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Dr. A Mohamed Sikkander
Department of Chemistry, Velammal Engineering College, Chennai, Tamil Nadu, India

Sangeeta R Mishra
Department of Electronics & Telecommunication Engineering, Thakur College of Engineering, Mumbai, Maharashtra, India

Khadeeja Yasmeen
Department of Biotechnology, North East Frontier Technical University, Arunachal Pradesh, India

Corresponding Author:
Dr. A Mohamed Sikkander
Department of Chemistry, Velammal Engineering College, Chennai, Tamil Nadu, India

Efficaciousness of A.I and M.L of biomarkers in brain

Dr. A Mohamed Sikkander, Sangeeta R Mishra and Khadeeja Yasmeen

Abstract
Machine learning is a subordinate field of artificial intelligence, which allows machines to be driven by data or experiences from previous periods without being explicitly programmed. Artificial intelligence is a technology through which we can create intelligent systems that can evoke human intelligence.
The artificial intelligence system does not have to be pre-programmed; instead, they use algorithms that can work with their own intelligence. It involves machine learning algorithms, such as basic learning algorithms and deep learning neural networks. Machine learning allows a computer system to make predictions or make some decisions using historical data that is not explicitly programmed. It involves machine learning algorithms, such as basic learning algorithms and deep learning neural networks. Machine learning allows a computer system to make predictions or make some decisions using historical data that is not explicitly programmed. Machine learning uses a considerable amount of structured and semi-structured data, so that a machine learning model can generate accurate results or provide predictions based on this data.

Keywords: Brain imaging, task-specific algorithms, classical machine learning, artificial neural networks, human intelligence, structured and semi-structured data

Introduction

In general, biotechnology firms, industrial companies and research laboratories have explored the use of AI and ML in three major areas: machine learning to predict biomarkers, and drug discovery goals by eliminating discrimination and scientific aspects in medical definitions to speed up the monitoring and evaluation of disease progression through computer-assisted handling of medical data and imaging devices; Gathering in-depth study methods in a variety of media, such as combining genomic and medical information to find new overseas techniques. Mechanical research and computer theories have improved many aspects of human medicine. Types, such as illustrated information, and visual aids are used for a variety of purposes, from the division of medical images, to the creation, organization and vision of general medical information (Lei Cai, *et al.* 2020) [20].

Strategies to improve clinical growth by combining digital AI and ML technology with computer science are protected by newly developed guidelines. We will conclude with a discussion of applications and a network of digital evidence to improve patient health care. The idea of medical development is about to undergo a major change due to the introduction of new information and the power of computers to identify the most important health practices in the media world, using artificial intelligence and machine learning algorithms and user acceptance.

This change in these areas includes ideas, improvements and recommendations for the implementation of medical practices in medical practice and health care from academics, the biotechnology industry, nonprofits, administrators and scientific institutions. Discusses research and study in the labs of biological and medical literature, real-world evidence from music, and medical reports on machine learning strategies (Conti, *et al.* 2008) [3].

This is surprising due to a lack of faith in the needs of tyranny, the possibility and lack of innovative technology, and the lack of biological information and intensive experiments for the development of ideas that can influence development. New experimental antimicrobials for safety and efficacy require a new strategy, as it has been shown that current drugs only work for the majority of the population developed (Christopher, *et al.* 2019) [4].

Medical advances have not changed in the last 30 years. This is unique in that it is due to the unpredictable use of bullying, the lack of opportunity, and the uncertainty of rapid growth, but technology has not yet been confirmed, and the lack of productive resources- in the light of planning and treatment plan. New experiments and biomarkers for safety and effectiveness require a new strategy, as it has been shown that the current treatment only works for the majority of selected people. Better understanding of disease mechanisms in a larger patient group and the potential for independent drug development (Cliff Meldrum, *et al.* 2011) [5]. (Figure: 1).

