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Bridging Technology and Healthcare: The Impact of AI in Surgical Instrument Classification

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Abstract: Emerging technologies have sparked a surge in demand for artificial intelligence (AI), aimed at optimising various industries and simplifying daily tasks. In response to the rapid evolution of technology and the evolving requirements of surgical practices, we introduce an innovative application leveraging machine learning. Utilising Cloud Annotations, Collaboratory, and Node-RED, we developed a platform for accurate surgical instrument classification. By training our model on a diverse set of instruments and enabling user-friendly image capture, our application stands poised to revolutionise surgical workflows. This paper highlights the role of AI in healthcare and outlines the potential of our application to enhance surgical practices, improve instrument recognition, and contribute to patient care advancement. We also address challenges and opportunities in integrating AI into healthcare while proposing avenues for future research and development.

Keywords: artificial intelligence; healthcare innovation; image recognition; machine learning; Node-RED

1 INTRODUCTION

The rapid growth of innovative technologies reveals a wide range of breakthroughs that have the potential to achieve unprecedented levels of development and practical implementation [1]. Industries such as artificial intelligence (AI), machine learning, biotechnology, and cybernetics are leading the way in this emerging period, bringing about significant advances and reshaping conventional frameworks. The inherent potential of these technologies to enhance socio-economic standards worldwide is a key factor in their revolutionary impact [2, 3]. Significantly, within the domain of healthcare, they provide a potential opportunity for augmenting diagnostic precision and spearheading innovative approaches to illness prevention and treatment. The context of innovation provides the foundation for the creation of an application that aims to identify and classify surgical tools based on camera input. This program application utilizes artificial intelligence and machine learning to optimize surgical processes by assuring the prompt availability and precise identification of appropriate equipment [4]. This undertaking not only encompasses the fundamental concept of utilizing developing technologies to address certain obstacles but also showcases the capacity of these technologies to enhance medical methodologies and enhance patient care results.

This paper presents the development of an application capable of recognizing surgical instruments [4] through camera input and categorising them into respective classes. The machine learning model was trained using the Python programming language and TensorFlow library in the Colaboratory development environment. Subsequently, the model was converted into the TensorFlow.js format for seamless integration into web browsers. The application's graphical interface was built using the Node-RED development environment. The application successfully implements the classification of specific surgical instruments, with future enhancements aiming at detection and localization to enable recognition of multiple instruments within a single photograph. Furthermore, suggestions for future improvements include expanding the repertoire of recognized surgical instruments. The development tools employed include Cloud Annotations, Colaboratory, and Node-RED. Cloud Annotations facilitated the annotation of surgical instruments, while Colaboratory was used for model development and training. Node-RED enabled the creation of the graphical user interface, offering users the convenience of capturing images directly for recognition or uploading images from their computers. The model was trained on five different surgical instruments: curved surgical scissors, straight surgical scissors, scalpel, surgical forceps, and artery forceps. Additionally, the paper outlines the hardware setup consisting of a Raspberry Pi computer connected to a camera, providing a cost-effective solution for edge computing. The software environment involved Colaboratory for model development, Node-RED for interface design, and Cloud Annotations for dataset annotation and storage. The resulting application bridges the gap between machine learning algorithms and practical surgical instrument recognition, with potential applications in healthcare settings. Previous research efforts have delved into the specific area of computer vision and machine learning for surgical instrument recognition. These studies have highlighted the potential [1-3] of mentioned technologies in streamlining surgical workflows and reducing the risk of errors associated with human intervention.

2 HEALTHCARE AND ARTIFICIAL INTELLIGENCE

Artificial intelligence has emerged with a significant impact technology in modern healthcare system, revolutionizing diagnostic and treatment methodologies. With the proliferation of medical data and advancements in big data diagnostic techniques, AI has seamlessly integrated into healthcare systems, heralding a new era of efficiency and precision [5-9]. Through its adept analysis of information, medical records, and systems, AI augments digital automation, yielding swifter and more consistent outcomes while aiding physicians in achieving superior results [10].

However, despite its transformative potential, skepticism persists among practitioners regarding AI's future role in primary care. Many express concerns over its perceived lack of empathy and ethical dilemmas, reflecting a nuanced dialogue surrounding the integration of AI into the healthcare landscape [11]. This scepticism underscores the importance of addressing not only the technical capabilities of AI but also its ethical and interpersonal implications as it continues to shape the future of healthcare delivery.

