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Applications of Machine Learning, Deep learning in diagnosis and treatment of Cancer Patients

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Abstract:
Matters of interest about artificial intelligence to deliver intelligible or explicable output to users have been raised collaterally with the quick developmental interest towards Artificial Intelligence in biomedical applications. This purpose is mainly in biomedical settings where patient safety is our priority. In order to evaluate artificial intelligence, NLP, and XAI in detail, this position paper highlights researchers who are keen in the field and have many responsibilities and opinions. Modern era for the definition is conceptual framework or the model to use when thinking about XAI. A set of conditions for getting interpretable in AI are then listed, each of which puts a spotlight on an important stream of biology.

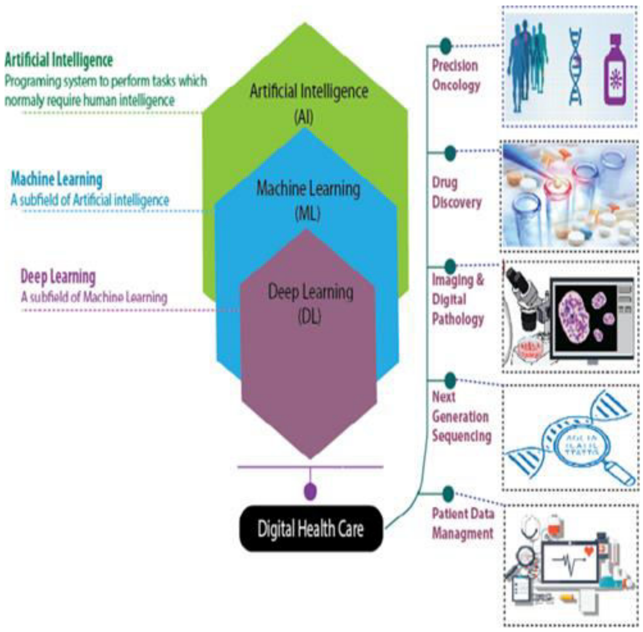
Key words: Collective Surgical Consciousness, Artificial Intelligence, cancer patients, diagnosis and treatment

I. Introduction

Machine learning and biomedical applications in cancer investigations provides much ascendancy namely, scaling information processing and increasing the correctness of clinical decision-making. Artificial Intelligence used in Medical science has manifold into clinical and medical field, English medicine, the biomedical research to treat the diseases and cancer too in more progressive. Modern artificial intelligence systems based entirely on ML techniques have found clinical applications, including computer-aided identification and diagnostic imaging, in various medical fields (e.g., pathology, imaging, ophthalmology, and dermatology). Interpretation of genomic data to identify genetic variation based on high-throughput sequencing technology. Prediction and monitoring of patients, discovery of new biomarkers by integrating omics and phenotypic data, determination of health status with biomarkers collected from wearable devices, and finally the development and use of autonomous robots in AI medical intervention. I will drive today. ; A broad learning method is capable of extracting patterns from a large amount of data, as well as generating inference systems that identify risk groups of patients and for better decision making [1]. For better patient-level predictions, predictive disease modelling and risk prediction, data mining and machine learning algorithms consistently shape traditional statistical methods. Machine learning-based methods have the advantage of automating the formulation and estimation process by assigning parameter weights to predictors based on their correlation with predicted outcomes [2].

II. Methodology

Artificial intelligence & Machine learning is an Extensible Markup Language-based Design for building artificial intelligence applications. AIML makes the creation of human interfaces while maintaining the implementation easy to program, easy to understand and particularly maintainable, and with the help of various Deep Learning and Natural language processing algorithms, it is becoming convenient and making progress as artificial intelligence has gained the focus of scientists. world, because of his DL and problem solving ability.