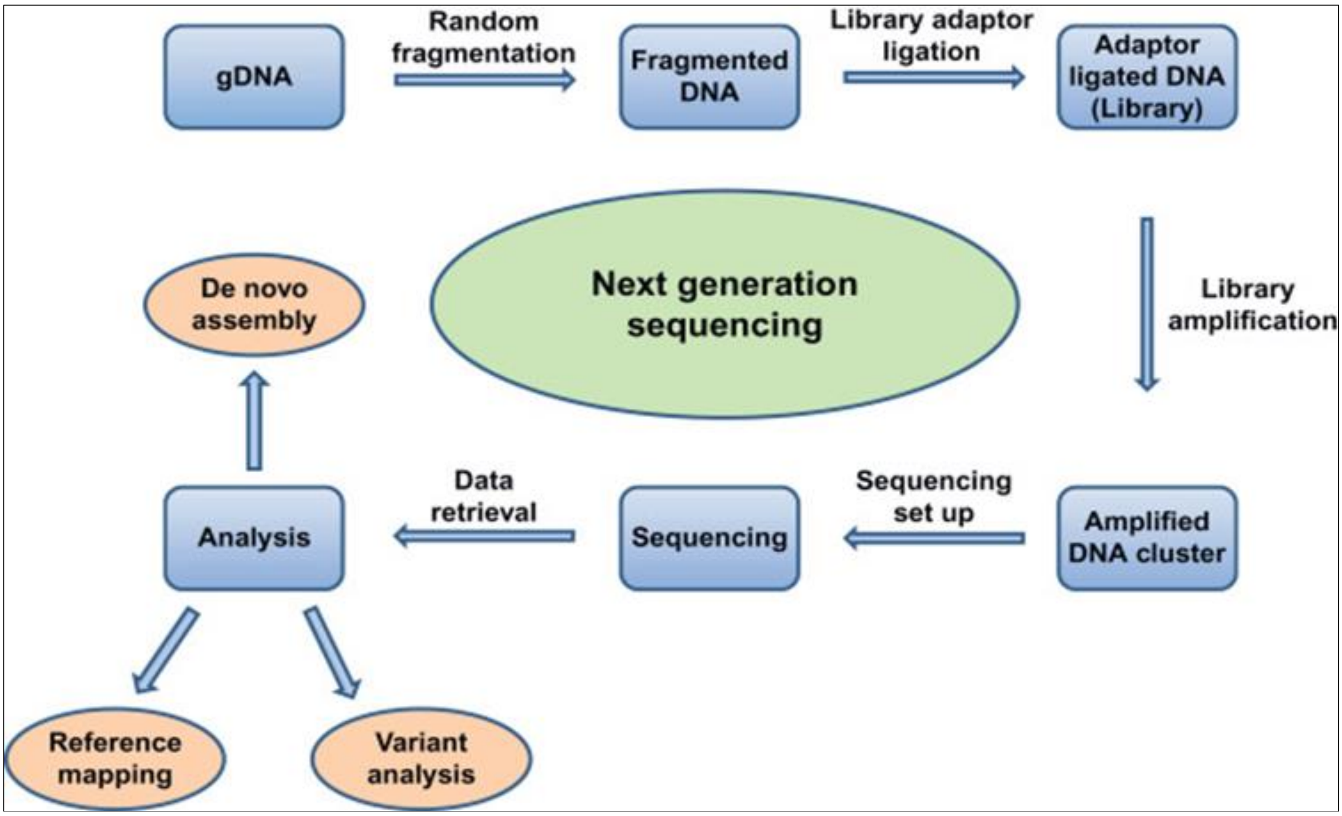

Fig 1: Emerging digital technologies and next-generation sequencing

Artificial intelligence (AI) is a major component of computer science that is widely used for the complex analysis of medical information and to extract links that work in data collection, for other medical purposes (Enrico Coiera 1996) [6]. In particular, with regard to brain care, many improvements have yielded positive results and opened up new avenues for diagnosis, planning, and prediction. In this work, we present a summary of the types of intelligence techniques used in brain care and to evaluate the most important medical procedures (Seynhaeve, *et al.* 2020) [7].

