LEVERAGING CONCEPT TECHNOLOGY IN MEDICAL APPLICATIONS FOR ALZHEIMER'S DISEASE

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ABSTRACT

The number of Alzheimer's disease (AD) cases is expected to double every two decades, and the need for effective diagnostic tools has become increasingly urgent to address this growing healthcare challenge. The hippocampus and magnetic resonance imaging (MRI) play a pivotal role in diagnosing AD. It could demonstrate utility in differentiating AD. Deep learning-based approaches to produce digital health technologies may offer valuable advantages to dementia researchers and clinicians as screening tools and diagnostic aids. The study aims to design a user interface (UI) for medical imaging apps to present the complexity of medical data and the critical nature of accurate interpretation. We found that our proposed model showed the best performance with more than 0.90 accuracy. From three views, axial view showed the highest performance, but coronal in MCI class showed the lower performance. However, the concept of interface design needs to consider the consistency, layout, and color of the design. We conclude that the detection performance is understandable to interpret the medical complexity region of MRI images. These result could be benefit for the medical apps, in order to create the interface design leveraging the deep learning models.

Keywords: Alzheimer, Technology, User Interface, Medical Apps.

1. INTRODUCTION

The global increase in life expectancy has contributed to a sharp rise in age-related diseases, with Alzheimer's disease (AD) standing out as the most common form of dementia, responsible for 50–70% of all cases. As the number of AD cases is expected to double every two decades, the need for effective diagnostic tools has become increasingly urgent to address this growing healthcare challenge (Carrillo, Bain, Frisoni, & Weiner, 2012). This trend poses a significant global challenge, as it will likely lead to an escalating demand for older adults and specialized services tailored to the needs of patients with AD. It often begins with subtle cognitive decline, most notably affecting episodic memory. Early signs commonly reported by patients and their families include difficulty recalling recent personal or family events, misplacing everyday items, and repeating questions or conversations. The hippocampus and magnetic resonance imaging (MRI) plays a pivotal role in diagnosing AD. It could demonstrate utility in differentiating AD from non-AD dementias. The diagnostic criteria recommend the assessment of structural MRI to detect abnormalities (Khatri & Kwon, 2022). Structural MRI provides critical data for detecting and monitoring brain atrophy, a key indicator of AD progression.

Deep learning methodologies introduce unique advantages, encompassing rapid computational processing and adaptability to diverse specific challenges, thereby potentially facilitating the clinical translation of PAI. Deep learning systems have demonstrated superior effectiveness across various research domains. In the context of AD, deep learning offers a powerful approach for analysing structural changes in the hippocampus, a region closely associated with the disease (Sarasua, Pölsterl, & Wachinger, 2022). Thus, deep learning-based by produce digital health technologies may offer valuable advantages to dementia researchers and clinicians as screening tools, diagnostic aids, and monitoring instruments. Previous studies found that digital technologies hold significant promise for individuals with AD by enabling objective, continuous, and repeatable monitoring of symptoms and functional abilities across various settings (Lott et al., 2024). Tools such as ambient sensors, mobile applications, and wearable devices can generate extensive real-world longitudinal data. This data not only supports clinical decision-making but also enhances research efforts to detect early signs of disease onset, track disease progression, and assess treatment response. As the demand for precision medicine grows, these technologies are increasingly valuable in identifying and targeting appropriate individuals for care and intervention, particularly during the prodromal or earliest stages of the disease (Forloni, 2020).