In the 19th century, Alan Turing first introduced the concept of AI in his book "Machines Computing and Intelligence" [2]. Surgical Computing (CSC) for individual and demographic data analysis has been introduced to surgical procedures in the operating room. Mathematical algorithms have been used in many clinical settings where a comprehensive preoperative risk assessment is calculated by an artificial neural network (ANN) based on digital image analysis. (AI) and (MO) are increasing their impact on daily life and are expected to have a significant impact on digital health in diagnosing and treating future diseases. Machine learning is a field of artificial intelligence in which neural network algorithms are developed to make machines learn and solve problems similar to the human brain. [3]. On the other hand, deep learning (DL) is a subset of ML that mimics the processing capabilities of the human brain for image and object recognition, language processing, better drug discovery, better accuracy in medicine , better diagnostics and assistance for people to make decisions. . solutions. It cans also work and offer loopholes without human intervention.

III. Background

We pointed that are raised related to XAI in the streams of artificial intelligence sciences in this section. Following that, we'll discuss the primary XAI-related difficulties in medicine before ending with a few sparse examples of XAI applications in clinical fields.

IV. Applications

Some examples of different machine learning algorithms, such as neural networks, are difficult to explain and are often referred to as "black box" models [4]. However, there may be cases where neural network models provide sufficient explanation to support the interpretation of the results. [5] Other authors have created a standardized CEFE (CNN Explanation Framework for ECG signal), a three-module post-specific analysis set for convolutional neural networks for understanding and local understanding. They started a channel on the website to help a small group research this disease.

In last few years, group learning has achieved good results by incorporating explanatory skills. Yeboah et al [9] presented the XAI cluster model for prognostic analysis and diagnosis of traumatic brain injury (TBI). The goal is to identify patient subgroups and key phenotypes that delineate these subgroups using imaging data by examining the relevance of features. In another example, the authors proposed an additional decision support system that combines collaborative learning with case-based reasoning (CBR) to help clinicians improve the accuracy of predicting cancer recurrence. They use extreme gradient boosting (XGBoost) to predict breast cancer recurrence risk and then use CBR to describe prognosis [10]. They interviewed 32 oncologists to understand the usefulness of the system known to users by examining the system through a series of questions.[11] There are many examples of systems that use explanations extracted from medical data through rule-based systems. They provided explanations in a readable format that builds confidence in the support system's results. El-Sappagh et al. proposed a fuzzy system of IF-THEN rules [12]. It combines reasoning with fuzzy reasoning on ontology. Therefore, they proposed and implemented a novel rule-based and semantically interpretable system framework for diagnosing diabetes that can provide adequate decision support. The Allergy Diagnostic Support System (ADSS) was developed by Kavya et al [13]. They used multiple ML algorithms and then selected the best performing algorithm using k-fold cross-validation. For the XAI method, they developed a rule-based approach by constructing a random forest. Each path in the tree appears as an IF AND THEN rule, and these rules are stored in the rule base for peer evaluation. In addition, the authors have developed a mobile application that will help young doctors confirm diagnostic predictions. While the user is at the center of the approaches we have just discussed, developing a system that is intuitive for use in a given context requires interdisciplinary collaboration, including collaboration with stakeholders. Schonderward et al. presented a case study of a human-centered design approach applied to AI-generated solutions and explanations. The approach consisted of three parts [13]: domain analysis to determine the concept and context of the statements; set and evaluate requirements to derive use cases and refine requirements; and design and evaluate multimodal interactions to create a library of defined design patterns. This system is used in Children's Health Factors. [14] Smoke et al proposed a logic-based XAI system that supports user behavior monitoring and encourages users to adopt a healthy lifestyle. First, they assessed the usability of the application through questionnaires completed by users. With this they confirmed the correctness of the explanation of the system. Then the final evaluation included an analysis of the effectiveness of the generated solutions and explanations.

V. Deep Learning Techniques

Artificial intelligence (AI) technologies are becoming increasingly important for improving research and clinical care. Natural languages processing (NLP) and deep learning (DL) techniques have been used to extract information from a large number of electronic records locked in history. Researchers have created a deep learning-based automatic detection algorithm (DLAD) to analyze chest X-rays and detect abnormal cell growth, such as possible tumour cancer. (Figure 2). By the algorithm's approach on the same images was compared to that of multiple physicians, performed 17 of 18 doctors [15].

