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KiBot in action: An AI-empowered hardware–lighting optimization for secure and scalable facial recognition

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ABSTRACT

Facial recognition systems continue to face challenges in maintaining consistent accuracy across different hardware and under varying illumination, which restricts their adoption in secure access control environments. To overcome this limitation, this study presents KiBot in Action, an AI-empowered framework that leverages the Design of Experiments (DOE) method to systematically evaluate and optimize the combined effects of hardware resolution and lighting on facial recognition performance. KiBot, a multipurpose robot developed under the KICT initiative, integrates facial recognition, liveness detection, and Bluetooth interaction to support real-world facility security. Ten devices, including smartphones, laptops, and webcams, were tested under controlled bright (~300 lux) and dim (~50 lux) lighting conditions to measure maximum detection distance and liveness detection capability. DOE-driven ANOVA and regression modeling revealed that lighting is the dominant factor influencing recognition distance, while the interaction between lighting and hardware resolution accounts for the superior adaptability of modern smartphones compared to webcams. Moreover, smartphones and laptops maintained robust liveness detection across conditions, whereas external webcams failed in low light, exposing critical vulnerabilities. The study contributes a replicable AI-empowered DOE framework and practical guidelines for deploying cost-effective and scalable facial recognition systems, enhancing security and reliability in real-world applications.

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1. INTRODUCTION

Facial recognition remains a vibrant and intensively studied domain, now recognized as a pivotal technology for enhancing safety and security across multiple operational scales: micro (residential households), mezzo (industrial complexes and correctional facilities), and macro (urban and smart city environments). As a subset of Human Activity Recognition (HAR), facial recognition enables critical functions such as identity authentication, video monitoring, and surveillance, which serve domains such as access control, traffic and congestion management, and smart home automation. Its rapid and widespread adoption in public spaces underpins its role as a foundational component of interconnected safety ecosystems in modern urban infrastructure.

Across global smart cities, facial recognition technologies are increasingly embedded in security and surveillance systems. Reflecting this growth, the global facial recognition market is expected to expand from around USD 6.94 billion in 2024 to approximately USD 7.88 billion in 2025, and then increase further to USD 15.05 billion by 2029, growing at a compound annual growth rate (CAGR) of 17.6% (The Business Research Company, 2025). More aggressive forecasts predict that the market will reach USD 21.12 billion by 2032 at a 17% CAGR (Coherent Market Insights, 2025), or potentially USD 24.28 billion in 2032 with a 15.5% CAGR (Fortune Business Insights, 2025). Under some projections, the market could even surge to USD 32.53 billion by 2034 at a 14.9% CAGR (Precedence Research, 2025). These projections highlight the accelerating commercialization and critical importance of facial recognition systems in public safety, smart infrastructure, and biometric-enabled applications.

Ultimately, facial recognition is an emerging biometric technique that uses computer vision and machine learning to identify or verify individuals based on their facial features (Cheon, 2025). Unlike passwords or cards, it is contactless and user-friendly, making it suitable for security, healthcare, and consumer applications (Cheon, 2025; Fabbrizio, 2025). The process includes identifying a face, extracting distinctive characteristics, and comparing them with a database (Dalvi et al., 2022; Fuad et al., 2021). Its performance is influenced by hardware, lighting, and algorithms, while liveness detection helps prevent spoofing (FaceOnLive, 2025).

Nevertheless, issues of privacy, inclination, and scalability persist. When properly optimized and used ethically, facial recognition can increase security and convenience in contemporary systems (Fabbrizio, 2025). Against this background, the Kulliyyah of Information and Communication Technology Robot (KICTbot) or KiBot, is a human-based multipurpose robot programmed to integrate facial recognition and Bluetooth-based smart interaction to enhance security and accessibility.

The latest version of the previous CoBot, which was created to improve the smart attendance and access control system, is called KiBot (Zainuddin et al., 2024). The enhanced version incorporates facial recognition and IoT interaction to perform identity verification more effectively. On 25 September 2025, the former dean, Prof. Dr. Murni Mahmud, launched KiBot in the Kulliyyah of Information and Communication Technology (KICT), IIUM.

Fig. 1, panels (a)–(d), illustrates the design and operational development of KiBot, beginning with its initial TV-head prototype, followed by early design sketches, the physical hardware casing, and a live demonstration of its facial recognition system. KiBot is one of the systems developed under the KICT programs at IIUM and has been implemented in practical environments such as offices and lobbies. It integrates liveness detection with facial recognition to authenticate users confidently while preventing spoofing (Suman & Salimath, 2025). Using the Design of Experiments (DOE), its behavior under various conditions and with different hardware can be explored. In addition to authentication, KiBot can be used for visitor management and for supporting citizen/visitor and IoT interactions, making it a scalable solution for smart facilities (Meddeb et al., 2023; Rajeshkumar et al., 2023). Facial recognition is one of the key

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capabilities of such systems, which aim to identify and locate faced in the digital images to classification and verification.