An effective and careful search of large documents, such as the Scientific Web, Pub med and Scopus, was allowed to use "artificial intelligence" and "brain" as keywords. Preliminary references are included with various references to key texts. 150 of the 2669 approved and fully implemented AI studies for various purposes. Artificial networks are some of the most widely used hearing aids (Giovanni Di Franco and Michele Santurro 2021)[8]. Old-fashioned machine learning techniques, such as continuous cutting machine and informal cutting, are widely used. A special operating system is designed to solve specific problems. Brain images are one of the types of data that everyone uses. AI does not have the potential to improve physician decision-making processes in the use of neurotransmitters (Mangor, *et al.* 2020) [9]. (Figure: 2).

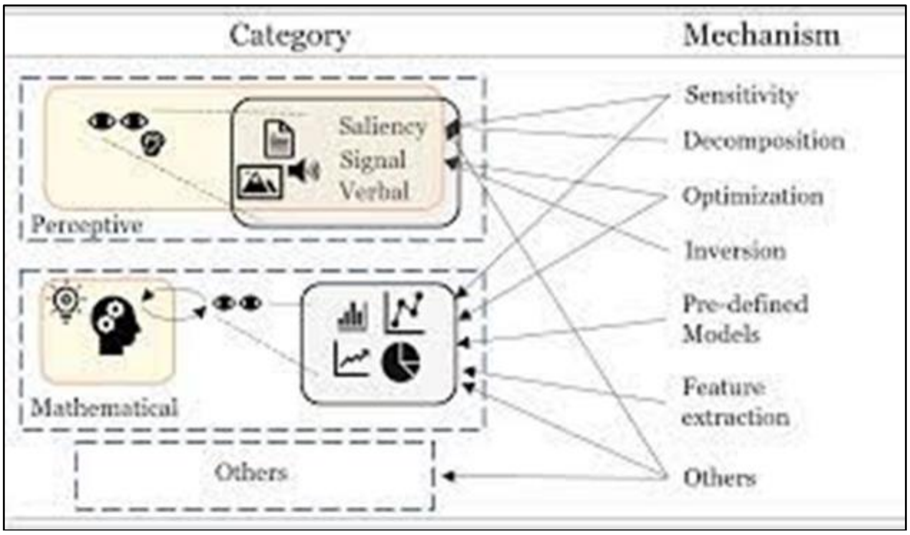

Fig 2: AI has the leeway to improve clinicians' decision-making facility in neuroscience applications

On the other hand, the most important issues have yet to be solved for a better practical use of AI in the brain. In this regard, it is important to both collect comprehensive data and build explainable AI algorithms (Thomas, *et al.* 2017) [10]. Deep learning has been helpful for a number of medical data. In scrupulous, current deep learning models show exceptional performance in specific tasks, sometimes provides greater accuracy than that of experts in discerning specific illnesses from medical images. The current state of deep learning applications for molecular imaging can be alienated into a certain subtype depending on their purposes: disparity diagnosis classification, image acquisition enhancement, and l-based quantification. 'Picture. Because well-designed physiological and pathological information is essential for molecular imaging, this review will focus on the need to properly acquire biomarkers through deep learning in molecular imaging. Additionally, this assessment addresses practical issues including clinical validation, data distribution, labeling, and harmonization issues to achieve clinically feasible deep learning models. When the time comes, deep learning will strengthen the role of Theranostics, which aims to precisely target pathology of the pathway by maximizing the functional molecular image in order. (Figure 3).