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Scale	MSE	Mean AUC	AMI	Accuracy %
Symptom Scale				
SVM(Linear)	0.02	0.90	0.92	97.37
SVM(RBF)	0.03	0.80	0.81	94.58
LR	0.02	0.72	0.82	94.34
ANN	0.03	0.85	0.82	87.56
Global Health/QoL				
SVM(Linear)	0.07	0.84	0.79	95.26
SVM(RBF)	0.08	0.80	0.20	93.12
LR	0.13	0.64	0.59	89.29
ANN	0.08	0.73	0.65	74.38
Functional Scale				
SVM(Linear)	0.13	0.85	0.77	95.81
SVM(RBF)	0.26	0.90	0.78	97.32
LR	0.16	0.60	0.34	93.12
ANN	0.13	0.83	0.90	71.28

MSE = Mean Squared Error, AUC = Mean Area Under ROC(Receiver Operating Characteristics) Curve, AMI = Adjusted-for-chance Mutual Information Index, SVM(Linear) = Support Vector Machine with Linear Kernel, SVM(RBF) = Support Vector Machine with Radial Basis Function Kernel, LR = Logistic Regression, ANN = Artificial Neural Network.
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Figure 2 Comparative accuracy

The following are some of the deep learning algorithms and techniques that used to train the models for many disease apprehensions:

• Convolutional neural network (CNN): this deep learning model for disease detection. It is an artificial neural network with at least three methods of layers adopted by Scientists: convolutional, pooling, and fully connected. By developing a disease-specific feature extraction model, CNN can be used for disease diagnosis.[6] It can also be used to predict disease and find out new drugs using medical images. Disease classification, disease segmentation, and disease identification to name a few disease prognosis problems that can be solved using CNN. CNN uses images for disease diagnosis. Examples of diseases that CNNs can be used for skin cancer, breast cancer, and heart ailment. A sample evaluation plot for breast cancer is shown in Figure 3 for true probability and predicted probability.

• Fully Convolutional Networks (FCN): A deep learning technique that can be used in electronic health record systems for disease diagnosis using textual data such as patient medical records.[6] It is a type of convolutional neural network that does not required to be partitioned and can be applied directly to disease diagnosis issues.

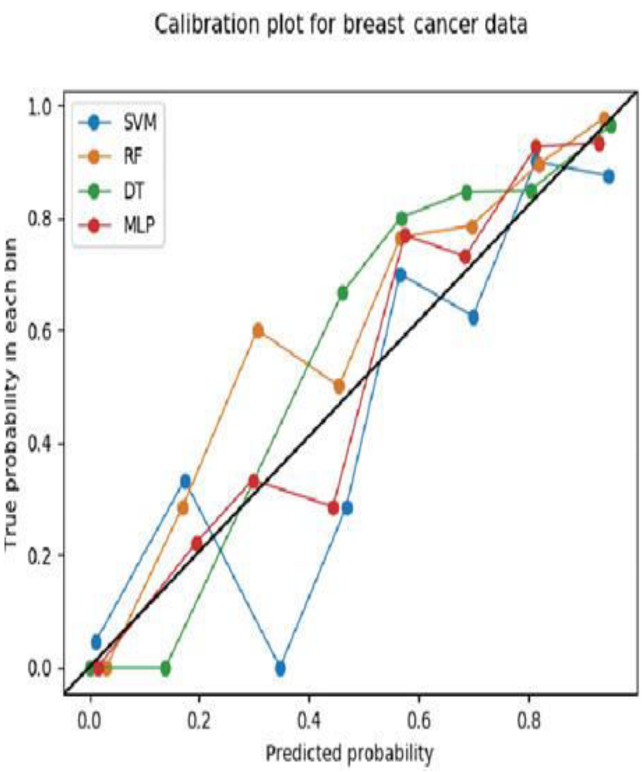

Figure 3: Calibration plot for breast cancer for True probability vs Predicted probability

Recurrent Neural Network (RNN) / LSTM: A deep learning technique popular in language processing applications such as machine translation models. It is made up of at least two stacks of recurrent neural network cells called Long Short-Term Memory units (LSTMs). RNN can be used for disease prognosis by making ailment-related language models, such as disease symptoms or patient medical records and reports. [6]. Alzheimer's disease, Parkinson's disease, and Crohn's disease are just a few of the ailments for which RNNs can be used to create disease prediction models.

