AI POWERED ECHOCARDIOGRAPHY

Joshua Hopkins and Datonye B. Omunguye-George

Northwood University, Midland, MI, USA

ABSTRACT

The purpose of this paper is to discuss the current technological developments in diagnostic cardiovascular care. Echocardiography, a widely known imaging tool, extracts insights about a patients' cardiac anatomy and perform necessary treatments or procedures based on their diagnoses. AI models respond to vast amounts of raw cardiac data and use Deep Learning algorithms to identify images with remarkable speed and accuracy. AI applications in computer vision offer key benefits in the healthcare industry. Companies such as Siemens are the key players – the commercialization of new AI technology has enabled healthcare organizations to streamline workflows, reduce errors, and lower costs.Potentially, there will be no reproducibility issues thereby redirecting clinical efforts towards patient treatment planning and research to prevent uptrends of heart disease.

KEYWORDS

Echocardiography, Convolutional Neural Networks, Artificial Intelligence, Medical Imaging, Patient monitoring, Clinical Analysis

1. INTRODUCTION

Cardiovascular health is a serious topic of concern in the United States and worldwide. Heart disease is the leading cause of death in the US and is one of the most expensive conditions treated in hospitals because of diagnostic tests, procedures, and the involvement of specialized healthcare professionals. The CDC states that heart disease costs our health care system $216 billion per year and $147 in lost productivity [3]. This challenge is further complicated as patient volumes increase while the number of cardiologists and sonographers decreases [4]. Echocardiography (Echo), a widely available, non-invasive, and portable bedside imaging tool, is the most frequently used imaging modality in assessing cardiac anatomy and function in clinical practice [2]. Compared to other imaging modalities, Echo has its advantages such as not using ionizing radiation, being less expensive, and portable for point-of-care (POCUS) applications and providing real-time imaging [2]. Current AI powered echocardiography requires clinicians to know which algorithms to use, but this is problematic when clinicians do not have sufficient training. This can introduce reproducibility issues between users. The SC2000 diagnostic tool, owned by Siemens, is an example of AI powered echocardiography that requires clinicians to tell which algorithms to use to quantify cardiac images. A breakthrough of the Acuson Origin by Siemens only requires a simple press of a button [4]. Expert knowledge combined with accurate diagnostic tests will promote better patient outcomes.

2. CHALLENGES WITH AI-ECHOCARDIOGRAPHY

The shortage of skilled clinicians requires that AI systems be easy to use. From a clinician's perspective, it is important to know which features the AI systems utilizes to validate the results. Challenges of these AI-echo systems discussed further in this paper are generalizability, dimensionality, and transparency. As this technology becomes more refined in the coming years,

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it will be a driving force in the medical industry and aim to reduce harm caused by delays in treatment and may also decrease morbidity and mortality due to patients' misdiagnoses.

2.1. Generalizability

Most AI-echocardiography systems are trained on small datasets. Small datasets have a lack of generalizability because they are prone to overfitting. Overfitting performs well on the training set but not on unseen data. Therefore, increasing the number of training sets enables the model to learn from multiple examples and make accurate predictions. Creating a database system with quality data and labels has been the most challenging [2]. This includes “data acquisitions of optimal angles, views, and measurements” [2]. “A typical echocardiogram consists of closer to 70 videos collected from different viewpoints, and viewpoints are not labelled in each study” [10]. Another DL method such as Deep Belief Networks (DBNs) can be chosen as an alternative when compromising for lack of labelled data. To control bias-variance, the data comes from different hospitals and their electronic health records. If access to larger datasets is small, one can introduce simulated data that mimic cardiac anatomy to improve the generalizability of the model, thus increasing the reliability of the model’s predictions [2].

2.2. Dimensionality

Two-dimensional and three-dimensional cross section images may impact the ability of the clinician to interpret images. 3D images will show the entire heart structure. This improves procedure planning and allows for more accurate device placements, because surgeons can better visualize these 3D reconstructions. However, during feature selection, redundant features are removed, hence the dimensionality of the data is also reduced [6]. There is a high computational cost associated with processing images with redundant features, so instead, “optimal features are elected by rank-based feature selection method" [6] to make the learning process simpler. The input is “a group of identified features that helps the classification model to spot the significant or needed patterns in the US (Ultrasound) image that is determined as a class label. The group feature includes definite irrelevant and redundant features” [6]. The features are evaluated based on a criterion then they are ordered based on their significance in descending order. The final output of the model is the top-ranked feature [6].

