

Enhancing Magnetic Resonance Imaging Safety Through Artificial In-telligence: A Support System for Healthcare Staff

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KEYWORDS:

Artificial Intelligence (AI); MRI safety; Computer Vision; Raspberry Pi; Machine Learning; Healthcare Tech-nology; Risk Management; Human Error Reduction;

ABSTRACT

The aim of this study is to integrate artificial intelligence (AI) into magnetic resonance imaging (MRI) workflows to enhance patient safety and reduce clinical risks. The STAID (Stretcher and Temperature AI Detection) system was developed as a Raspberry Pi 5-based model equipped with computer vision and thermal detection technologies to monitor body temperature and detect the presence of stretchers, for the most part incompatible with the MRI environment. The system was tested on an image sample, achieving an accuracy of 80.85% in stretcher recognition with an average inference time of 0.1172 seconds. Results indicate that STAID is easily integrated into clinical workflows, with positive acceptance from healthcare staff and patients, though some concerns remain regarding privacy and the reduction of human interac-tion. The introduction of STAID demonstrates AI's potential to improve risk management in MRI, paving the way for further adoption of AI technologies in clinical settings. Future prospects include deeper inte-gration with hospital systems and the development of training protocols for personnel, contributing to a safer, more technologically advanced healthcare environment.

INTRODUCTION

Magnetic resonance imaging (MRI) is one of the most advanced diagnostic techniques in medi-cine, known for its ability to produce detailed images without the use of ionizing radiation. How-ever, the MRI environment carries inherent risks due to the presence of strong magnetic fields, which can lead to hazards such as projectile effects from ferromagnetic objects, interference with implanted medical devices, and tissue heating due to radiofrequency energy absorption. These risks can be mitigated through a structured workflow and advanced risk management sys-tems [1]. Recently, artificial intelligence (AI) and computer vision have revolutionized radiological practice by integrating deep learning algorithms to improve diagnostic accuracy and optimize risk management processes [2][3]. In 2024, the European Union introduced the AI Act, which catego-rizes AI applications based on risk levels, ensuring the safe and responsible use of advanced technologies in healthcare [4]. This study describes the STAID (Stretcher and Temperature AI Detection) project, designed to enhance MRI workflow safety by monitoring body temperature and detecting the presence of stretchers. The system was tested in a clinical environment to assess its accuracy and operational impact.

MATERIALS AND METHODS

The STAID (Stretcher and Temperature AI Detection) project was designed to enhance safety in high-risk clinical environments, such as MRI environments. In clinical practice, patient body tem-perature and the presence of metallic objects are two of the main risk factors during MRI exams, where incompatible objects with magnetic fields can cause accidents, while a high temperature can have detrimental effects on febrile patients, pediatric patients, unconscious patients, or indi-viduals with impaired thermoregulation, as they may be more vulnerable to tempera-ture-induced complications during the scan [5][6]. The STAID system is designed to monitor body temperature in real-time and automatically detect the presence of incompatible stretchers using an AI-based computer vision system. The Rasp-berry Pi 5 8GB, which serves as the core of the system, is a compact, low-power, single-board computer equipped with a quad-core processor and enhanced memory capacity. It is widely used in embedded systems and AI applications due to its affordability, flexibility, and ability to handle computational tasks efficiently. The project architecture includes a Raspberry Pi 5 pro-cessor and an MLX90640 thermal camera, which respectively detect images



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and abnormal temperatures, signaling potential issues with an audible alert. This hardware architecture ensures flexibility and low power consumption, making STAID a potentially integrable system within existing workflows.

Since STAID's hardware components are not MRI-safe, the system is ideally placed in the controlled area preceding the MRI room. This positioning allows it to detect incompatible stretchers before they enter the MRI environment, providing an additional layer of security to the workflow and reducing the likelihood of high-risk incidents.

The STAID system also incorporates body temperature monitoring primarily as a pre-exam screening tool. Since it is positioned outside the MRI room, it is not designed for real-time temperature monitoring during scans. Instead, it helps identify febrile patients before they undergo MRI, preventing potential adverse effects from radiofrequency-induced heating. The system employs an MLX90640 thermal camera, which captures thermal data at a resolution of 32x24 pixels, processing it in real-time to detect elevated temperatures. Given its current placement, STAID provides an initial assessment to ensure patient safety before MRI procedures commence. Future developments could focus on making STAID MRI-safe, enabling continuous temperature monitoring during the imaging procedure, which could be beneficial for high-risk patients or those undergoing lengthy scans, where thermoregulation plays a crucial role in patient safety.