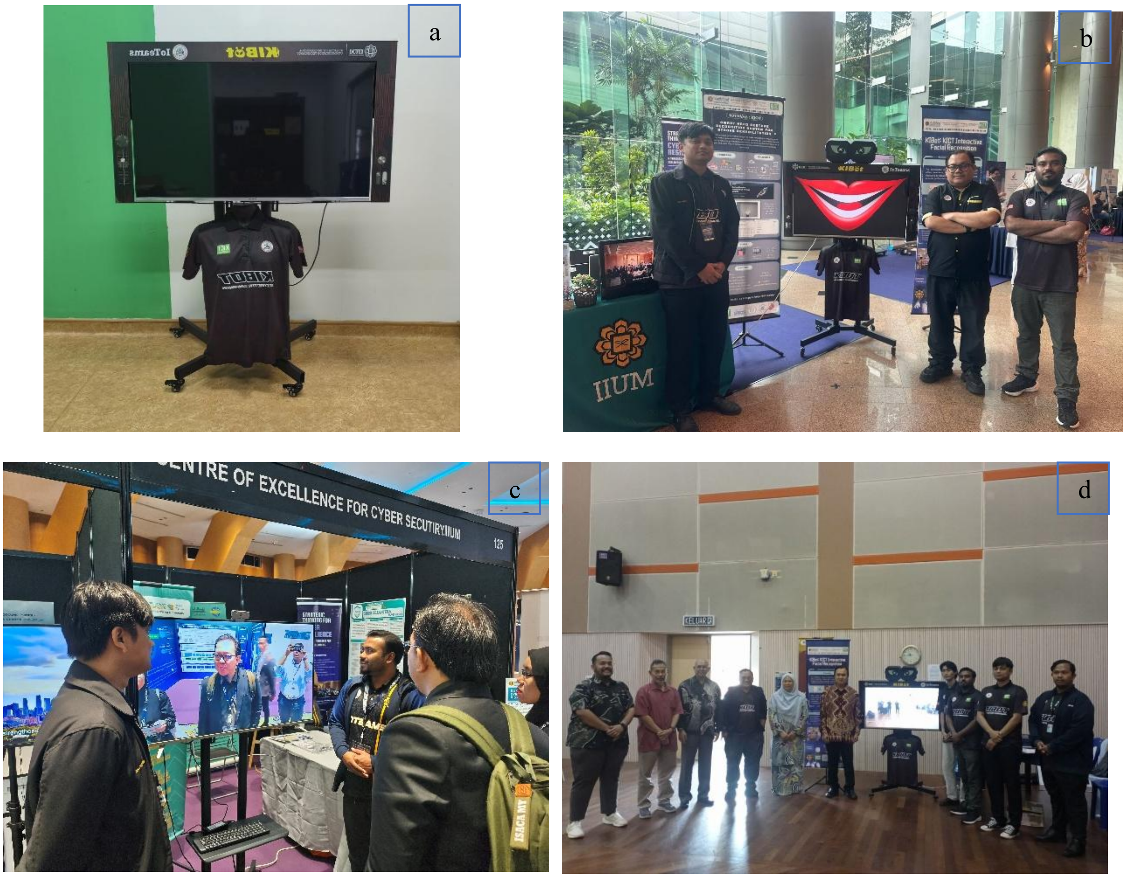

Fig.1 Development of KiBot: (a). Latest updated version of the complete KiBot system, (b). KiBot presented at INTAN, PICC, (c) KiBot presented at CYDES, PICC, and (d) Opening ceremony of KiBot at MPH Hall, KICT, IIUM

Source: Authors' own photograph

Concurrently, Design of Experiments (DOE) is a statistical method for systematically designing and analyzing experiments (Lian et al., 2022). DOE does not test factors one at a time as trial-and-error does but examines the effects of several factors simultaneously, including both individual and interaction effects. This is beneficial for process optimization, quality enhancement, and cost savings across industries. In DOE tests, key variables that can affect performance, such as hardware, lighting, or algorithm design, are isolated. Factorial designs and response-surface methods help make experiments more efficient and save time and resources. DOE leads to evidence-based decision-making, and it contributes to innovation in intricate systems because it quantifies variability (Babu et al., 2024).

In addition, liveness detection performance determines the effectiveness of biometric systems in differentiating between a genuine user and a fraudulent impersonation, such as a picture or video (Khairnar et al., 2023; Suman & Salimath, 2025). It is particularly important in security-sensitive applications such

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as banking, access control and mobile authentication (Suman & Salimath, 2025). Techniques such as motion tracking, eye tracking, and depth sensing are typically augmented by AI models trained on a broad range of data. Accuracy, however, depends on lighting, hardware, and processing power. Effective liveness detection not only enhances system reliability but also instills user confidence in the system's fairness and inclusivity under different conditions (Khairnar et al., 2023).

Finally, detection distance is the maximum distance at which a system can correctly identify or verify subjects. It is also an important consideration for surveillance and access control, particularly in populated areas. It depends on camera resolution, lens quality, and algorithms. (Carrasco-Jiménez et al., 2023; Zaremba & Nitkiewicz, 2024). Longer detection distances are suitable for large spaces such as airports, whereas shorter distances may suffice for personal devices. At longer ranges, problems such as poor image quality and less effective liveness detection can arise. Optimizing detection distance requires balancing `hardware and software, with DOE used to test performance under different conditions. Optimizing this metric can help increase the scalability, usability, and security of real-world applications.

