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REVIEW ARTICLE

A SWOT ANALYSIS OF BREAST CANCER DIAGNOSIS IN DIGITAL MAMMOGRAPHY USING DEEP CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT

Breast cancer is a significant global health challenge that affects both men and women, leading to cause-specific deaths. Current early screening interventions, such as digital mammography (DM), are susceptible to high false-positives and false-negatives. This paper explores the potential of convolutional neural network (CNN), a form of artificial intelligence (AI), to support screening mammography with the aim to enhance accuracy in lesion detection, image classification and diagnostic prediction. Because the adoption of AI in cancer diagnosis is still in its infancy, the objective of this paper is to provide insight into the benefits and limitations of deep learning-based approaches to detect and diagnose cancer. An analysis of the implementation of CNN in AI-screening mammography models was conducted, using the SWOT strategic analysis tool. Internal strengths that improve the predictive accuracy of CNN include transfer learning and data augmentation, whereas the internal weaknesses include a lack of data standardisation and reproducibility. External opportunities consist of increased sensitivity in differentiating between microcalcifications and non-tumorous structures, improved predictive diagnosis and reduced workload. Nevertheless, integration within clinical settings must also consider the external threats of breaching patient privacy, automation biases and the role of clinical judgement.

INTRODUCTION

Breast cancer is presently the most commonly diagnosed cancer in women globally, and the second-leading cause of mortality from cancer. Accurate cancer diagnosis of symptomatic patients at an early stage is pertinent to improve cancer outcomes, thereby reducing cause-specific deaths. In the early 1990s in Australia, screening mammography programs were implemented for the early detection and treatment of breast cancer, but their accuracy in sensitivity and specificity remains error-prone, leading to the reporting of false-positives and false-negatives, respectively. The additional imaging tests and biopsies ensuing false-positive recalls can contribute to unnecessary emotional stress for the patient. Similarly, health hazards from high radiation exposure should also be considered. Errors in interpretation and detection of abnormalities can be attributed to different breast densities, small tumours or artifacts.[1] Another limitation is subjectivity in image analysis due to varied perceptions across interpreters, known as inter-reader variability. During double reading to improve diagnostic accuracy, two radiologists independently read the same screening mammography.[2] Despite image analysis performed manually by experts, factors such as fatigue and decreased attention can adversely affect the results findings. Furthermore, double reading is labour intensive, implying that the time constraints on clinical evaluations and examinations can lead to a delegation of tasks from radiologists to other physicians or breast clinicians. This can lead to unfavourable outcomes for the patients, being subjected to higher positive recall rates and false-positive interpretations, because physicians may lack in sufficient radiological knowledge to exert accurate clinical judgement.[3]

With rapid development in computing power and data, AI has been increasingly integrated in clinical settings. Among them is machine learning and, in particular, deep learning with CNN diagnostic-based approaches, whereby the technology is trained to recognise complex patterns from raw input with its multi-layered networks and make accurate connections based on the context. Its utility in lesion detection, image classification and diagnostic prediction enable additional aid to radiologists to achieve higher accuracy when interpreting DM, thereby serving as a prospective application to improve diagnosis of breast cancer.[4] The applications of these technological innovations have understandably raised concerns among healthcare professionals, in regard to its feasibility and diagnostic efficacy. To address the concerns of AI applications in medical imaging, an understanding of the benefits and limitations of AI tools is necessary.[5]

METHODS

A literature review of research published during the last 5 years was conducted to evaluate the strengths, weaknesses, opportunities and threats (SWOT) of CNN in AI models used to diagnose breast cancer. A brief analysis is provided, while the primary points are outlined in Table 1. This SWOT analysis forms the basis for governmental decision-makers and health care providers to understand the potential implementation of AI within clinical settings, and to consider future improvements in approaching the problem.

Section 2 introduces the functionality of CNN, Section 3 elucidates the strengths of applying CNN in mammography to diagnose breast cancer, Section 4 explains the external opportunities, and Sections 5 and 6 discuss the weaknesses and threats or ethical challenges. Finally, Section 7 presents the suggested future directions and the conclusion.