The STAID system uses various hardware and software components, including:

- Raspberry Pi 5 8GB as the core of the system, for control and data processing, valued for its affordability and energy efficiency.
- USB webcam for video capture to detect stretcher presence, providing real-time video feedback compatible with the OpenCV library.
- MLX90640 thermal camera connected to the Raspberry Pi through GPIO for accurate thermal data acquisition.
- HDMI touchscreen display for real-time monitoring and data visualization directly on the system, which allows healthcare staff to view alerts and data onsite.
- Lenovo K3 Pro Bluetooth speaker to emit an audio alert when incompatible objects or abnormal temperatures are detected.
- Passive cooling case for thermal regulation of the Raspberry Pi, crucial for preventing overheating during continuous operation in clinical settings.

The primary software components include Python and various libraries such as Keras, for deep learning, OpenCV for image processing, pygame for audio management, adafruit_mlx90640, used to interact with the thermal camera and gpiozero for GPIO connection control.

For automatic object recognition, STAID uses a

convolutional neural network (CNN) of the MobileNetV3 type, optimized for low computational capacity systems such as the Raspberry Pi. CNNs are ideal for image processing because of their ability to extract specific features through multiple convolutional and pooling layers. MobileNetV3 was chosen for its efficiency in real-time object recognition and its "separable convolution" structure, which reduces parameter count and speeds up processing [7].

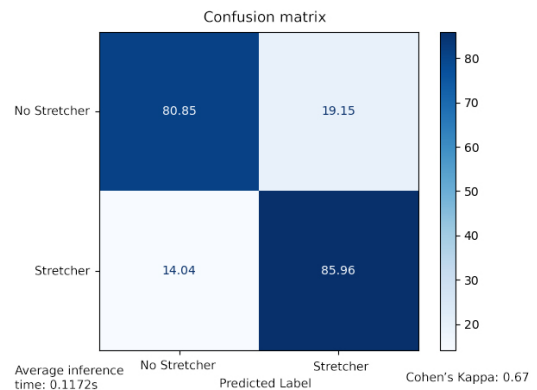


Figure 1. Performance evaluation of the AI stretcher detection model – confusion matrix, median inference time and Cohen's Kappa

The MobileNetV3 model was trained on a dataset of stretcher images taken from the ImageNet dataset [8]. The network was optimized for fast inference and high accuracy, ensuring that stretchers are identified in real-time to reduce the risk of incidents related to metal presence in the MRI room.

During the testing phase, the STAID system was experimented on a set of 416 images, collected from the web, of which 228 contained stretchers of various models in different settings, while 188 did not contain any stretchers. The system showed an overall accuracy of 80.85% for images containing stretchers and 85.96% for images without stretchers. Additionally, the average inference time per single image was 0.1172 seconds, ensuring immediate data processing and real-time response capability.

It is important to note that the object recognition algorithm is designed to detect only stretchers and does not identify additional objects that may be present alongside them, such as oxygen tanks or multiparameter monitors. A potential future development could involve training the model to recognize other common hospital objects that pose a risk in the magnetic resonance imaging (MRI) environment.

RESULTS

STAID demonstrated a high level of reliability, achieving a Cohen's Kappa of 0.67, indicating good agreement between automatic detections and actual conditions. This accuracy measure is crucial as it reflects STAID's capacity to detect critical cases

accurately without overwhelming staff with false alarms. Additionally, the choice of Raspberry Pi as the primary hardware allowed for cost containment, making the system accessible even for hospitals with limited resources.

The integration of the STAID system into clinical workflows was evaluated through surveys administered to both healthcare staff and patients. These surveys were conducted solely for re-search purposes to assess public interest and opinions regarding AI-based support systems like STAID. Given that the general public may have preconceptions about AI in healthcare, the study also aimed to determine how their trust in these technologies evolves when they understand their functionality and observe them in operation. The results indicate that users who

experi-enced STAID firsthand developed a higher level of trust and a more positive perception of its benefits compared to those who only received theoretical explanations. Healthcare staff re-sponses were divided into a control group and those with firsthand experience using STAID.

When asked, “To what extent do you believe a system like STAID can support healthcare per-sonnel?”, 14% of the control group responded “very much”, 79% responded “quite a bit” and 7% responded “a little”. In contrast, 56% of those with firsthand experience of STAID responded “very much,” while 44% responded “quite a bit.” These results indicate that those who interacted directly with STAID perceived it as a highly supportive tool for their work.