This paper is set out as follows: Section I presents the background and the objectives of the research, highlighting the use of facial recognition systems, limitations associated with their use in different environmental and lighting conditions, and the development of KICTbot (KiBot) as a human-friendly testing environment. Section II reviews related literature on biometric authentication, liveness detection, detection distance, and previous methods for optimizing system performance using methodologies such as Design of Experiments (DOE). In Section III, the research methodology is presented, including hardware selection, novelty testing under different lighting conditions, and user perception surveys. Section IV reports the results, including comparisons across camera hardware, liveness detection accuracy, and maximum detection distances, to ascertain system robustness across various conditions. Finally, Section V concludes the study, discusses issues such as privacy, cost, and scalability, and outlines future research directions for building superior, reliable, and accessible facial recognition systems in real-life situations.

2. LITERATURE REVIEW

Facial recognition boasts of being the key to modern access control systems due to its use of contactless and efficient identity verification that is especially important after the global health crises. Its importance is that it can improve security levels in a wide variety of environments ranging between corporate lobbies and High-security environments. But then the issues of variability of hardware as well as environment like lighting, present complications that need to be approached in a systematic way to guarantee reliability (Deshpande et al., 2025).

2.1 Facial Recognition and Hardware Dependence

Facial recognition systems have evolved since their early statistical approaches, to current deep-learning-based systems, which have the ability to extract rich hierarchal facial representations. The majority of the modern recognition pipelines are based on Convolutional Neural Networks (CNNs), which allow achieving high-quality feature learning and improving accuracy significantly in comparison to classical algorithms (Banimelhem & Al-Khateeb, 2024; Fuad et al., 2021). However, the improvement of algorithms does not ensure the stability of the field performance: the quality of images at the camera point has a direct impact on the performance of recognition.

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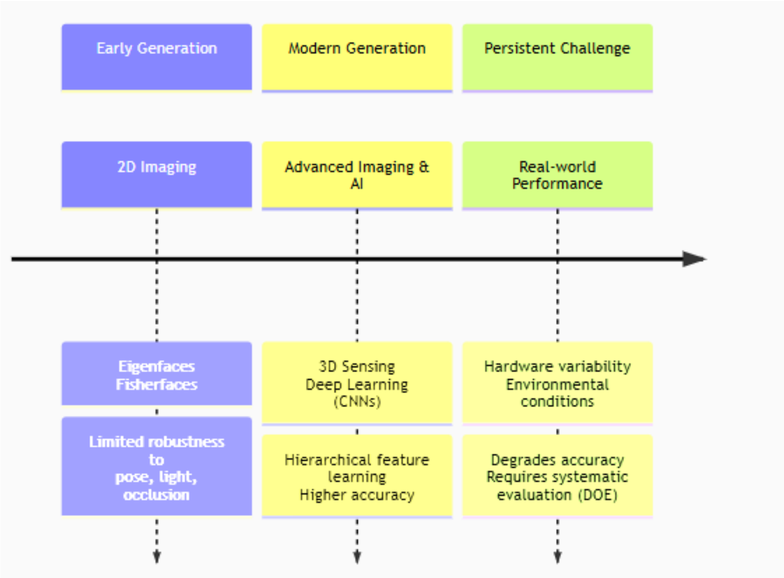

Fig. 2. Key developments and ongoing challenges in facial recognition technology

Source: Authors' description of evolution of facial recognition

The evolution of facial recognition depicted in Fig. 2 indicates that persistent challenges related to environmental factors (e.g., light and sensor noise) remain. Even state-of-the-art models can be taken down by the effects of these external factors with poor hardware capturing (see Fig. 2). Hardware properties, especially sensor type, lens quality, and resolution, have a direct influence on the fidelity of faces that recognition algorithms must work with. The low-resolution sensors distort discriminative landmarks and decrease signal-to-noise ratio, raising false rejection and decreasing the detection distance (Carrasco-Jiménez et al., 2023; Rusia & Singh, 2023).

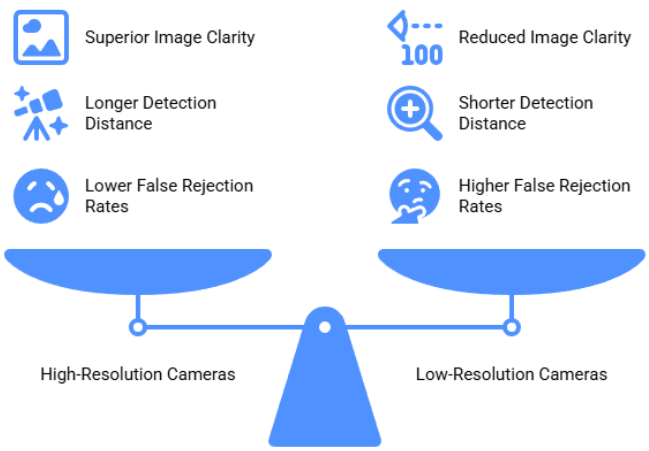

Fig. 3. Comparison of camera hardware types and their influence on recognition accuracy

Source: Authors' illustration of comparison

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Fig. 3 makes a comparison between the common types of cameras in practice (smartphone sensors, laptop webcams, and external webcams) and indicates in how the higher-spec sensors retain features in a broader range of lighting conditions.

