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Evolution of Artificial Intelligence in Mammography: A chronological review

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Abstract: *This is a review of literature to trace the origin of artificial intelligence abbreviated as AI, particularly in relation to its applications in mammography for detection of breast cancer. This topic appeared thought-provoking secondary to the fact that artificial intelligence or AI is a subject undergoing intense study and attracts significant attention in radiology. The idea of AI occurred in human minds as early as the eighth century. However, it was about twenty five years ago that medicine saw a prominent venture of artificial intelligence. Lung and breast neoplasms were among areas that received explicit concentration from researchers involved in computerised detection of medical images. AI algorithms complementing radiologists in minimising errors and expediting diagnoses with diminished ethical issues can be a prospective development in the near future.*
Keywords: *Artificial intelligence, Computer-aided diagnosis, Convolutional neural networks, Deep learning, Feature extraction, Machine learning, Mammography*

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I. Introduction

The father of artificial intelligence, John McCarthy who was an American computer scientist coined the term “artificial intelligence” in 1956 at the Dartmouth Summer Research Project on Artificial Intelligence (DSRPAI) conference in Dartmouth, Hanover, New Hampshire. [1] McCarthy defines AI as “It is the science and engineering of making intelligent machines, especially intelligent computer programs.”[2] It was also in the 1950s that British mathematician Alan Turing devised the Imitation Game, later named as the Turing Test for deciding whether machines can intelligently mimic humans. [3]However, a period known as ‘AI Winter’ swept in soon after due to the general hype that the concept of artificial intelligence was overestimated. [4] A major breakthrough in the history of AI eventuated when IBM’s ‘Deep Blue’ computer defeated the then chess champion Gary Kasparov in 1997. [5] Correspondingly, research into the numerous prospects of artificial intelligence in the field of medicine was also progressing with time.

II. Chronological review of AI in mammography

The initial use of computers as decision-making aids in medicine in the 1950s was based upon the set standard that computers should be able to replace humans. This led to the evolution of automated computer diagnosis which was later found to be flawed. The failure of automated computer diagnosis is attributed to non-availability of adequately powerful computers and image-processing techniques. [6]In addition, image storage portals like Picture Archiving and Communications System (PACS)came to the fore only in the early 1980s. [7]RN Engle Jr at the department of Public Health, New York in his article titled “Attempts to Use Computers as Diagnostic Aids in Medical Decision Making: A Thirty-Year Experience” stated “We concluded that we should stop trying to make a computer act like a diagnostician and concentrate instead on ways of making computer-generated relevant information available to physicians as they make decisions.”[8]

It was only in the 1980s that extensive research in computer-aided diagnosis (CAD) schemes began; the Kurt Rossmann Laboratories for Radiologic Image Research in the Department of Radiology at the University of Chicago being a pioneer in this regard. In lieu of automated computer diagnosis used in the 1950s where diagnosis was reliant on computers, a novel concept called computer-aided diagnosis materialised during this period where computers were used solely for a ‘second opinion’. [6]Chan et al devised a computer-detection system for microcalcifications in mammograms in 1987 with a true positive cluster detection rate of around 80% with a false-positive detection rate of one cluster per image.[9] Hence, computer-aided diagnosis came into use to distinguish benign from malignant lesions on the basis of detection of features such as microcalcification clusters. [10]

An “intelligent” workstation as a prototype CAD system was built at the University of Chicago’s Kurt Rossmann Laboratories for Radiologic Image Research by Nishikawa et al around the year 1993. A high speed computer, film digitizer, image archive, and a hard and soft copy output were incorporated in the workstation.

The workstation acted as a 'second pair of eyes' for the mammographers, highlighting suspicious areas on the digitised images not detected on initial reading by the mammographers. The image recognition algorithms could detect masses and clusters of microcalcifications. On initial analysis, the false positive rate was found to be 1.2 false masses and 0.87 false clusters per image. Nodular densities triggered over 70% of the false positive masses while benign calcifications were held accountable for approximately 50% of the false positive clusters. [10] [11] [12] [13]

A company called R2 Technology was foundedin 1993 in Los Altos, USA to market the CAD research product which was named 'ImageChecker M1000'. Radiologists were not quite approving of the claims made by R2's clinical research that ImageChecker detects up to 85% of the 15% cancers missed by mammographers. 'It's measurably better than nothing, but not as good as another radiologist, said Dr. Edward Sickles, chief of breast imaging at the University of California, San Francisco. The question for radiologists is, would you be willing to spend ($179,500), plus what it costs to run it?' [13]

The year 1998 saw Food and Drug administration [FDA]approving this CAD system as the maiden commercial enterprise in computer-aided diagnosis in mammography. [13] [14]