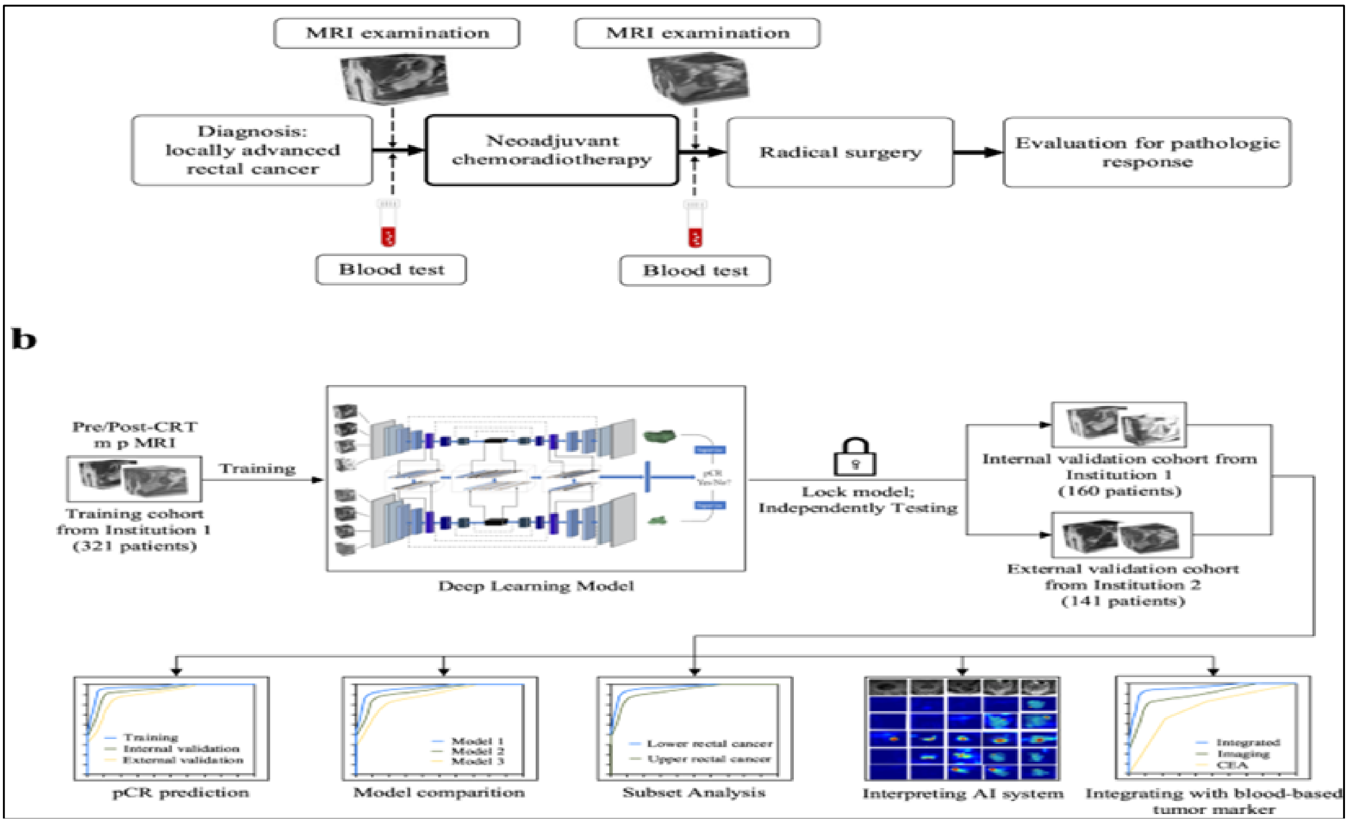

Fig 3: Appraisal addresses practical issues that comprise clinical validation, data distribution, labeling issues, and harmonization to accomplish clinically practicable deep learning models

Deep learning can quickly become useful in the medical field. Recently, a number of medical devices and deep learning software have been developed and used in clinical fields. The most important contribution of deep learning to medical data has been the passionate evaluation of large-scale medical data and the visible reduction of laborious tasks, such as segmenting and recognizing objects in high-resolution images. The most important medical application is in the field of medical imaging, because the boom in deep learning began with the computerized visual field initiated by Image Net Challenge. The neural network methods and architectures developed for the Image Net Challenge have been functionalized for medical imaging to explain radiological and pathological investigations, as well as expected photographic metaphors. These approaches based on computer vision have worked surprisingly to the degree of differential diagnosis. For natural photographic metaphors such as skin imaging and fundoscopy, deep learning techniques have been adopted relatively easily, as convolutional neural network (CNN) models created for Image Net Challenge are transferred to such images in a way that is constant (Hoo, *et al.* 2016) [11]. In addition, CNN, which has a good presentation in image classification and processing, has been applied to radiological examinations, such as chest radiography and mammography. Later, CNN models were used for image-based diagnostics and image processing. The deep learning function included three-dimensional imaging, such as computed tomography (CT), positron emission tomography (PET) and magnetic resonance imaging (MRI), as well as two-dimensional radiological examinations (Zhenwei and Ervin 2019) [12]. The basic principle of clinical use has been broad to encompass a variety of applications, such as imaging difference diagnosis, image segmentation, and enhancement. (Figure: 4).