While deep learning algorithms have demonstrated strong potential in several tasks in MRI images for early AD diagnosis (Khatri & Kwon, 2022; Lott et al., 2024), their complexity often poses a challenge for non-technical users, such as clinicians and caregivers, who may find it difficult to interpret the results effectively. The display screen remains the most common output modality in user interfaces; however, audio and haptic feedback are increasingly utilized to enhance user interaction and improve accessibility (Berman & Stern, 2011). Currently, there is a notable lack of intuitive, user-friendly interface designs that can bridge the gap between complex deep learning outputs and clinical usability. Without a well-structured interface, the diagnostic insights generated by these systems risk being underutilized, limiting their practical application in real-world healthcare settings. To address this, there is a critical need to develop a visually accessible and interactive interface that integrates deep learning outputs directly with MRI images. Such an interface should prioritize interpretability, ease of navigation, and clear communication of diagnostic information, ultimately empowering users to make informed decisions and improving the overall utility of AI-assisted AD diagnosis. We hypothesized that by developing a user-centered interface design that integrates MRI image visualization with deep learning-based outputs by presenting complex model results through an intuitive and interactive interface, users will be better able to understand, navigate, and trust the system's findings, thereby improving decision-making in the early detection and diagnosis of AD.

2. METHOD

Data collection

The data employed in this study were sourced from the publicly accessible Alzheimer's Disease Neuroimaging Initiative (ADNI) database, specifically the initial phase (ADNI-1), accessible via the following link: https://adni.loni.usc.edu. The ADNI-1 database comprises baseline data acquired using a 1.5T Tesla scanner and preprocessed with Magnetization Prepared Rapid Gradient Echo (MP-RAGE), offering a resolution of 256 × 256 × 170 voxels. ADNI-1 is widely used in AD research because of its extensive utilization and widespread recognition. MRI data are sourced from repositories such as ADNI in the DICOM format and are then converted to. png of images to ensure model compatibility.

Figure 1. The raw data od ADNI dataset.

In total, we utilized 2,250 raw ADNI imaging datasets. These were divided into training and validation sets using an 80:20 split. The training set consisted of 1,800 images, with 200 images allocated to each category and view. The remaining 450 images formed the validation set, with 50 images per category and view.

Figure 2. The dataset.

Deep Learning Approach

In the following step, we labeled the five slices using the labelImg software (https://github.com/tzutalin/labelImg). Finally, we used the labeled images from the proposed YOLO models. YOLO is a state-of-the-art deep-learning framework for real-time object recognition. The architecture employs 24 convolutional layers to extract image features and two fully connected layers for bounding box detection. The network was constructed using the Darknet framework. The previous study has been done, which used the YOLO models to detect the hippocampus region (Pusparani et al., 2024). An illustration of the study is shown in Figure 3.

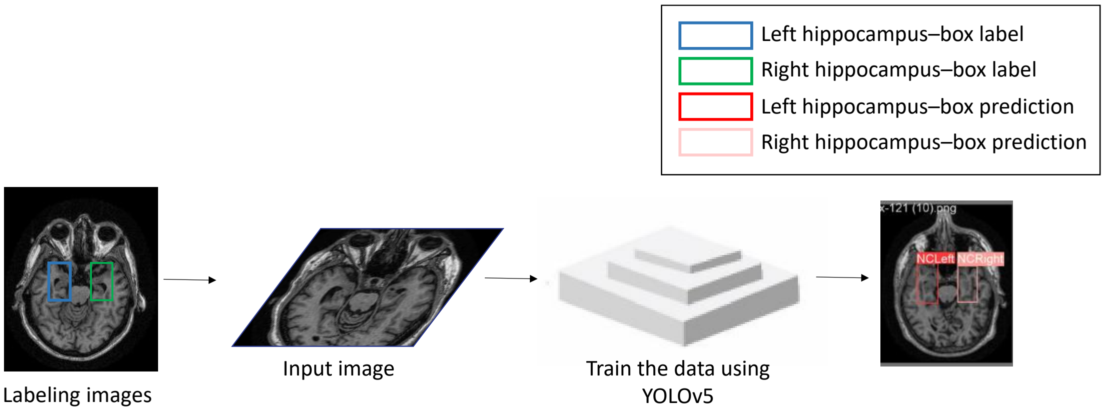

Figure 3. The illustration of the study.