2.3. Transparency

To demystify the black box, AI-echo models need to provide explanations for their predictions. This is particularly crucial because a disease can be influenced by a range of factors, and without proper care, the disease may worsen. Given that AI-echocardiography relies on Deep Learning, the ultimate output is a composite of layers, wherein features are automatically assigned and may not be inherently comprehensible because “none of the studies have provided an insight on which heart regions play an important role in any disease prediction” [2].

3. AI Methods and uses in Echocardiography

Deep learning (DL) models have superior performance compared to Machine Learning (ML) models [8]. It is capable of automatically extracting notable features while analysing data in a hierarchical manner i.e., layers of lower-level features in an image such as edges and textures put one after the other and define higher-level features such as object shapes and patterns. The commonly used DL algorithms for computer vision include Convolutional Neural Networks (CNNs), Deep Belief Networks (DBNs), Deep Boltzmann Machines (DBMs), and Stacked Autoencoders (SAs) [2]. The tasks for AI in Echo include view classification and quality assessment, image segmentation, cardiac measurements, and disease diagnosis [2]. Acquiring measurements and cardiac performance is further complicated in Echo due to the “intrinsic beat-to-beat variability” as well as “variability from the process of approximating a 3-dimensional object using 2-dimensional cross-sectional images” [11]. One of the most important advantages of CNNs for computer vision is that they are less susceptible to image variability from transformations such as translation, scale, and rotation [8].

DBNs perform well in the presence of adversarial attacks, a way of modifying the pixels in an image whereas a CNN will incorrectly identify an image. This is due to the learning approach. CNNs use a supervised learning approach which requires large samples with annotated target labels to train the network. DBNs use a semi-supervised learning approach which allows for potentially rich features to be extracted from the input images. Yang et al. conducts a study with CNNs and DBNs trained and tested on original images and then on MNIST modified-pixel images. CNNs perform better when the training samples are high, but DBNs perform better when the number of labelled training samples are low [9]. Like DBNs, DBMs can be trained on unlabelled data. It also “incorporates top-down feedback in addition to the usual bottom-up pass, allowing Deep Boltzmann Machines to better incorporate uncertainty about ambiguous inputs” [6]. This makes DBMs more computationally expensive. When data first passes through a SA, it encodes it to fit a smaller dimensional space. At the same time, this removes a lot of noise in the hidden layer and solely focuses on the latent features. Then, the data is decoded back in the output layer. The success of SAs may be limited if there are multiple hidden layers.

Big Data (Cardiac Images)

⇓

Image Data Processing – t-SNE from Scikit Library; NL-means filter; body mass normalization (BMN)

⇓

Feature Selection using rank-based approach

⇓

Deep Learning Model such as CNN

Figure 1. AI methods

Overall, CNNs are an excellent choice for supervised image classification tasks and is the most used. Convolutional Neural Networks consist of convolutional layers to extract features from images. When an image is processed, the convolutional layer applies the same weights to the various parts of the image known as parameter sharing. As the kernel moves across the image, the model can detect feature patterns that are translation invariant into class predictions in the final output layer therefore reducing the number of trainable parameters compared to the number of layers.

The number of convolutional layers is associated to a convolutional block, and each convolutional block will consist of one or more 2D convolutional layers followed by a pooling layer. This will depend on the CNN architecture. Some common types of top tier CNN architectures are VGG-16, ResNet50, and EfficientNet. Each convolutional layer that the image passes through will depict the image’s spatial dimension and depth dimension. Each layer uses filters (a container of kernels) that matches the dimension of the image, and a convolution operation is applied to the filters. The value of the convolution operation, elements of the filter multiplied by the elements of the image, is passed through a ReLU activation function and produces an activation map which is a summary of the features (horizontal lines, vertical lines, and diagonal lines) from the input layer which can be the input image to the model or the output from a previous layer in the form of highly activated neurons.

Using a pooling layer helps to reduce the number of parameters to the number of layers therefore reducing the number of computations required in the training process. Two types of pooling are average pooling and max pooling. The max pooling operation summarizes the local features in the activation map.

Using the VGG-16 as reference, it is important to take the final output layer through a set of fully connected layers that will classify the image because the neurons in the output layer is equal to the number of classes. Each of the neuron's values after the softmax layer represents a probability of the class of neuron belonging to a specific class in the input image. The highest probability is the classifier.