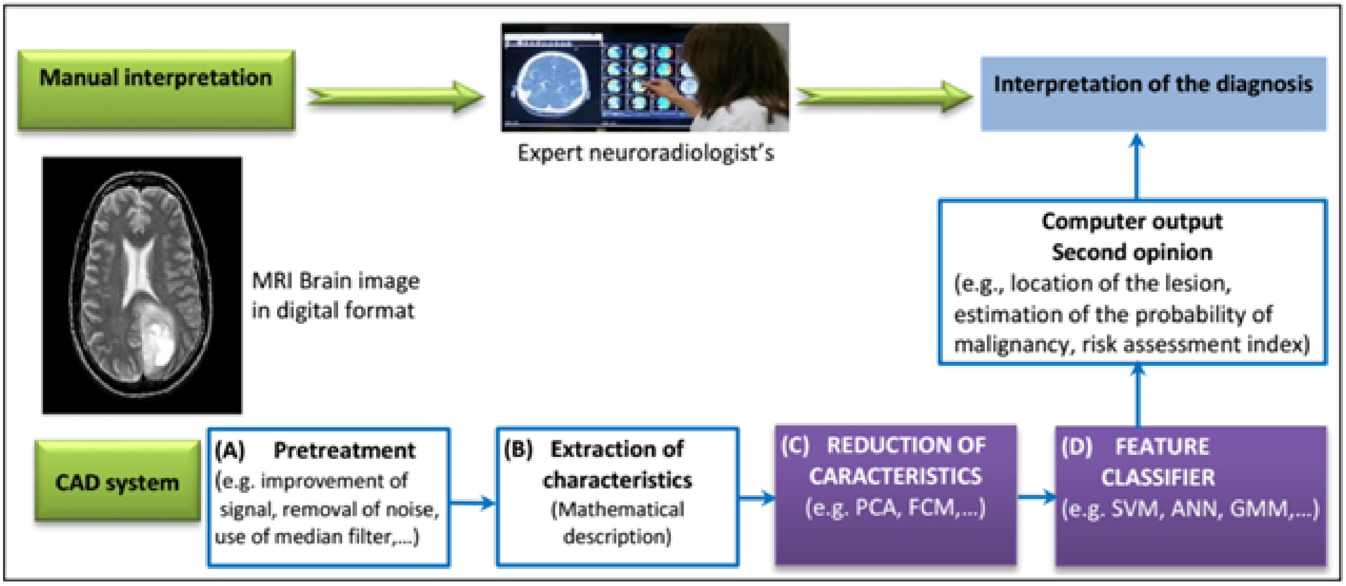

Fig 4: The underlying principle of clinical use was also long-drawn-out to include various applications such as image-based degree of difference diagnosis, segmentation, and image enhancement

Due to substantially different aspects of molecular imaging, including PET and simple photon emission computed tomography (SPECT) from natural images, there has been some concern about the application of deep learning (Magdy, *et al.* 2011) [13]. However, various deep learning techniques have suggested viable applications for improving molecular imaging and problem solving, such as image resolution and sensitivity. This assessment summarizes current models of deep learning for nuclear medicine and molecular imaging for clinical purposes (Hongyoon, 2018) [14]. To develop robust deep learning models and guide their correct direction for clinical use, this paper introduces practical issues related to current deep learning (Alexander, *et al.* 2019) [15]. All discussions in these studies with human participants were in line with the ethical standards of the Institutional or National Research Committee and the 1964 Helsinki Declaration and subsequent amendments or comparable ethical standards.

