For germ-free hand surface test data, the model provided an average confidence rating of 94%, with a maximum confidence rating of 100% and a minimum confidence rating of 88%. The overall average confidence rating for classification across the entire dataset was 97%.

Overall, the model maintained its high confidence ratings across both test datasets, suggesting good generalization and minimal overfitting to the training data. Also, results across the three volunteers revealed consistent performance, with no significant differences. This suggests that the model's performance is generally robust across variations in hand size and individual characteristics.

4. DISCUSSION

This study illustrates the viability of using a no-code machine learning classification model for real-time detection of germs on hand surfaces. By utilizing no-code machine learning classification, this approach becomes an accessible and practical tool for nurse educators and infection preventionists. Using a combination of fluorescent visualization techniques using Glo Germ, and an automated, real-time machine learning-based monitoring system utilizing the Google Teachable Machine offers a few advantages in terms of efficiency of teaching hand hygiene techniques to nursing students. Prior research has demonstrated that incorporating fluorescent visualization alongside immediate visual feedback significantly enhances hand hygiene [22]. Studies have indicated that although healthcare students initially recognize the importance of hand hygiene in hospital settings, their perceived ability to properly wash their hands often proves to be misguided, a perception that positively shifts following visual feedback from fluorescent visualization [9, 11, 23]. Additionally, nurses show a particular inclination towards interventions that provide tangible evidence of handwashing practices when adhering to hand hygiene guidelines [24]. The method used in this study, which utilizes fluorescent visualization with Glo Germ, inherently encapsulates the findings of previous studies by offering immediate, automated visual feedback on the effectiveness of handwashing. Secondly, the integration of the simple, real-time, no-code machine learning classification method in this study, brings inherent efficiency by mitigating the limitations associated with in-person hand hygiene observation such as bias. The validity of in-person observation is greatly limited by the Hawthorne effect, or altered behavior of healthcare workers in response to being observed [25]. Previous studies have indicated that using applications to monitor hand hygiene compliance, coupled with the widespread use of smartphones and tablets in healthcare settings, leads to less intrusive data collection and diminishes Hawthorne effect [26]. Therefore, it is reasonable to infer that the current study could potentially experience a reduction in the Hawthorne effect, given that monitoring is conducted using an application and a computer interface. Lastly, the method in this study captures hand images instead of face/ body images, mitigating any concerns related to privacy.

While this study presents promising potential, several limitations should be acknowledged. Firstly, the performance of the GTM classification model may be influenced by the quantity of the training data. Although a diverse training dataset was collected, further expansion with additional training data (e.g., under different lighting, backgrounds, distance from camera, additional angles of hands to show nail beds, under nails, between fingers) can be studied to determine effect on classification confidence rating. Additionally, the images used for training were derived from a limited set of volunteers, and the number of volunteers could be increased for more comprehensive coverage. Secondly, although the present study used simulated germ-contaminated hand surface images at two levels of contamination, further datasets with progressively lower levels of Glo Germ can be generated to train the model more broadly. Thirdly, while this approach suffices in terms of accuracy, speed, and scalability by using default GTM parameters for epoch, learning rate and batch size, there may be room for improvement. For instance, optimization of the hyperparameters could enhance inference time and reduce memory consumption.

5. CONCLUSIONS

In addressing the question posed in the study objective, this investigation affirms the viability of pairing fluorescent visualization techniques using Glo Germ with an automated machine learning monitoring system based on Google Teachable Machine®. Through the assessment of this novel approach, this study demonstrated the potential to serve as an effective tool for enhancing hand hygiene training methodologies for nurse educators and infection preventionists. Moreover, the accessibility and practicality of this approach, particularly for individuals lacking expertise in machine learning or programming, underscore its relevance and applicability in healthcare settings.

Future research can address the limitations identified in this study and expand upon its promising results. Increasing the diversity and quantity of training data, including images captured under varied conditions and from a larger pool of volunteers, could enhance the model's robustness and generalizability. Further investigation into the model's performance with lower levels of simulated contamination may refine its sensitivity. Additionally, exploring the integration of this system with existing hand hygiene monitoring protocols in clinical settings could provide valuable insights into its real-world applicability and impact on infection prevention practices. Finally, longitudinal studies evaluating the long-term effects of this automated monitoring approach on hand hygiene compliance and healthcare-associated infection rates would be instrumental in validating its efficacy as a training and quality improvement tool.

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