3.1. Big Data Increases Generalizability

Big data is prominent in healthcare and defined in terms of the 3 Vs: Volume, Velocity, and Variety. DL models train with hundreds or thousands of heart image samples that represent a diverse range of scenarios and variations, due to advancements in graphics processing units (GPU), which increases the 3 Vs for a more robust model [2]. A more robust model will generalize well and predict future new observations. The NL-means filter applied to heart ultrasound images removes noise, and body mass normalization (BMN) normalizes muscle mass to account for differences across individuals. By addressing these aspects through data pre-processing, the data becomes better suitable for model training leading to improved performance, generalizability, and interpretability. Next, is feature selection. Optimal set of features are selected using a rank-based approach. Then, an output is reached that classifies the features based on labels assigned to individual images. Kumar B P et al. conducted a study with six hundred images, and the CNNs performs higher with 96.7% accuracy than the other ML methods, SVMs, histogram features with BPNN, neuro fuzzy and ML-Boosting [6]. Zhang et al. conducted a study with 14,035 echocardiograms trained on CNNs over a ten-year period and compared results to 8666 echocardiograms obtained from manual, routine measurements. The models created were able to detect hypertrophic cardiomyopathy, cardiac amyloid, and pulmonary arterial hypertension [10]. In other words, these training samples exhibit high volume, high velocity, and high variety.

Essentially, Big Data includes a wide range of data values from diverse sources which leads to more robust samples and prevents overfitting. This ensures that the results can be applied to the real-world. For example, databases serve as great resources to capture patient specific characteristics for clinical studies. In the past few years, the EHR has been widely adopted due partly to the Health Information Technology for Economic and Clinical Health Act which encourages the use of electronic health records to improve health care quality, safety, and efficiency. "Population representativeness—measuring the study population's coverage of the target population—is a key determining factor for generalizability [12]. The studies described in this section depict good population representativeness of patients over a longitudinal period within a hospital. The large sample sizes increase the statistical accuracy of the CNN model for future echocardiograms.

3.2. t-SNE Algorithm Solves for Dimensionality

t-SNE or t-Distributed Stochastic Neighbour Embedding is a machine learning algorithm in the scikit-learn library for visualizing high-dimensional data according to the number of pixels in an image. “It seeks to find a simple low-dimensional representation (i.e., 2 or 3 dimensions that can be visualized by humans) of a complex high-dimensional space” [10]. It helps to reveal the underlying relationships between different regions of the heart to conclude on a diagnosis. The way it works is the features are extracted from the CNN and put into the algorithm, and the algorithm maps it to a 2D, or 3D space. The result is a scatterplot where each point represents a cardiac image. Points that are closer together share similar features and those that are distant do not share similar features. This further corresponds to the different classes or categories of cardiac conditions.

3.3. Deconvolutional Neural Networks Increases Transparency

While CNNs have superior performance to other DL models for “visual tasks such as object classification and detection,” the major drawback for decades has been the lack of interpretability [11]. In the studies reviewed by Akkus et al., there was no indication as to “which heart regions play an important role in any disease prediction” [2]. Specialists and clinicians can adopt the AI faster due to improved interpretability so it can become a part of the healthcare industry. A model getting the correct prediction is a minimum requirement, but specialists will want to understand the logic used by the model to make the prediction before adopting it [11]. Therefore, new techniques are applied to CNN architectures such as “deconvolutional networks, gradient back propagation, class activation maps (CAM), gradient-weighted CAM, and saliency maps” [2, 11]. These techniques aim to provide “clear semantics in high conv-layers" so clinicians can see “what patterns are memorized for prediction” [11]. In the proposed works by Zhang, each filter in the convolutional layer of the network includes a simple loss function that pushes the filter to encode specific object parts [11]. This allowed them to produce a CNN that was more interpretable without requiring any “additional annotations of object parts or textures for supervision” [11]. The author presents potential future works that will increase their interpretable CNN model’s flexibility [11].

4. ACUSON ORIGIN AIMS TO SOLVE AI-ECHO’S CHALLENGES

To address the rising Echo demands and lack of AI trained clinicians, Siemens Healthineers said “the AI-enabled Acuson Origin can help greatly speed workflows” [4]. The Acuson Origin “detects all the cardiac anatomy immediately after the transducer is placed on the patient, and it knows what the next steps in exams are based on what it is looking at” [4]. By pressing one button on the Acuson Origin, the artificial intelligence scans the image on screen and knows the anatomy and the view [4] in real-time, an industry first, “as well as the next steps to process the image and will automatically perform contouring and measurements for the user to assess” [4]. “The system delivers automated contouring and quantification of all four cardiac chambers without the need for an ECG (Electrocardiogram) via the 2D and 4D HeartAI features” [4]. The AI guiding the process in this way accomplishes the tasks required for AI in Echo while increasing the usability as well as the accuracy and reproducibility of the measurements by eliminating variability between operators [4]. It is expected that the Acuson Origin’s AI features are powered by a DL model as it is said to have been trained on “the world’s largest cardiac image database of more than 80 million cardiac ultrasound exams” [4]. This scale of a training data set increases this model's ability to generalize. Siemens has not published the method that the Acuson Origin AI uses but as stated in the previous section CNNs have been the preferred DL method for other computer vision applications in medical imaging [2, 8].