Convolutional Neural Network

In deep learning, a CNN is a class of deep neural network that uses algorithms to process a large quantity of data with a grid pattern, notably in image-related analysis.[6] CNN is employed for image examination, identification or classification because it can efficiently extract features from images and simplify them for better analysis. It consists of three distinct layers with functions that interconnect each other, namely an input layer, multiple hidden layers and an output layer. The initial DM image undergoes filtering in the first convolutional layer, which enhances the features, removes unwanted noise, and helps to differentiate the edges and shapes of the region under investigation. Subsequent convolutional layers enhance the feature patterns to facilitate identification of tumour contour and enable the extraction of specific features, such as structural patterns or dominant outliers in the image, making CNN highly efficient for image processing.[7] The pooling layer filters the minimum, maximum, mean or median of the set of pixels within the image that fall within the filter, to reduce the spatial size and maintain only the most crucial information.[8] Decreasing the parameters increases the processing speed. The information is subsequently passed through the fully connected layer, where extraction of inputs from feature analysis and application of weights and predicts the output into classes of cancer. For example, in the study by Ragab and colleagues[9], the fully connected layer classified abnormal areas as benign or malignant, while various other studies classified regions as benign, malignant or without tumour. Figure 1 depicts the structure of a classic CNN architecture.

DISCUSSION

Strengths of the Convolutional Neural Network Design

Transfer learning

Transfer learning refers to leveraging the learned features of a pre-trained model as the foundation for training a model to perform a new task. It takes advantage of the fact that neural networks trained on large databases of images, such as those with ImageNet, have learned and established parameters in the early layers relevant to numerous visual tasks, despite the specific task they are programmed to perform.[10] Salehi and colleagues explained that certain functions of CNNs in lower layers, such as those dedicated for edge, texture and pattern detections, can be calibrated and applied to higher layers of the network.[10] However, the specific features that must be learned will increase in complexity where, for instance, the output layer would only respond to images of a specific tumour that it had been trained to detect. Thus, using a pre-trained model and customising the new model with additional new layers and adjustments to the number of neurons or classes depending on the specific task requirements has the benefit of minimising training time and requires limited data. This means earlier models can be refined and adapted to various tasks, including detecting and classifying lesions, without retraining a deep neural network from scratch.

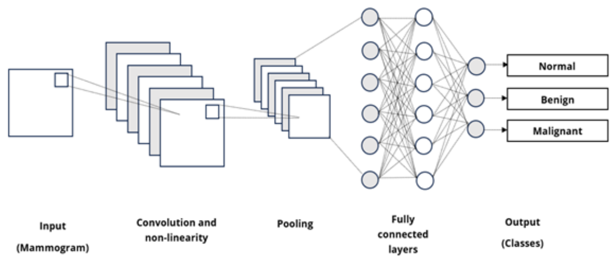

Figure 1: Convolutional Neural Network (CNN) architecture comprised of a stack of convolutional layer, non-linear layer, pooling layer, and fully connected layer

Note. The final output is classified as normal, benign or malignant.

Data augmentation

In medical imaging where the number of fully annotated mammograms available is limited, training a deep learning model with data augmentation ensures improvement to the models while also minimising data overfitting. Overfitting is a statistical error whereby the model fits too closely to the trained dataset and cannot be generalised to new data.[11] Data augmentation enables artificial expansion on existing datasets to generate modified copies and, hence, introduces a vast variety of patterns that the model can recognise and learn from. Improvement to data variability is demonstrated to enhance the predictive accuracy of the AI models in detecting suspicious regions of interest when presented with normal and abnormal DMs.[12,13] This provides the radiologist with psychological support, by reducing the cognitive burden associated with identifying potential lesion regions.

For example, GAN-based augmentation, an unsupervised deep learning method that extracts hidden properties from data to formulate its decision-making process, has shown potential to improve accuracy in mass classification after geometric transformations from unrelated masses or increase in noise distortions.[12] As such, it has also been a widely used approach in breast mass detection and mass segmentation.[13] As the use of data augmentation methods expands, it is pertinent to evaluate the quality of the output and recognise that building upon minimal databases can restrict the generalisation ability of the model and potentially reinforce inherent biases.