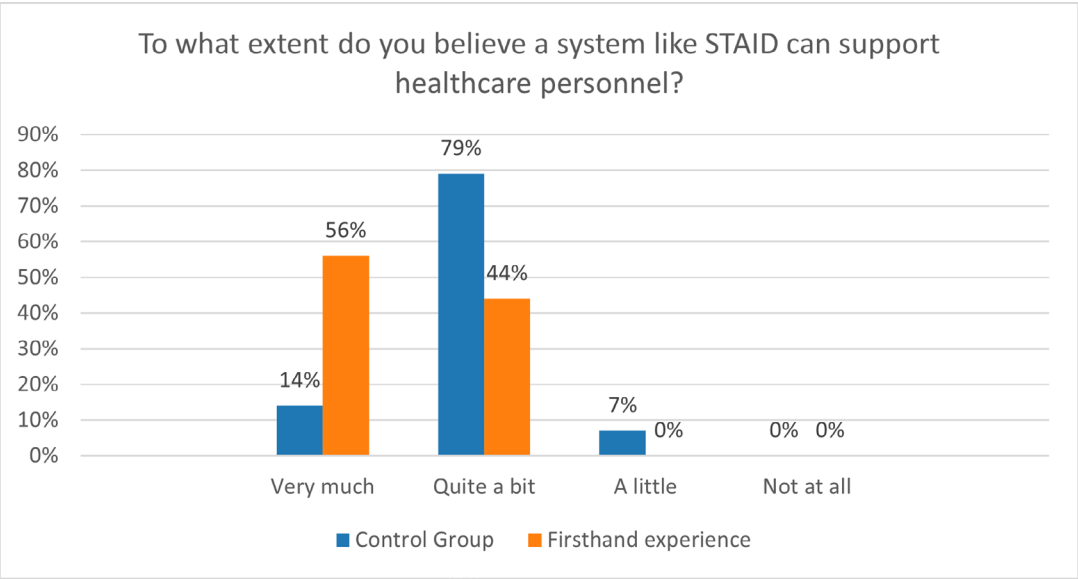


Figure 2 – Survey answers from healthcare staff, divided into control group (blue) and those who had first hand experience (orange)

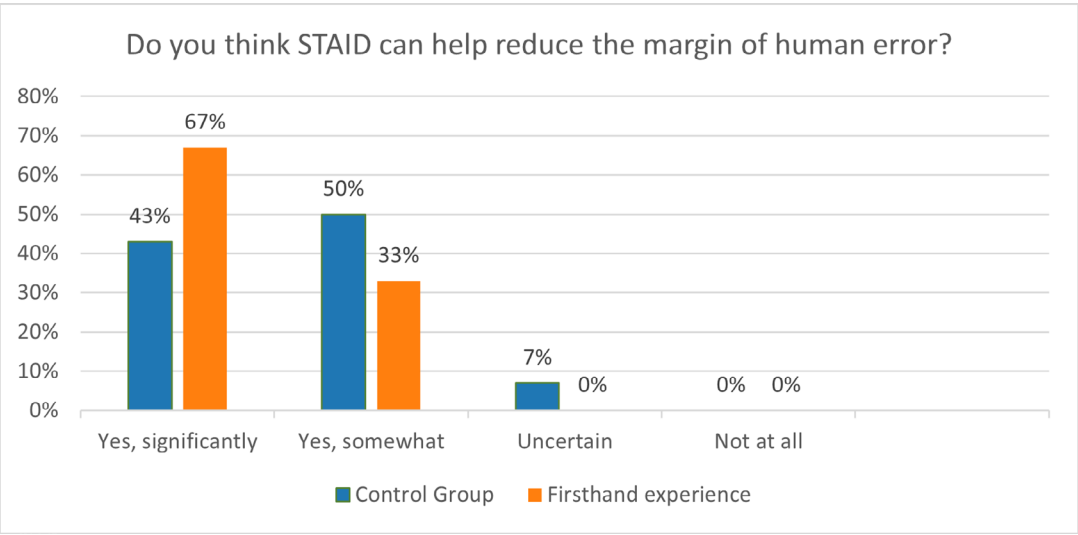


Figure 3 - Survey answers from healthcare staff, divided into control group (blue) and those who had first hand experience (orange)



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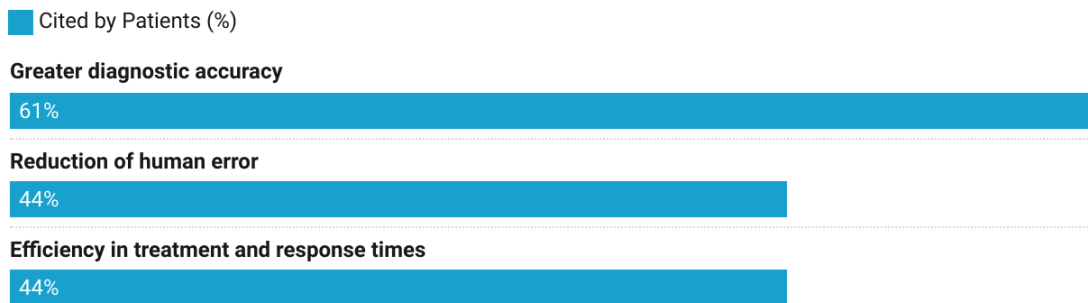