• Dilated Convolutions are a deep learning method that can be used to diagnose disease. It is a type of convolutional neural network with flexible weight matrices (dilation). Dilated ConvNets have mostly used methods in computer the vision and the image processing layers for the object detection and segmentation. [6]. Disease classification and disease segmentation are two examples of Dilated Convolutions-based disease that diagnosis the problems as shown below in Figure 4

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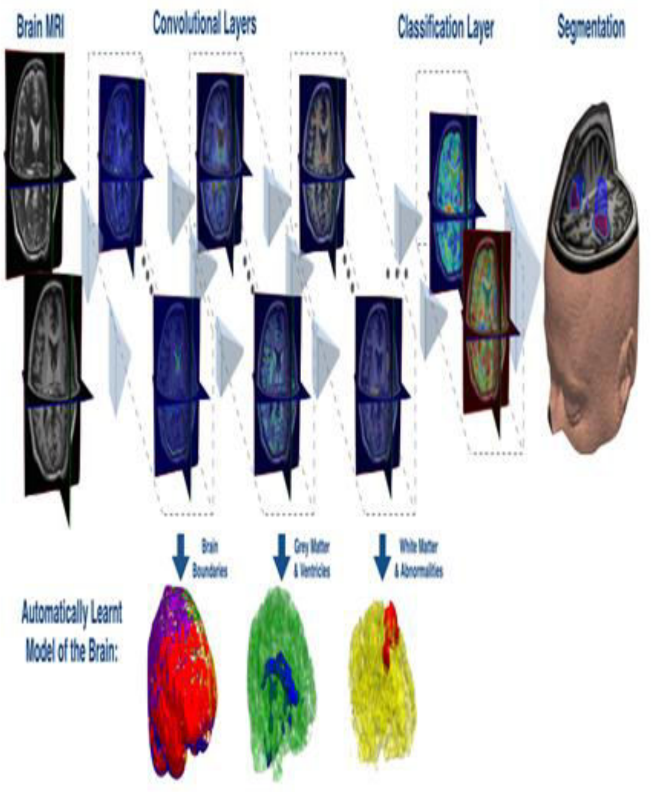


Figure 4: Classifying automatically learned model of the brain through segmentation.

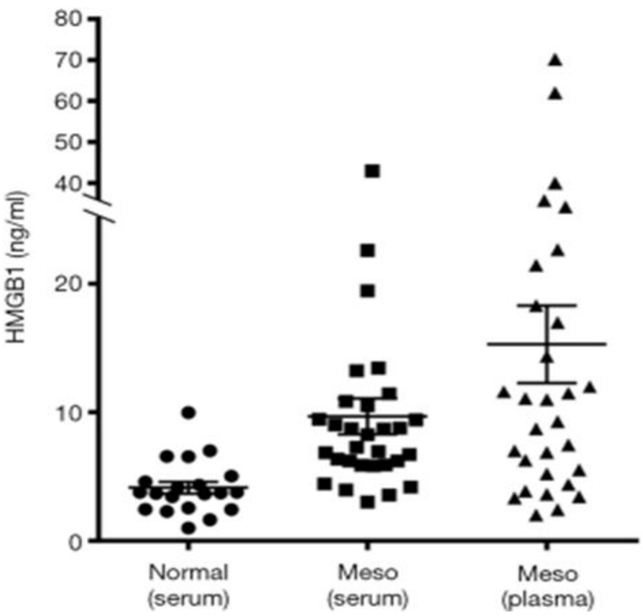
Generative Adversarial Networks (GANs): this learning technique is used detect the disease and disease prediction onset. Generative Adversarial Networks made up of 2 famous neural networks: one to create samples and another is for the assessing them (the discriminator). GAN can detect diseases using medical images such as MRI, CT, and X-ray. [6] Generative Adversarial Networks uses disease symptoms and patient medical reports to build a predictive model of disease for the inception in the disease prediction problems and solutions. Leukaemia and myocardial infarction are two diseases for which Generative Adversarial Networks is used to develop the disease prediction of (diseases) models example of (heart disease).