2.2 Environmental Factors and Lighting Conditions

One of the most decisive external factors of accuracy in facial recognition is lighting. Proper lighting and good, uniform working conditions generally improve performance whereas shadows, glare and low light conditions usually inhibit performance (Fan et al., 2024). Comparative studies of visible light with infrared (IR) light-based systems have shown that the latter is less sensitive to changes in illumination conditions, although this is usually restricted to professional level devices. Studies of lux level revealed that at below 100 lux the FR accuracy falls precipitously with significant increases in both false acceptance and false rejection rates (Revilla-León et al., 2021). In addition, directional lighting tends to give the results with uneven shadows, covering important facial features, and making a more consistent outcome with diffused lighting. Nevertheless, most of the testing involves only individual devices as opposed to comprehensive testing that considers both multi-device testing and lux-controlled testing environments (Al-Shakarchy, 2023; Sime & Balcha, 2023). A dearth of studies based on DOE comparing performance on one or more devices under different light intensities, such as 300 lux (bright) and 50 lux (dim) exists. According to this gap KiBot experimental framework specifically aims at deciphering how the variations in lighting interact with hardware differences with the aim of determining their impact on recognition performance (Goswami et al., 2023).

2.3 Liveness Detection Techniques

Liveness detection has become a key component of facial recognition technology to counter spoofing attacks, including, but not limited to, photo, video or mask-based impersonations. Methods in this domain can broadly be categorized into three groups as motion analysis, texture analysis, and 3D-depth based methods as described in Fig. 4 (Anjum et al., 2023). As summarized in Fig. 4, liveness detection methods vary in complexity and hardware requirements. Motion-based detectors like eye blink or head tracking feature minimal requirements of hardware but are so common in consumer applications. Instead, texture-based designs examine details of skin to make a difference between live subjects and printed images. Higher resolution methods use 3D depth sensing to acquire the facial geometry, which is more resistant to spoofing but needs special sensors. A major difference lies in the active and the passive approach where the user is asked to do something (e.g. blink or nod), and passive where non-interactively observed cues are used. In addition to the effectiveness of such methods proven in many studies in controlled environments, there is a lack in incorporating liveness detection methods with assessments of hardware and environmental variability (Wang & Peng, 2021). By evaluating blink and head movement detectors-an active, motion-based approach that was tested on a variety of devices and under different lighting conditions, KiBots directly fills the current research gap and provides an overall assessment of robustness in the real-world environment (Dewi et al., 2022).

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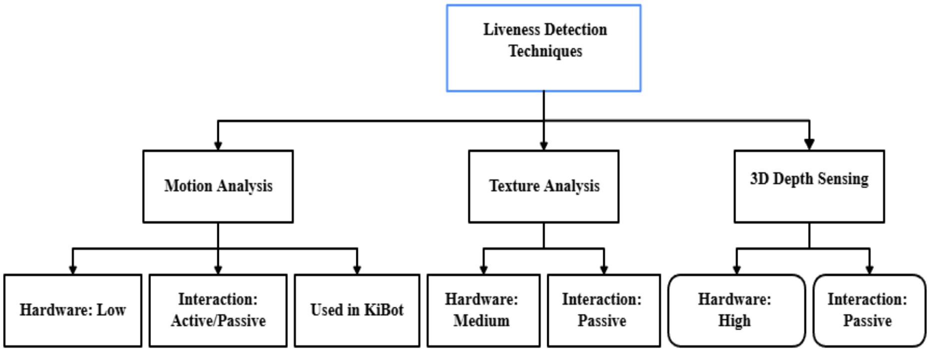

Fig. 4. Overview of liveness detection techniques: motion-based, texture-based, and depth-based

Source: Authors' overview

2.4 Design of Experiments (DOE) in Biometric Systems

The Design of Experiments (DOE) method provides a methodological system to determine the interplay between various variables to affect system performance. In comparison to one factor at a time testing, DOE tests the major and interaction effects of multiple factors at the same time giving a more effective and statistically viable test. DOE has also been used in multimodal verification experiments and fingerprint recognition to determine optimal accuracy and robustness in biometric research (Borgianni & MacCioni, 2020; Hidayat et al., 2024). Its use in facial recognition is however minimal, especially in testing hardware-lighting interactions in controlled experimental settings. This paper builds upon the DOE method of facial recognition by numerically estimating the impact of lighting intensity and camera resolution on the combined effect on detection distance and liveness detection rates.