In response to the question, "Do you think STAID can help reduce the margin of human error?", responses differed notably between the two groups. Among the control group, 43% indicated "Yes, significantly," 50% said "Yes, somewhat," and 7% were uncertain. Among those with firsthand experience, 67% responded "Yes, significantly," and 33% responded "Yes, somewhat." This suggests that direct exposure to STAID reinforces confidence in its potential to mitigate human error.

sufficient precision to meet the needs of a clinical setting.

Despite these promising results, some limitations emerged, including the need for further optimization to minimize false positives and ensure higher detection accuracy. Building trust and acceptance among healthcare personnel is essential and can be strengthened through training and awareness initiatives, especially given the AI Act, which regulates the use of artificial intelligence in

In your opinion, what are the main advantages AI could bring to healthcare?



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Figure 4 – Answers from patient's survey

Patient surveys reflected a positive perception of AI's potential in healthcare. When asked, "In your opinion, what are the main advantages AI could bring to healthcare?", 61% of patients cited "greater diagnostic accuracy," 44% noted "reduction of human error," and another 44% highlighted "efficiency in treatment and response times." Together, these findings suggest that STAID and similar AI tools are perceived by both staff and patients as valuable assets, enhancing accuracy and supporting safer, more efficient healthcare operations, especially in continuous monitoring and high-risk settings [9].

DISCUSSION

The integration of an AI monitoring system like STAID in MRI environments has proven both effective and advantageous. This project has shown that artificial intelligence can be a valuable support for healthcare staff, enhancing patient safety and reducing the risk of incidents associated with incompatible metallic objects in the MRI environment [3]. Accuracy tests have confirmed that STAID is capable of operating in real-time with

healthcare [10][11].

The introduction of STAID highlights the potential of AI technologies to improve risk management in MRI, demonstrating the system's effectiveness in promptly stretching and monitoring body temperature—both crucial elements for patient safety in clinical settings [12]. The findings indicate that integrating STAID into clinical workflows is not only feasible but also beneficial for a safer and more optimized MRI environment.

Looking forward, the expansion of STAID's functionality is proposed, aiming to integrate it with hospital information infrastructures, such as HIS and PACS, while developing new operational guidelines to promote broader adoption of AI in clinical settings. These future prospects underscore STAID's potential as a tool for a safer, digitalized, and interconnected healthcare system, reducing human workload and improving the quality of patient care. Additionally, efforts to develop an MRI-safe version of STAID could enable real-time patient temperature monitoring during MRI scans, further enhancing safety standards in radiology.

REFERENCES

1. Cohen, J. (1960). A coefficient of agreement for nominal scales. *Educational and Psychological Measurement*, 20(1), 37–46. <https://doi.org/10.1177/001316446002000104>
2. Esteve, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature*, 542(7639), 115–118. <https://doi.org/10.1038/nature21056>