Opportunities in CNN implementation

Pixel-level image classification

With higher resolution DM images, conventional computer-aided diagnosis (CAD) models can distinguish between benign and malignant lesions by assessing their greyscale levels, homogeneity, gradient, patterns and shape.[14] However, because dense breast tissue appears white and has similar shade and intensity values as tumorous regions containing microcalcifications, dense breast tissue, with relatively high amounts of glandular tissue and fibrous connective tissue, can hide lesions and is prone to misdiagnosis and reporting of false negatives. With AI screening, it can perform detection of potentially tumorous region and compare its intensity value with other regions of the breast followed by segmentation of the tumour area surrounded with malignant tissues.[15] This can reduce the lower sensitivity from human perceptual error, because it separates pixels of cancer region from normal region. Geras et al. showed that the addition of the deep learning method, which learns the intermediate and abstract representations of the data, can improve accuracy in lesion classification in DMs, reaching similar sensitivity to radiologists' assessment.[14]

Improve patient value through predictive diagnosis

Given the large processing capacity of AI, its capability of analysing and processing data from wide-ranging sources, including medical images, laboratory test results and patient history, enables identification of patterns and abnormalities that may otherwise be missed by human experts. Missed microcalcifications can be attributed to their small size or concealment by overlying high amounts of fibrous and glandular tissues.[16] Therefore, implementing AI in mammography has the potential to increase sensitivity in differentiating between the microcalcifications and non-tumorous anatomic structures, such as increased breast density. It employs image processing techniques to spatially filter the DM and improve signal-to-noise ratio, yielding higher sensitivity for detecting true abnormalities.[15] In a study by Kim et al., the classification performance of AI-CAD demonstrated a higher accuracy value of 0.938–0.970 compared to an accuracy value of 0.810–0.881 achieved by radiologists.[17] Findings by Liu and colleagues also reported that combining the deep learning model into mammography attained similar diagnostic performance to that of an experienced radiologist, and significantly surpassed the performance of a junior radiologist ($p=0.029$; $p<0.05$).[18] The improvement indicated promising results in reducing the quantity of unnecessary biopsies performed, showing potential for early detection and intervention of breast cancer.

Reduced workload

Numerous European countries have employed double reading with arbitration, whereas the United States typically has employed single reading with CAD.[19] While standard double reading has been shown to reduce recall rates, it is labour intensive. A study by Dembrower and colleagues compared the cancer detection rates and efficiency of varying methods of interpretation: single reading by AI, double reading by two radiologists, double reading by one radiologist and AI and triple reading by two radiologists and AI.[20] The findings suggested that the performance for triple reading (95% CI 1.04–1.11) outperformed the double reading by one radiologist and AI or by two radiologists (95% CI 1.00–1.09). Triple reading increased recalls by 5% and consensus discussion by 50%, while double reading by one radiologist and AI decreased recalls by 4% with a reasonable number of consensus discussion. In triple reading, the perception of the combined radiologists was favoured over the perception of the AI, indicating that the ability of AI in detecting cancer was under-estimated rather than over-estimated, explaining the slightly higher recall rates. Because the higher abnormal interpretation rate for AI and one radiologist did not translate into an increased recall rate, it would help reduce workload time, which had been demonstrated to be by nearly 40%.[20,21] Replacement of the second reader with AI would substantially reduce the time radiologists spend reading mammograms. Another study by Lång and colleagues determined that mammography screening supported with AI yielded similar cancer detection rate as standard double reading, with the recall rate being 0.2% higher at 2.2% , suggesting that the use of AI in mammography can be considered.[22]

Weaknesses

Lack of standardisation

Standardisation within a clinical setting can help improve interoperability and vast exchange of health data and information. This is pertinent to improve performance of the models in imaging acquisition and processing, because the quality of image acquisition affects radiomic feature calculations, radiomics being the extensive image-based phenotyping of abnormalities through extraction of diverse feature values from medical images.[23] Currently, insufficient standardization is evident in the collection and storage of unstructured data, as well as in the process of unifying data that represents a single healthcare system.[24] Substantial information technology and systems resources is required to implement this, and the feasibility remains under active investigation.

One method proposes using patient-reported outcomes (PROs) and validated questionnaires, as they are valuable survival indicators that can benefit cancer care delivery, research and clinical operations.[25] Nonetheless, several limitations are

Table 1: Summary of SWOT analysis of implementing CNN in AI-screening mammography within clinical settings