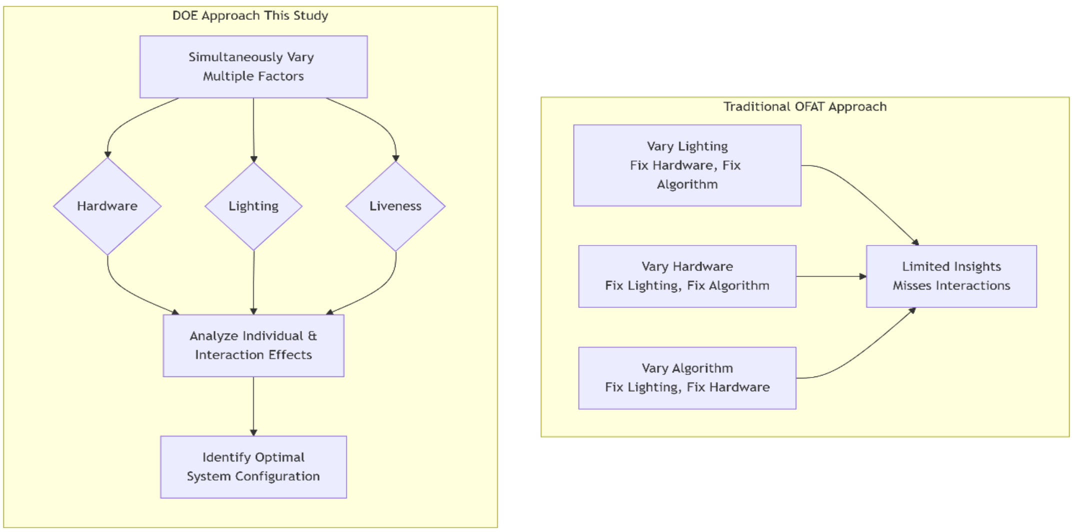

Fig. 5. Comparison between traditional One-Factor-at-a-Time (OFAT) and multi-factorial Design of Experiments (DOE) methods

Source: Authors' illustration of comparison

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Fig. 5 illustrates the advantage of DOE in capturing interaction effects between variables. This diagram shows graphically the differences between the haphazard wasteful experimental approach of working individually on each factor (nicknamed the One-Factor-at-a-Time (OFAT) method) and the systematic method of multi-factorial Design of Experiment (DOE), which can identify interaction effects.

2.5 Gaps and Research Justification

The literature always refers to the fragility of face recognition systems on the requirement of changes in the hardware, change of environmental conditions, and threats of spoofing. However, a major missing link is a systematic evaluation of the interaction of these aspects that should be studied under controlled conditions by multiple consumer-grade devices with the use of structured Design of Experiments (DOE) approach. The absence of multi-device testing, especially where such multi-device testing was used to measure the interaction between different lighting conditions and liveness detection performance, constrains the applicability of recommendation to real-world implementation (Oloyede et al., 2020). The controlled experiment design of this study directly meets this gap by testing a critical number of ten devices in two varied lighting conditions and was able to incorporate liveness checks across repetition runs. The main contribution is not a particular new measurement but a complete attentional procedure. Using a general linear model ($Y = \beta_0 + \beta_1 L + \beta_2 R + \beta_3 (L \times R) + \varepsilon$) in a factorial DOE, this study estimates the main and the most important, the interaction effects on the detection distance (Y) between hardware resolution (R) and lighting condition (L). The method is replicable and statistically rigorous by giving a quantitative way of assessing system robustness in an identical manner (Giap et al., 2023).

Although the quality of hardware and the effect of lighting and liveness detection have been studied separately, few studies have focused on a controlled performance comparison using a device under unified DOE framework that considers these factors. Solid research usually considers controlled, single variable settings without paying much attention to the interactions that characterize deployment challenge in the real-world. The study fills this gap because it is conducting an exhaustive comparison that explains performance variations across multiple conditions, rather than merely listing them (Amirgaliyev, 2025).

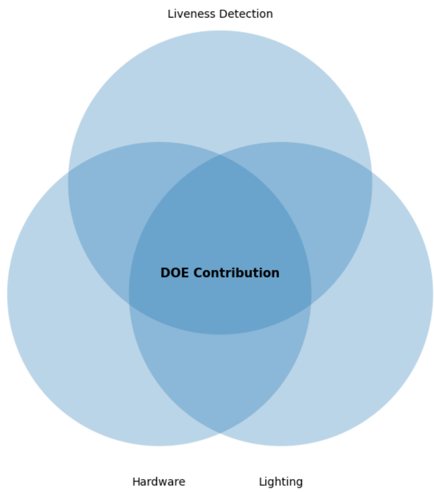

Fig. 6. Conceptual Venn diagram showing the overlap between hardware, lighting, and liveness detection research, highlighting the unique contribution of this study

Source: Authors' conceptual Venn diagram

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Fig. 6 shows the overlap of the studies between hardware, lighting and the detection of liveness and this DOE may form a unique part of its contribution. As depicted in Fig. 6, this study occupies a unique position by integrating all three factors under a DOE framework. This paper contributes to the literature as we provide a comparative analysis between the performance of facial recognition on different hardware under varying lighting conditions. The DOE-based methodology is an approach that has been identified as a representative to overcome occurrence of practical deployment issues and, therefore, partakes in the creation of effective, cost-efficient facial identification systems.