The primary objective of this research is to enhance the classification of surgical instruments, thereby streamlining the workflows of medical personnel and improving operational efficiency in clinical settings.

The incorporation of machine learning models for identifying and categorizing surgical instruments marks a significant advancement in the operational efficiency of surgical settings. By automating instrument recognition, these models considerably reduce the time required by healthcare personnel to locate necessary tools, thereby facilitating the optimization of surgical procedures. This is especially critical during urgent operations where time efficiency is paramount, enhancing both the safety and effectiveness of surgical interventions. Machine learning technologies are proving invaluable as educational tools within the medical field, particularly for training medical and nursing staff. These technologies enable quick and precise identification of various surgical instruments, enhancing the training process and ensuring medical trainees are better prepared for real-life clinical environments. These models in healthcare systems can reduce the cognitive load on medical staff, allowing them to concentrate more on patient care and less on ancillary tasks.

The integration of such sophisticated machine learning models not only streamlines surgical operations but also significantly improves the training and preparedness of medical personnel, thus elevating the standard of patient care across healthcare settings. There are key constraints that affect the implementation of new technologies in clinical settings. These include challenges in compatibility and integration with existing systems, the need for high computing resources, ensuring data security and privacy in accordance with regulations, and the need for regular maintenance and technical support. Understanding and addressing these limitations is critical to the successful integration of IT tools into medical practices. The use of this application in the identification and classification of surgical instruments represents a significant advance in the technological support of operative procedures. However, the role of nurses who assist surgeons during operations remains irreplaceable. Although the app can improve efficiency and accuracy in identifying and preparing surgical instruments, nurses have a wide range of responsibilities that include managing the operating room.

The surgical instrument classification application described in this article potentially improves surgical operations by enabling rapid identification of required tools, reducing operative time and risks of human error. It also may serve as an educational tool for medical staff, improving in a certain way instrument inventory management in healthcare facilities. Also, in situations where surgeons perform remote operations using robotic systems, the application can possibly provide additional support in the identification and selection of the necessary instruments in real time.

2.1 Materials and Methods

The study employed a combination of implemented additive manufactured housing with hardware and software system: machine learning techniques and edge computing to develop a surgical instrument recognition application. It involved data collection, model training, and application development phases, each of which is described below.

Hardware and 3D model:

- 3D printed special housing to implement easy access of surgical instruments.
- Raspberry Pi 3 Model B: This credit card-sized computer served as the main processing unit for edge computing.
- Camera: A camera was connected to the Raspberry Pi for capturing images of surgical instruments. Compatible with all models of Raspberry Pi using the CSI (Camera Serial Interface) port. Supports up to 3280 x 2464 pixels for stills and video resolutions of 1080p at 30 fps, 720p at 60 fps, and VGA at 90 fps. Uses a 15 cm ribbon cable for connection to the Raspberry Pi board, allowing for flexible integration into various setups.
- MicroSD Card: A 15 GB microSD card with Raspbian GNU Linux 10 operating system was used as storage.

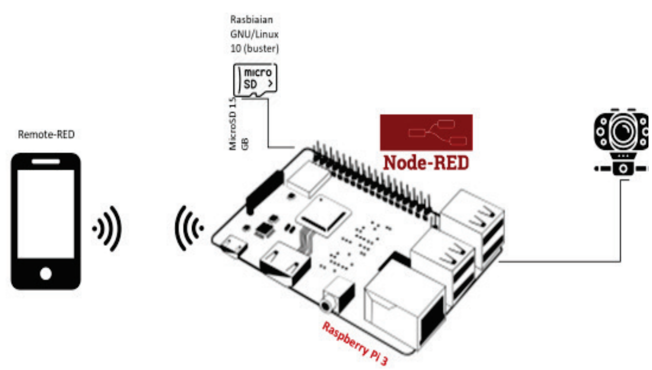

Figure 1 Schematic representation of the development environment [12]

Software:

- Python: The primary programming language used for model training.
- JavaScript: employed to develop the user interface, enabling interactive and dynamic interactions within application.
- TensorFlow: An open-source machine learning framework utilized for developing and training the model.
- Colaboratory: An integrated development environment (IDE) provided by Google for Python-based machine learning tasks, used for model training.
- Node-RED: A flow-based development tool used for creating the graphical user interface of the application.
- Cloud Annotations: A tool employed for annotating surgical instrument images to create a labelled dataset.