Until this time, digitisers were used to retrieve film images on computer. Digital mammography was finally approved for commercial purpose by the US FDA in 2000. The approved model was called General Electric's Senographe 2000D. [15] The emergence of digital mammography coupled with the advancement of PACS enabled rapid progression of computer-aided diagnosis. It has been opined that the ability of CAD algorithms to detect microcalcifications with better contrast is greater than diverse lesions like spiculations and architectural distortion, each of which can be a distinguishing feature for breast cancer diagnosis on mammographic images. Image segmentation, feature extraction and classification are the techniques employed by image-recognition algorithms to characterize lesions. [16]

Initial research in computer-aided diagnosis for upto 10 years was based on laboratory settings. [16][17] A shift of focus ensued henceforth from the beginning of the 21st century to investigate the usefulness of CAD in routine clinical practice. One such endeavour in a clinical setting is a prospective observer performance study conducted by Ulissey et al on 12860 mammograms over a 12-month period in 2001 which demonstrated no undue effect on the recall rate of CAD systems on mammograms [7.7%]compared to reading by a single radiologist [6.5%]. [18]

Despite the dubiousness, CAD did make a foray into clinical practice mostly in private hospital setups in an attempt to improve diagnostic accuracy of cancer in mammographic studies. 74% of screening mammograms and 50% of diagnostic studies utilised CAD by 2008 as per a study conducted by Rao et al in the United States.[19]

The DM [Digital Mammography] DREAM [Dialogue for Reverse Engineering Assessments and Methods] challenge hosted between November 2016 and November 2017 witnessed participation of 126 teams across 44 countries. The top-performing teams had to fine-tune their algorithms into a 'Challenge Ensemble method' [CEM] model, which was subsequently combined with the radiologist's assessment into a 'CEM+R' model. Albeit improved interpretative accuracy with the CEM+R model, none of the algorithms alone could outperform radiologists.[20]

Mc Kinney et al in collaboration with Google Health retrospectively investigated the effectiveness of an AI algorithm in predicting breast cancer in mammograms with biopsy-confirmed breast cancer outcomes. Image datasets from both UK and the USA were used. The image dataset from the UK comprised of mammograms collected between 2012 and 2015 which were used for screening 25,856 women at two centres in Englandwhich screened women every three years. Each mammogram had been double read by two radiologists. The recall rates of radiologists were compared with the prediction made by the AI software.A non-inferior performance was elicited and there was a reduction of workload of the second reader by 88%. An absolute reduction of false positives by 1.2% and false negatives by 2.7% was demonstrated by the study in the UK.Likewise, in the USA dataset, an absolute reduction of 5.7% in false positives and 9.4% in false negatives was elicited. [21]

III. Technological advancements

From the 'Golem', the clay android structure of Jewish folklore in the late medieval times[22] to current deep learning computational systems, mankind has witnessed colossal evolution of artificial intelligence over the centuries. The branch of AI that has been widely researched in medicine is machine learning that is feeding machines with data, selecting features of differentiation and developing algorithms to 'teach' the machines to predict the occurrence of those features in new datasets. Machine learning can be supervised or unsupervised. [23]

Computational functions or layershave been termed as 'neural networks' in view of the fact that they can process the input information, amplify or dampen the input signal through coefficients called 'synaptic weights' which are connections between the layers, consequently generating the desired output information.Neural networks can be 'deep' or 'shallow'. [23] [24]

Convolutional neural networks [CNN] are a subset of deep learning, so termedbecause a specialised mathematical function called 'convolution' is applied between the layers.The output signal remains unaltered despite changes in the input measurements, a phenomenon called 'invariance'. [23] [25]CNNs are inspired by biologic processes. Fukushima's 'Neocognitron', one of the initialCNNswas based on The Hubel and Wiesel experiment on the visual cortex pathway. [26] [27] [28] However, the concept was revolutionised only with the CNN called AlexNetconquering the 2012 ILSVRC [ImageNet Large Scale Visual Recognition Challenge].[29]

IV. Conclusion And Discussion

The applications of artificial intelligence in medicine can be manifold. If ethical constraints can be overcome, an increasing number of AI algorithms can be tested on mammograms and their accuracy evaluated for implementation in routine diagnostics. Further research is mandated to ameliorate validity of artificial neural networks so that they can be employed as useful diagnostic tools in areas with a dearth of radiologists. In addition, appropriate training of machines to derive rapid diagnoses can enable optimum patient satisfaction. However, patients might not consent to machine-dependent diagnoses with no "human touch"; the trust of patients on the healthcare system may be endangered if machines are allowed to replace radiologists. Moreover, machines work on feature extraction, better explained by the fact that humans have to feed data in a machine-comprehensible language to obtain the necessary output which is again dependent on human intelligence. Furthermore, unlike human neural networks which are governed by emotions and socially learned values, artificial neural networks are not amenable to circumstances. There is also a substantial cost associated with the implementation of AI in routine imaging.

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