3. METHODOLOGY

3.1 Experimental Procedure

The main research goal is to objectively evaluate three important performance metrics, namely (i) effectiveness of facial recognition with the use of a wide range of cameras, including smartphones, laptops, and external webcams; (ii) the maximum distance over which facial recognition works under controlled lighting conditions; and (iii) the precision of liveness detection with each of the devices under both bright (~300 lux) and dim (~50 lux) luminosity conditions. The experimental sample is composed of ten devices representing smartphones (Redmi 14, iPhone 12 Pro, iPhone 13, Infinix GT 20 Pro), laptops (HP Ryzen 5, HP Pavilion, MSI GF63 Thin), and external webcams (HD Digital Camera, Microsoft LifeCam, Lenovo 300 FHD) and tested under two common lighting conditions, including acquire bright and secure environments. The experimental setup involved a controlled situation that involved adjustable LED panels which were calibrated using the digital lux meter to provide certain levels of illumination. The test distance was set to 50 cm in the initial position and increased by 10 cm until the subject failed recognition whilst performing liveness verification behaviors (e.g., blinking or tilting the head) to ensure that they were alive through embedded motion analysis algorithms. To increase reliability and reduce variability, three replications/device and subject were made with a mean maximum measurement distance and associated performance parameters systematically determined to be recorded as required later in statistical analysis.

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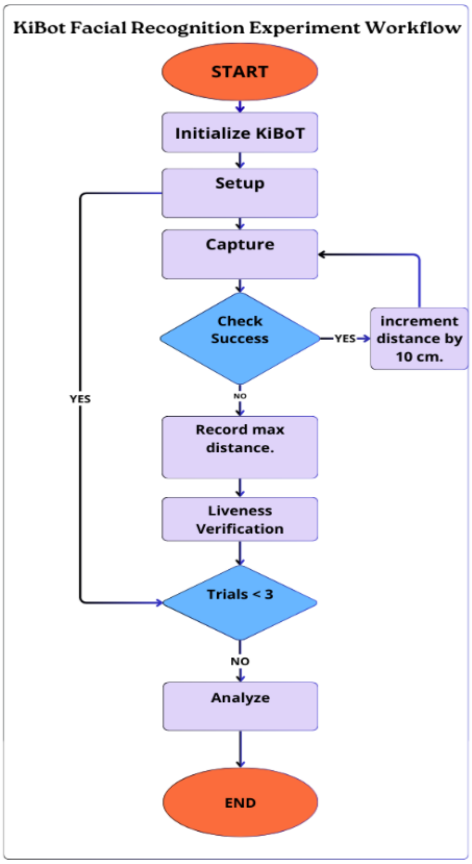

Fig. 7. Flowchart of Experimental Procedure

Source: Authors' flowchart

Fig. 7 illustrates the descriptive flow chart of the KiBot facial recognition experiment and exhibits a well-organizational flow of process as at present evaluation time. The first process is "Start" followed by the initialization and calibration of KiBot system and the camera. After that, the subject is placed at an initial distance of 50 cm with controlled lighting, and the facial recognition is recorded after a liveness prompt (blink or head movement). The workflow can then be evaluated as successful, and the process returned to the capture step again (with a distance increment of 10 cm) or when maximum distance is recorded as failure. This is then followed by a liveness verification and a decision of whether to repeat trials up to three times each condition followed by a data analysis across the ten devices and finally ends with the statement: End to compile graphical and statistical results.

The sequence of phases of the experiment as described in Fig. 8 starts with the calibration of the system through the KiBot utility. After calibration, test fodder is put at a prescribed distance of 50 cm in front of the sensor under an artificially set lighting condition. The system conducts facial recognition capture followed by a liveness challenge at random, e.g. ask the user to blink or move the head.

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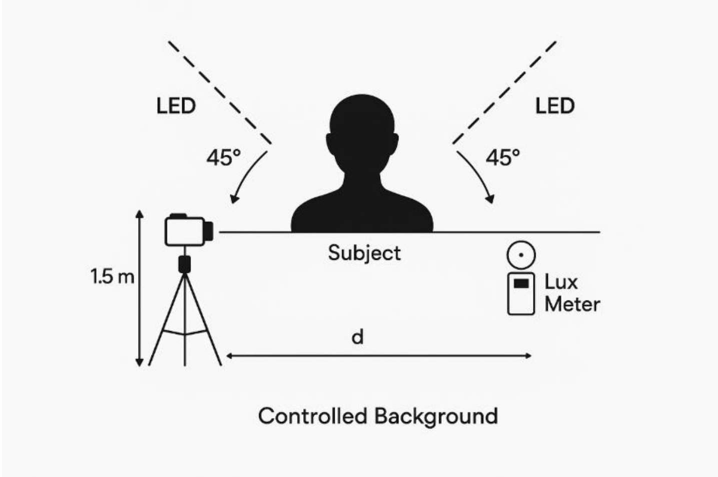

Fig. 8. Layout Diagram

Source: Authors' layout diagram

A correct verification fires an extend-increase procedure during which the subject distance is advanced in 10 cm increments until recognition fails upon determining the greatest effective distance. Each of these sequences is repeated in three separate trials per subject to assure statistically valid results, with recalibration prior to each trial. Once all the trials have been completed the resulting data in the test cohort is pooled together and is compared by means of a comparative study, and ultimately a final clear analysis of graphs and statistics is completed to complete the performance evaluation.