Medical applications

The use of interface design in medical applications, particularly in medical images, for improved self-management and a more engaging user experience, is a fundamental need in today's society. Mobile applications can be applied to various medical images of several diseases, focusing on disease progression. This study followed the previous studies. In this step, research and discovery will elaborate on the problem and target audience. We identified the problem of understanding the core issue to be solved. This is beneficial for gathering insights and engaging potential users through surveys, interviews, or focus groups.

Table 1.The concept

Functional specification	Content requirements
Logo	Create a logo
Home	An introduction to the apps
User account creation	Log in with personal data, email, or Facebook
Patient information	Age, BMI, and visiting time
Classification flow	Input the MRI images and the classification result
Detection flow	Input MRI images and detection with bounding box result
Segmentation flow	Input MRI images and segmentation with volume estimation result
Decision flow	Decision based on the class (AD, MCI, and NC)
Back to home	Back to home or reset

Note: Alzheimer's Disease; MCI, Mild Cognitive Impairment; NC, Normal Control; MRI, Magnetic Resonance Imaging; BMI, Body Mass Index.

3. RESULTS AND DISCUSSION

According to Table 2, we found that the proposed model is suitable to detect the hippocampus region among three views, axial (0.99), coronal (0.92), and sagittal (0.98) accuracies. In addition, we found that the axial view demonstrates higher performance.

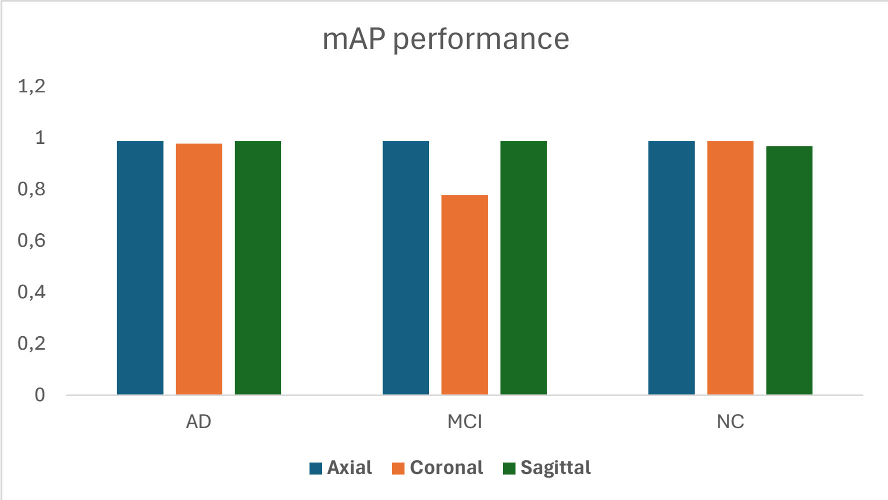

Figure 4. The mAP performance of YOLOv5 model in three views and classes.

An intuitive and useful interface design for reading and understanding data makes it easy for users to access. Users may have difficulty communicating the priorities of a tool or data, and as a result, many of their interactions are intuitive and unconscious. The review challenges in creating an interface design are presented in Table 2.

Table 2. The challenges in interface design

Challenges in Medical Imaging Interfaces		**Challenges in Elements of Design**	
Complexity	Medical imaging data is often dense and layered (e.g., CT, MRI, PET scans), but the interface must be clear, intuitive, and navigable.	Color	Color is crucial in differentiating tissues, lesions, and functions. But color choices must avoid misinterpretation (e.g., red may signify danger or inflammation).
Consistency	Challenge: medical systems are used by multiple roles (radiologists, technicians, oncologists), and interfaces must remain consistent to reduce errors.	Typography	Challenge: fonts must be legible in various lighting conditions and screen resolutions. Medical terms are complex, and tiny text can cause eye strain or misreading.
Affordance Usability	UI elements can confuse users, especially in high-pressure scenarios like surgery planning.	Spacing and Layout	Medical UIs often have to fit large volumes of data into a single screen. Poor spacing can make interfaces feel cluttered and hard to scan.