Procedures Followed:

Data collection: The dataset used for model training comprised 1500 original images, covering five distinct categories of surgical instruments: bandage and plaster scissors, surgical forceps, scalpel, straight surgical scissors, and artery forceps. Each category represents a different type of surgical tool commonly utilised in medical procedures, ensuring diversity in the dataset (Fig. 2). The overall accuracy is determined by adding the count of accurately identified values and dividing it by the entire count of values.

Figure 2 A sample set of surgical instruments.

Model training: To train the object detection model, a dataset with labelled bounding boxes was prepared using IBM Cloud Annotations tool. This tool facilitated systematic labelling of images, ensuring efficient data annotation and storage in IBM Cloud Object Storage. The Machine Learning model was created using Convolutional Neural Networks (CNN), TensorFlow and MobileNet CNN for analyzing visual images. Convolutional Neural Networks (CNNs) are a type of deep neural network primarily used for analyzing visual imagery. Also, it is worth to mentioned that the confusion matrix is important tool for enhancing Convolutional Neural Networks (CNNs) as it provides a detailed breakdown of accuracy and mistakes for each class, allowing for focused improvements. Additionally, it aids in the improvement of the network by fine-tuning thresholds, hence enhancing performance in practical applications. TensorFlow, a free, open-source machine learning library, excels in training and deploying neural networks, featuring tools for symbolic math and differentiable programming. MobileNet, a TensorFlow component, is an optimized CNN for mobile vision applications with low computational demands. Neural networks, central to TensorFlow, are algorithms that mimic the brain's function to detect data patterns and can be either organic or synthetic neuron systems.

The training process involved accessing the labelled dataset, installing necessary dependencies such as TensorFlow Object Detection API, and initiating training in Colaboratory. Once trained, the model was converted to TensorFlow.js format for web deployment and downloaded for integration into the application. Testing of the trained model confirmed its efficacy, with high accuracy in detecting surgical instruments (Fig 3). In order to further increase the accuracy, the model was trained several times with an increased number of images in the dataset. In addition, controlled environmental lighting was also identified as a key factor influencing the improvement of model performance. Adjusting these parameters enabled more precise identification and classification of surgical instruments, thereby minimizing potential room for error and increasing overall efficiency in the operating room.

Figure 3 Data training procedure

Application development: For the application development phase, the trained model underwent conversion into TensorFlow.js format, facilitating seamless integration into web browsers. Leveraging Node-RED, we crafted a user-friendly graphical interface enabling users to either capture images directly for recognition or upload images from their computers. The application was meticulously designed to process these images, utilizing the trained model, showcasing the recognized instrument along with its classification in an intuitive manner (Fig. 4).

Deployment: The developed application was deployed on the Raspberry Pi, enabling real-time instrument recognition at the edge. Users could access the application interface via smartphones using the Remote-RED application.

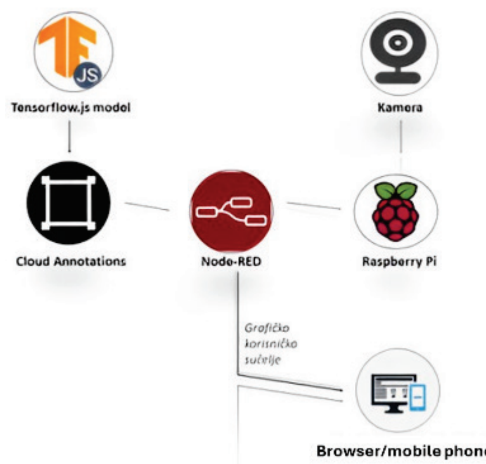

Figure 4 Schematic representation of the system

3 INTERFACE MODELLING

The development of the application for the classification of surgical instruments in the Node-RED environment is divided into several key functional subgroups that enable efficient image management and processing. These functionalities include:

Flow for uploading images from a computer: Allows users to upload images from a computer to the application, which is the first step in the processing process.

- **Direct image capture**: Enables direct image capture via a built-in or connected camera, allowing users to instantly capture and send images of surgical instruments for analysis.
- **Display of uploaded or captured images on the application interface**: After uploading or capturing, images are displayed on the application's user interface, providing visual feedback to users.
- **Saving captured images to the computer:** This functionality enables saving captured images to the local computer, thus ensuring that all data is safely archived.
- **Detection and display of detection results:** After image processing, the application identifies and classifies surgical instruments and displays the detection results on the interface.
- **Display of time and date:** The interface also displays the current time and date, which can be useful for records and documentation in clinical settings.
- **Remote access:** Allows users to remotely access the application, which is especially useful in situations where fast and efficient remote diagnostics are required.