3.2 DOE Analysis Procedure

The results of the experiments were explored following a structured Design of Experiments (DOE) algorithm to interpret in a systematic way the impact of the controlled factors and the interaction between them on the performance of the system. The variable that measures the dependent variable in this analysis was the Maximum Detection Distance (Y), in cm. The resulting data on the factors and the response was modelled as being of a General Linear Model (GLM) of a 2k factorial design, the common method to isolating the main and the interaction impacts of the controlled experiment (Montgomery, 2017). The statistical model can be written as follows:

$$Y = \beta_0 + \beta_1 L + \beta_2 R + \beta_3(L \times R) + \varepsilon \tag{1}$$

The dependent variable is the Maximum Detection Distances (Y), which variable code was assigned according to the experimental results. The independent variables include Lighting Condition (L) and Hardware Resolution (R), which are represented as a dummy variable 1 = Bright Light (~300 lux), 0 = Low Light (~50 lux), and a continuous variable measuring in Megapixels (MP); respectively. The least squares technique was used to fit the experimental data to the model coefficients (β_0, β_1, β_2, β_3). Each model term (null hypothesis H_0: $\beta_i = 0$) was statistically tested with an ANOVA approach at a confidence level of 95 percent (alpha = 0.05). All the calculations were done in MATLAB R2024a using the Statistics and Machine Learning Toolbox.

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4. RESULT AND DISCUSSION

4.1 Maximum Detection Distance

The Microsoft LifeCam had the greatest detection distance at high illumination (150 cm), but smartphones performed much better in low-light scenarios, because they featured more advanced light sensors and to process them. The laptops performed moderately and are again variable depending on in-built quality of webcams.

Table 1. Maximum Detection Distance

Device	Bright Light (cm)	Low Light (cm)
Redmi 14	75	75
HP Ryzen 5 Laptop	120	95
HD Digital Camera	80	-
Microsoft LifeCam	150	-
Lenovo 300 FHD	60	-
iPhone 12 Pro	90	60
iPhone 13	85	75
Infinix GT 20 Pro	70	60
HP Pavilion	93	75
MSI GF63 Thin	100	95

Source: Authors' results

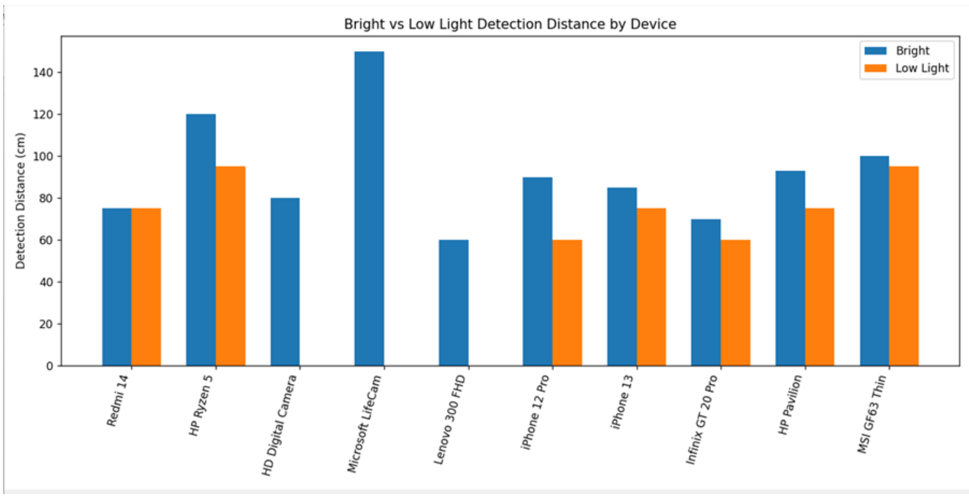

Fig. 9. Bar chart on Device & Lighting vs Detection distance.

Source: Authors' bar chart analysis

The bar chart in Fig. 9 includes a comparative analysis of the maximum distance at which different devices can make proper detection by the KiBot facial recognition system under high-intensity light (300 lux) and low intensity light (50 lux) as was assessed in the Design of Experiments (DOE) Draft.pdf at 01:52

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PM +08, Tuesday, August 26, 2025. All devices performed notably better in high-intensity light with the Microsoft LifeCam having the maximum detection distance of 150 cm. Nevertheless, there is a general performance drop that cuts across all cameras, especially when liveness is not detected using cameras such as the HD Digital Camera, Lenovo 300 FHD, and Microsoft LifeCam in low light. Newer smartphones like the iPhone 12 Pro, the iPhone 13 and the Infinix GT 20 Pro exhibit performances comparable to older models, with an ebb and flow of comparable responses to low light conditions, which is more adaptable than using laptops and other webcams.

4.2 Liveness Detection Capability

The highest success was in smartphones and laptop Liveness detection considering that it retained the same outcome of success in both conditions with most results. Externalized webcams could not work in low light and could not detect movements because of the low sensitivity.