5. ETHICALAND PRIVACY CONCERNS OF AI-ECHO

In the medical industry, AI aims to reduce operational costs, increase efficiency, grow revenue, and improve patient experience. The effectiveness of AI-Echo correlates to the amount of data available and the ability to ask the right questions about the data and make intelligent decisions using methods such as Deep Learning. This raises the question of whether the data satisfies fundamental privacy rights and regulatory standards. "The European Union data protection regulations that entered into force in May 2018 will strengthen our privacy rights, while intensifying the requirements made of those processing such data, and the General Data Protection Regulation (GDPR) govern the data controller's duties and the rights of the data subject when personal information is processed" [1]. The principles of the GDPR requires data to be processed in a lawful, fair and transparent manner; to be collected for specific, expressly stated and justified purposes and not treated in a new way that is incompatible with these purposes; to be not stored in identifiable form for longer periods than is necessary for the purposes relating to data retention; to be correct and, if necessary, updated; and to be adequate, relevant and limited to what is necessary for fulfilling the purposes for which it is being processed [1]. This prevents misuse or exploitation of one's personal data. In culturally diverse contexts, the data in AI-echo systems must be void of bias and discrimination. This will be evident in the results given by the AI-echo system. The more diverse and voluminous the data is, the more precise response the system can provide for patients of various backgrounds.

6. CONCLUSION

The Acuson Origin addresses many of the challenges of Echo. Nevertheless, the extent of interpretability concerning the AI and its outcomes, along with the rate of adoption of the Acuson Origin, is yet to be determined in this scholarly context. The Acuson Origin first must obtain Food and Drug Administration clearance in the US and then it will need to gain widespread adoption. The Acuson Origin could begin an AI movement in Echo that will start to bridge the gap caused by increasing patient volumes and decreasing clinicians. This would foster a cheerful outlook towards this technology and facilitate new methods in medical education to train future cardiologists. At the same time, we evaluate the ethical use of AI-echo While there is no evident harmful intent, it is essential to exercise prudence regarding the utilization of limited or non-representative data. Further study is recommended to assess for the presence of AI related bias. Among the challenges explored in this paper, transparency emerges as a significant factor concerning the ethics of medical AI development. "The World Health Organization has enumerated the following six principles in ethics for AI: ① protecting human autonomy; ② promoting human well-being and safety and the public interest; ③ ensuring transparency, explainability, and intelligibility; ④ fostering responsibility and accountability; ⑤ ensuring inclusiveness and equity; and ⑥ promoting AI that is responsive and sustainable" [5].

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Authors

My name is Datonye Omunguye. I graduated with a Bachelor's in Global Disease Biology from the University of California, Davis and currently pursuing my Master of Science in Business Analytics at Northwood University. I am a Health Informatics Consultant for Oracle Health. My primary responsibilities include deploying IT solutions to DoD military treatment facilities and providing consulting services to hospital quality managers. With almost 4 years in this role, I have successfully led initiatives that involve analysing data sets to identify operational inefficiencies, improve patient outcomes, and drive strategic decision making. One of my recent achievements was becoming team lead now covering over 30 DoD hospitals both in the US and abroad. My passion lies at the conjunction of healthcare/AI and prioritizing cybersecurity in health systems. I am also open to career opportunities in these areas. I am in Conroe, TX. Outside of work and school, I enjoy CrossFit and spending time with family and friends.

My name is Josh Hopkins, and I am an Engineering Manager for Star SU. I have 8 years of experience in gear tool manufacturing and degrees in Physics, Mechanical Engineering, and a Six Sigma Black Belt that I use to lead a team of engineers and technicians. We drive advancements in technology and processes to ensure a safe work environment, quality products and profitable operations at the Tawas Tool Company location. I am always looking towards emerging technologies to better understand how they can improve or disrupt our companies' operations and the larger gear industry we serve. My focus is on two main technologies, Additive Manufacturing and Artificial Intelligence. This focus has led me to become the Chair for the Additive Manufacturing Technical Committee hosted by the Emerging Technology group of the American Gear Manufacturing Association and to pursue my Master of Science in Business Analytics at Northwood University. I reside in Tawas City, MI where my wife and I follow our two children attempting to keep up with all their activities in hockey, soccer, gymnastics, and dance.