• Auxiliary Classifier GANs: This deep learning method is helpful for identifying diseases. Generative and discriminative networks, also known as generator and critic networks, make up this particular type of adversarial network [6]. Compared to GANs, AC-GAN generates results that are more accurate because it gets knowledge from both models. By developing disease-specific feature extraction models using disease images, disease symptoms, or medical records, ACGAN can be used to predict diseases.

• Convolutional Auxiliary Classifier Generative Adversarial Network: This deep learning method is suitable for many signal classification problems, such as disease diagnosis and prognosis. [6] The combination of classification networks for diagnosis and generative networks that generate disease images, disease symptoms, or medical records is called CAC-GAN.

• Attention-Based Deep Neural Network (Attention NN): A Deep Learning Approach to Disease Detection. [6] It is a type of neural network that assimilates the content of the input data into the prediction of the output through a tracking process, making it suitable for complex tasks such as disease detection and treatment.

• Adversarial auto encoders: EAA is a deep learning technique that can be used to build disease-specific feature extraction models. It consists of an encoder and a decoder, the former converts disease images or signs into disease-related signals, and the latter converts these signals into disease images or symptoms. [6].



• GANs with complementary output this is a deep learning program for the disease detection. It is a discriminant network uses an additional classification of the network to distinguish the condition of patients based on disease images, such as malignant or benign tumors in lung cancer or healthy and diseased kidneys in diabetes. [6].

VI. Conclusion

Interpretability in AI has developed at a fast pace. Although a lot of research has been done on XAI, as we have seen in this paper, there is still much to be done. Here, we list five important areas that demand more study and possess further scope.

• Collaborating the symbolic (ante-hoc) and sub-symbolic (black-box) approaches. Sub-symbolic and symbolic ML advances are presently being taken into account by two research communities with frequently diametrically

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contradicted viewpoints and backgrounds. XAI requires that such a division be overcome. Indeed, symbolic approaches such as logic-based proposals, ontologies, query systems, Bayesian networks, and so on would be grounded in order to be used in establishing explain ability. Research into the use of "hybrid" systems that combine analogue and analog systems continues to show many collaborative efforts.

• With our conceptual framework for thinking about XAI, we still need to address the conditions of individual intelligent systems and their users. Further research should focus on the structural, functional and communication characteristics of these systems and their environments.

• The evaluation of intelligent systems as a scientific and methodological method to adopt this developing, but there are a good need for good and innovative research and implementation need to adopt the valued methods. The Emphasis is placed on the accuracy for such decision made by such systems or on more subtle indicators example the sensitivity, specificity, predictive values, or their derivatives, such as F-scores or areas under the receiver operating characteristic curve or accuracy of the recovery curve. These methods of effects that require detailed research and investigation in mixed methods.

• AI systems may not necessitate real-time explanation. However, we would argue that explaining the ability to develop the software that need for such subsystems critical analysis. However, to the back users must validate the program of that workflow, it may not be as important in practice.

• Investigating user-specific design custom-tailored explanations of ability artifacts. This design should be sensitive to the context of the workflow, but there are other things that are important as well. One of the most important is user participation in the design process. A rapid prototyping paradigm should be used to ensure that users are considered at every stage of AI system development and implementation.

Hopefully, our review of XAI system development issues won't be seen as the last word on earth. Rather, we hope that the topics discussed here will inspire further thought and hopefully research and development of XAI systems, particularly in the medical context, but also in other contexts.

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