The integration of effective interface design in medical applications, especially those involving medical imaging, is increasingly essential for enhancing self-management and delivering a more engaging user experience. Mobile applications, in particular, offer versatile platforms for analyzing medical images across a range of diseases. These applications can support disease progression tracking, ongoing monitoring, and other clinical tasks, ultimately contributing to improved patient outcomes.

In Table 2, we found that YOLO v5 shows the best performance. It is because the most important benefits of YOLOv5, compared to previous versions, are a smaller volume, higher speed, higher precision, and implementation in the ecologically mature PyTorch open-source ML framework (Horvat, Jelečević, & Gledec, 2022). Still, it is aligned with previous studies, which found that YOLOv5 is the fastest and accurate method, indicating a greater potential for clinical application (Kumar, Pilania, Thakur, & Bhayana, 2024). Further, we found the challenges to making a medical app. Thus, we may say that it could be a guideline for the designer to design an app, for example, showing the detection result using the technology based on YOLO models. Yet, we only focused on the color, typography, and spacing and layout. Future, we could consider using other design element to create an Apps. As an example for hippoctor, which stands for the hippocampus and medical doctor, we may propose a concept based on the layout, colors, and typography (Figure 4).

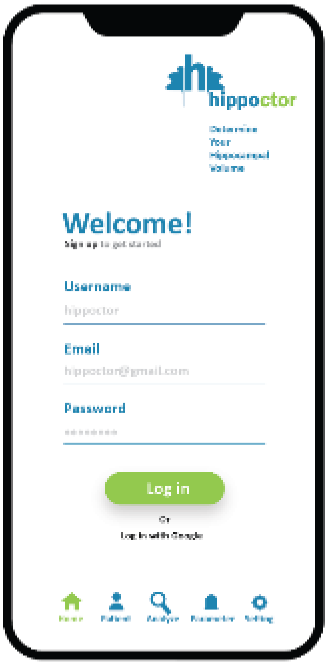

Figure 5. The example concept for the medical apps.

Therefore, further studies need to develop other tasks, such as classification and segmentation by leveraging the technology, such as deep learning (Figure 5).

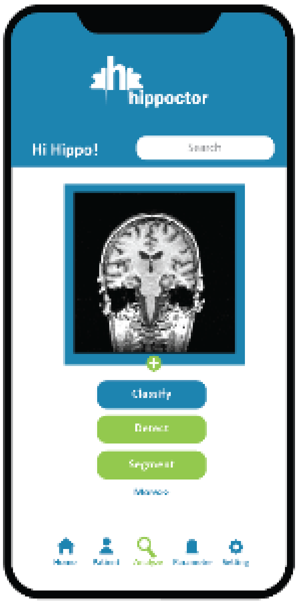

Figure 6. The example concept for the medical apps in other tasks.

This study has the limitations. First, we only used the YOLOv5 model in future studies as the pilot study, we should consider using other state of the art models which can help more complex interpretation of the result, which is beneficial for the AD diagnosis. Second, we only provided the concept of the interface design. Future studies, we could build the code for the detection apps in order to create medical apps.

4. CONCLUSION

In conclusion, the YOLOv5 deep learning model has proven to be highly suitable for the task of hippocampus detection in MRI images, demonstrating robust accuracy and efficiency in object localization. Among the various MRI views analyzed, the axial view yielded the highest performance, likely due to its clearer anatomical representation of the hippocampal structure. Still, the coronal view in MCI class showed lower performance. Furthermore, these findings suggest that incorporating sagittal MRI views into diagnostic workflows could enhance the precision of automated hippocampal detection systems, potentially aiding in the early diagnosis and monitoring of AD. On the other hand, these result could be benefit for the medical apps, in order to create the interface design leveraging the deep learning models.

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