3. McBee, M. P., Awan, O. A., Colucci, A. T., Ghobadi, C. W., Kadom, N., Kansagra, A. P., Tridandapani, S., & Auffermann, W. F. (2018). Deep learning in radiology. *Academic Radiology*, 25(11), 1472–1480. <https://doi.org/10.1016/j.acra.2018.02.018>
4. Regulation—Eu—2024/1689—En—Eur-lex. (s.d.). Recuperato 11 novembre 2024, da <https://eur-lex.europa.eu/eli/reg/2024/1689/oj>
5. Van Den Brink, J. S. (2019). Thermal effects associated with rf exposures in diagnostic mri: Overview of existing and emerging concepts of protection. *Concepts in Magnetic Resonance Part B*, 2019, 1–17. <https://doi.org/10.1155/2019/9618680>
6. Dill, T. (2008). Contraindications to magnetic resonance imaging. *Heart*, 94(7), 943–948. <https://doi.org/10.1136/hrt.2007.125039>
7. Howard, A., Sandler, M., Chu, G., Chen, L.-C., Chen, B., Tan, M., Wang, W., Zhu, Y., Pang, R., Vasudevan, V., Le, Q. V., & Adam, H. (2019b). Searching for mobilenetv3 (No. arXiv:1905.02244). *arXiv*. <https://doi.org/10.48550/arXiv.1905.02244>
8. Deng, J., Dong, W., Socher, R., Li, L.-J., Li, K., & Fei-Fei, L. (2009). Imagenet: A large-scale hierarchical image database. In *2009 IEEE conference on computer vision and pattern recognition* (pp. 248–255).
9. Erickson, B. J., Korfiatis, P., Akkus, Z., & Kline, T. L. (2017). Machine learning for medical imaging. *Radiographics: A Review Publication of the Radiological Society of North America, Inc*, 37(2), 505–515. <https://doi.org/10.1148/rg.2017160130>
10. McKee, M., & Wouters, O. J. (2022). The challenges of regulating artificial intelligence in healthcare: Comment on «clinical decision support and new regulatory frameworks for medical devices: are we ready for it? - a viewpoint paper». *International Journal of Health Policy and Management*, 12, 7261. <https://doi.org/10.34172/ijhpm.2022.7261>
11. Daye, D., Wiggins, W. F., Lungren, M. P., Alkasab, T., Kottler, N., Allen, B., Roth, C. J., Bizzo, B. C., Durniak, K., Brink, J. A., Larson, D. B., Dreyer, K. J., & Langlotz, C. P. (2022). Implementation of clinical artificial intelligence in radiology: Who decides and how? *Radiology*, 305(3), 555. <https://doi.org/10.1148/radiol.212151>
12. Alfano, V., Granato, G., Mascolo, A., Tortora, S., Basso, L., Farriciello, A., ... & Moggio, G. (2024). Advanced neuroimaging techniques in the clinical routine: A comprehensive MRI case study. *Journal of Advanced Health Care*, 6(2).

Supplementary Materials:

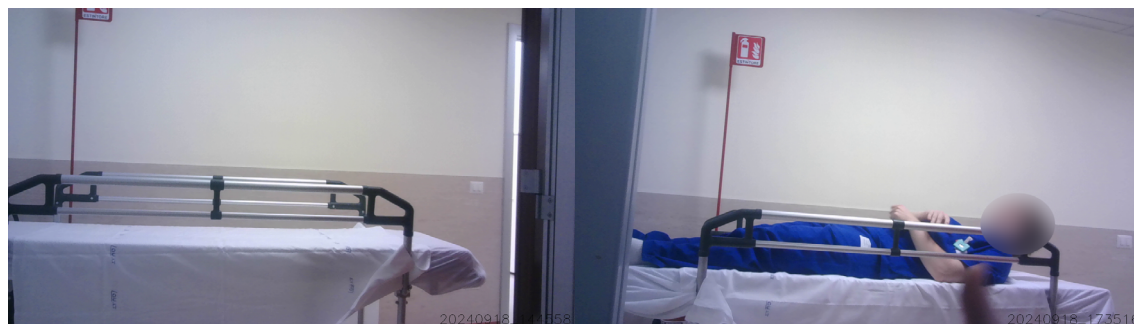
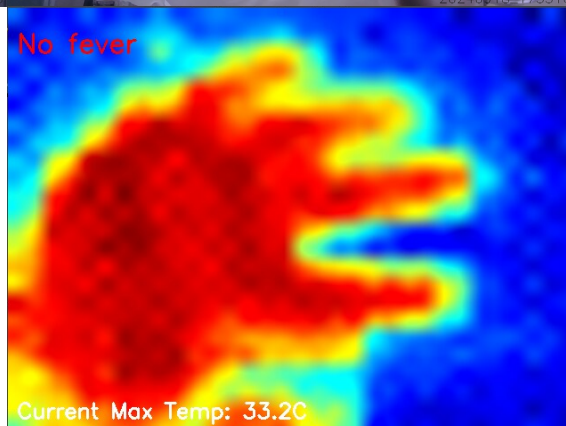


Figure 6 - The image displays the thermal camera view: in the top left corner, a "fever/no fever" flag is shown, while in the bottom left corner, the temperature of the hottest pixel in the image is displayed.



Author Contributions: Conceptualization, Giuseppe Walter Antonucci; Methodology, Domenico Tarantino and Giuseppe Walter Antonucci; Formal analysis, Domenico Tarantino; Writing—original draft preparation, Domenico Tarantino; Writing—review and editing, Giuseppe Walter Antonucci, Domenico Tarantino, Alessandra Terenziani, Savino Magnifico, Gerard Del Negro, Miriam Miracapillo and Maria Urbano; Super-vision, Giuseppe Walter Antonucci and Maria Urbano. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest: The authors declare no conflict of interest.



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