Table 2. Liveness Detection Capability

Device	Bright Light	Low Light
Redmi 14	Yes	Yes
HP Ryzen 5 Laptop	Yes	Yes
HD Digital Camera	Yes	No
Microsoft LifeCam	Yes	No
Lenovo 300 FHD	Yes	No
iPhone 12 Pro	Yes	Yes
iPhone 13	Yes	Yes
Infinix GT 20 Pro	Yes	Yes
HP Pavilion	Yes	Yes
MSI GF63 Thin	Yes	Yes

Source: Authors' results

4.3 DOE Analysis Results

Design of Experiments (DOE) was employed to measure the influence of lighting condition (L), hardware resolution (R) and their interaction (L×R) on the maximum distance of facial recognition detection. Table 3, which presents the results of ANOVA, shows that the overall model is statistically significant ($p < 0.001$), which proves the fact that the chosen factors can affect performance.

Table 3. ANOVA Table for the Maximum Detection Distance Model

Source	**Sum of Squares**	**Degrees of Freedom**	**Mean Square**	**F-Value**	**p-Value**
Model	38945.31	3	12981.77	20.52	**< 0.001**
L (Lighting)	23793.10	1	23793.10	37.61	**< 0.001**
R (Resolution)	1082.29	1	1082.29	1.71	0.209
L × R	12465.63	1	12465.63	19.70	**< 0.001**

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Source	Sum of Squares	Degrees of Freedom	Mean Square	F-Value	p-Value
Residual	10123.69	16	632.73		
Total	49069.00	19			

Source: Authors' results

The findings indicate that the condition of lighting was the most influential in the detection distance ($F = 37.61$, $p < 0.001$). However, hardware resolution was not statistically significant as an effect ($p = 0.209$). Nevertheless, the lighting and resolution interaction ($L \times R$) had very much importance ($F = 19.70$, $p < 0.001$), which shows that the difference in performance of high-resolution cameras is more noticeable in bright light settings.

The regression model derived from the DOE analysis is summarized as:

$$Y = 20.36 + 81.93L + 0.32R + 1.59(L\times R) \quad (2)$$

Practically, the transition between dim and bright lighting ensured that there was an average increase of the detection distance of approximately 82 cm, and an even greater advantage was gained by higher-resolution cameras under such conditions. The results confirm that the influence of lighting is an overwhelming factor on the performance of facial recognition, and the effect of camera resolution enhances the effect of light in the best case.

5. CONCLUSION

This paper used a Design of Experiments (DOE) model to test the joint effect of lighting conditions and hardware resolution on the performance of facial recognition based on the KiBoT system. The findings indicated that lighting is the most significant aspect that influences the detection distance whereas hardware resolution does not have a significant influence. Nevertheless, when comparing lighting and resolution, it can be stated that the higher the resolution of the camera, the better performance in case there is enough light. Practically, it would imply that the bright environment significantly enhances the accuracy and range of recognitions and that high-resolution cameras can partially address the shortcomings of low-light situations. The results give a straightforward indication of cost-efficient implementation: the use of high-quality webcams can be effective in a controlled environment such as lighting, but in unpredictable real-life conditions, sophisticated equipment, like a smartphone with built-in image processing, is needed. DOE methodology has been found useful in evaluating the interactions of environmental and hardware parameters in a systematic way to provide a model that can be used to optimize facial recognition systems in a replicable manner. Future studies ought to incorporate this framework to cover algorithmic parameters, user movement and presentation attack variations to further provide robustness in the system in various applications in the real world.

6. ACKNOWLEDGEMENTS/FUNDING

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7. CONFLICT OF INTEREST

The authors agree that this research was conducted in the absence of any self-benefits, commercial or financial conflicts and declare the absence of conflicting interests with the funders.

8. AUTHORS' CONTRIBUTION

Md Sariful Islam contributed to the conceptualization, methodology, software development, data curation, and writing of the original draft. Ahmad Anwar Zainuddin was responsible for supervision, conceptualization, project administration, and manuscript review and editing. Murni Mahmud provided supervision, validation, and writing contributions (review and editing). Haikal Khusairi Ahmad and Rabi'atul Adawiyah Mohd Nazri assisted with validation, resource provision, and manuscript review and editing. Amir 'Aatieff Amir Hussin conducted the investigation, data curation, and visualization. Finally, Mohd Khairul Azmi Hassan and Mohd Izzuddin Mohd Tamrin carried out the investigation, data curation, and formal analysis.

9. DECLARATION OF GENERATIVE AI IN THE WRITING PROCESS

The authors declare that generative artificial intelligence (AI) tools may have been used solely to support language refinement during the preparation of this manuscript. Such tools were used only to improve grammar, sentence structure, clarity, and overall readability. All aspects of the research, including the study design, data collection, data extraction, analysis, interpretation of findings, and final academic decisions, were conducted, reviewed, and approved by the authors. The authors take full responsibility for the accuracy, integrity, originality, and scholarly content of this manuscript.

10. DATA AVAILABILITY/SUPPLEMENTARY MATERIALS

The data and/or supplementary materials supporting the findings of this study are available from the corresponding author upon reasonable request, where applicable.

11. ETHICS STATEMENT

The authors declare that this study did not involve human participants or animal subjects. Where applicable, all procedures were conducted in accordance with relevant institutional guidelines, safety requirements, and ethical standards.

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