These functionalities within the Node-RED environment form the basis for an efficient and flexible application that can be adapted to the specific needs of medical and research institutions.

4 RESULTS

The interface of the application is depicted in Fig. 5, enabling users to capture a picture or upload it from their computer. The results of the recognized class, along with their probabilities, are displayed in a table.

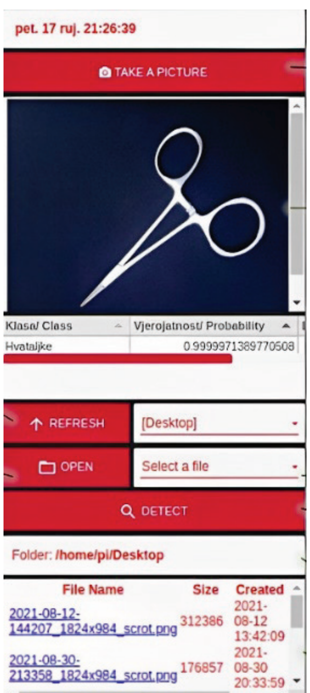

Figure 5 Application display

Additionally, remote access is facilitated through a gateway node, allowing users to access the website locally or remotely from a mobile application. By downloading the mobile application Remote-RED, available on Google Play, users can access the application from a remote location.

During the implementation of the project, we encountered significant challenges regarding the functionality of the software and hardware components. The main problem we faced was the limitation of our system to perform only the classification of surgical instruments, without the possibility of detection. This means that our current model can identify the type of instrument within a given pattern but cannot locate the presence or position of an instrument within an image. This limitation represents a significant obstacle for further application in real surgical environments, where precise detection and localization of instruments is crucial for successful operational support. In response to this problem, we plan to develop and integrate more advanced object detection algorithms into future versions of our system. These improvements will enable more precise tracking and identification of surgical instruments during operations, thereby increasing their operational efficiency and patient safety. These upgrades represent a key focus of our future research and development efforts.

5 CONCLUSION

In this study, we have presented an innovative application leveraging machine learning techniques for the classification of surgical instruments. By combining edge computing with image recognition algorithms, we developed a platform capable of accurately categorising surgical instruments in real-time. Our approach involved the utilisation of Python programming language, TensorFlow framework, and Node-RED development environment for model training, conversion, and interface design, respectively. Through systematic data collection, model training, and application development phases, we successfully created a user-friendly interface enabling both image capture and upload for instrument recognition. The deployment of the application on Raspberry Pi offers a cost-effective solution for edge computing, ensuring accessibility in healthcare settings. The results demonstrate the effectiveness of our approach in recognizing surgical instruments with high accuracy, paving the way for enhanced surgical workflows and improved patient care. Future enhancements will focus on expanding the repertoire of recognized instruments and integrating additional functionalities to address the evolving needs of surgical practices. Overall, our study contributes to the advancement of surgical practices through the integration of machine learning technologies, fostering innovation in healthcare delivery. The study on AI-based surgical instrument recognition holds several notable advantages for healthcare. By integrating machine learning with surgical practices, it offers improved training opportunities, minimises errors during procedures and enhances patient safety. Additionally, the application streamlines surgical workflows, leading to increased efficiency and potentially shorter operation times. Its deployment on edge computing platforms ensures cost-effectiveness, making it accessible to a wide range of healthcare facilities. Moreover, the tool's capability for remote access enables surgeons to utilise it beyond the operating room, facilitating telemedicine and expert consultations. With the flexibility to customise and scale according to specific surgical needs, this study represents a significant stride towards advancing surgical practices and patient care. By combining machine learning with edge computing and web technologies, this study showcases a scalable and adaptable approach to deploying intelligent applications in medical environments. It sets the stage for further advancements in medical technology and opens doors to innovative solutions for healthcare challenges. In summary, integrating advanced machine learning models into healthcare practices not only streamlines operational procedures but also significantly enhances educational outcomes for medical personnel, thereby reinforcing the overall quality of patient care. This work establishes the scientific foundations for future research and enables potential patenting and practical application of observed innovations, which are currently not implemented in healthcare.

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