Strengths	Transfer learning: - Minimises training time and requires limited data through modifying a pre-trained model, tailored to suit specific requirements Data augmentation: - Minimises data overfitting - Improves generalisability, image recognition, segmentation accuracy and analysis - Enhances predictive accuracy in tumour classification
Weaknesses	- Lack of standardisation limits interoperability - Limitations in obtaining and implementing patient-reported outcomes - Data reproducibility is subjected to data drift - Lack of high-quality and multi-institutional datasets may reduce generalisability - Different mechanisms performed at each CNN layer require varying levels of complexity during programming
Opportunities	Pixel-level image classification: - Reduces false positives due to ability to discern between tumorous and non-tumorous regions - Improves cancer detection rates Improved patient value through predictive diagnosis: - Increases sensitivity for detection of true abnormalities - Improves tumour classification accuracy - Potential to reduce quantity of unnecessary biopsies and medical costs. Opportunities for healthcare professionals: - Enhances reading efficiency by reducing number of tests requiring radiologist interpretation - Reduces workload
Threats	Patient privacy: - Breach of health and personal information - Lack of transparency Algorithmic biases: - Biases in input training data can produce skewed results and exacerbate health care inequality - Ethical concerns regarding the role of AI in clinical judgement Role of human judgement: - Medico-legal responsibility for healthcare providers if incorrect diagnosis is made - Potential discordance between clinical practices and AI suggestions - Impairment in clinical judgement from over-reliance on AI technology, resulting in potential patient injury - Jeopardization of the learning process and clinical reasoning abilities of medical students or novice radiologists

present. These include patient-level barriers such as disability, challenges in reading and responding to the questionnaires or with recalling their symptoms, clinical-level obstacles like lack of staff training with interpreting and implementing PROs into clinical practices, and service-level challenges like lack of PRO data logging into electronic medical records within a hospital setting.[26]

Data Reproducibility

Data reproducibility is limited when transferred across healthcare systems and global communities, but even within the training environment, data drift over time for AI algorithms and advanced CDSS can affect their performance. This is a result of variations in distribution, formatting or quality of data, flawed data transformation, absence of natural drift when training the model or covariate shift.[27] Thus, standards must be incorporated to continuously monitor AI algorithms and ensure their validity even if AI were to be successfully implemented as a technological practice in medicine due to their evolving nature.

Threats regarding Ethical Challenges

Patient Privacy

Precision medical technology relies on extensive medical information for cancer diagnosis, screening, data processing, optimising care delivery and conducting clinical operations. To train models effectively, medical researchers need access to patients' personal health records. However, concerns arise regarding the potential misuse of data, leading to issues like identity theft, insurance fraud and illegal acquisition of prescription drugs. To ensure ethical use of patient data in clinical practice, medical researchers must be transparent about how data will be used. Additionally, they should implement robust safety measures to safeguard patient privacy and obtain informed consent from individuals contributing their data.

Algorithmic Biases

Bias within AI algorithms is affected by the bias within the data they are trained on. If a dataset is biased towards a particular demographic group, the validity in the AI-generated results to predict the cancer outcomes of individuals from other demographic groups is reduced – either over-representing or under-representing certain populations. To prevent perpetuation of inequalities in healthcare by AI algorithms that may contribute to potential harm, diverse and more representative range of datasets should be used instead, while inherent biases should undergo careful investigation to ensure they are not overlooked.

Role of Human Judgement

Although radiologists are blinded to the output of the AI system to prevent double reading or over-reliance on AI, the validity of the consensus decision may be influenced depending on the under- or over-estimation of the accuracy of AI systems.[19] This will result in variations in recall rates and cancer detection. A strength may be a reduction in recall rates by introducing higher specificity by experts to mitigate the higher cancer detection rates of AI. However, over-reliance on AI could lead clinicians to overlook their critical clinical judgement, irrespective of their experience. As such, it can increase the risks of accountability when performing incorrect diagnosis, as recommended by AI, which results in avoidable harm to patients.

CONCLUSION

Current evidence regarding the integration of AI in clinical settings has shown promising results in that AI-supported screening mammography improves cancer detection rates or is level with senior radiologists, while also enhancing patient outcomes and alleviating radiologists' workload. A main advantage is its enhanced sensitivity in discerning between benign and malignant lesions from dense breast tissues, a challenging diagnosis, thereby minimising perceptual errors. This can improve accuracy in diagnostic performance and facilitate predictive diagnosis for early intervention. Nevertheless, the availability of well-curated datasets to ensure high-quality result outcomes by AI systems that enable sufficient, reliable data generalisation and cancer detection is yet to be assured. As the results of this paper showcase, considerable risks could emerge that impact the accuracy of the data and, if not mitigated, would affect the patient safety. These incorporate ethical issues around medical responsibility for any diagnostic errors made, human oversight and transparency. Thus, investment to support clinical trials in researching and evaluating the outcomes and performance of AI algorithms on the patient and providers regarding breast screening mammography is encouraged, to validate the efficacy, validity and reliability when applied as routine clinical practice.

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