Molecular Imaging: Today's deep learning research focuses specifically on, for example, a wide variety of programs: deep learning, improved facial reconstruction, evidence-based evidence, quality imaging, and the application of image-based summaries (Figure: 5).

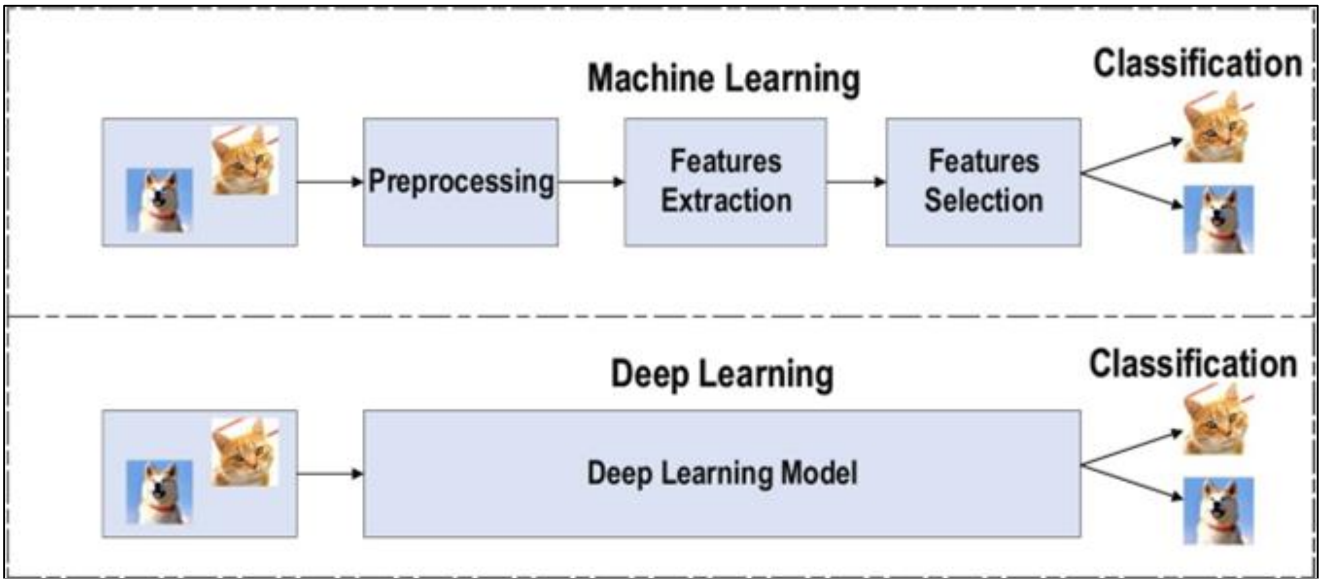

Fig 5: Machine Learning and Deep Learning

No need to ask questions, one of the almost essential applications of in-depth research in the medical field is the diversity of evidence with an interest in studying molecular models, such as in-depth study of the basic elements of the subject required several teaching pages, many types of PET or SPECT images are often found in the hospital. One of the priority applications is the differentiation of problems with norms. Recently, using fluoro-deoxy-glucose PET (FDG) images, several deep CNN modeling models have been recommended. For example, using a PET-FDG image, the depth of the sample was set separately to separate metastatic peripheral lymph nodes from benign lymph nodes in lung cancer. Using in-depth CNN, finding positive evidence for metastatic lymph node differentiation was 86%, which was higher than conventional machine algorithms.

An additional CNN model for different T levels of breast cancer showed comparative results to identify pathological T levels. The region of the acceptance activity curve characteristic was 0.68 for different progression to T level in a single test set. In-depth CNN models were developed for the degree of differentiation of brain diseases using SPECT or PET imaging of the brain. As a dual-class issue, dopamine transporter imaging has been described by specific analysis and is therefore a good competitor to CNN's in-depth applications. A 3-part example from CNN demonstrated a high level of competence for the variability of SPECT I-FP-CIT images of Parkinson's disease from those controlled (Hongyoon, *et al*., 2017) [17]. Because the accuracy of visual evidence and predictions of future problems in patients with Alzheimer's disease (AD) and dementia (MCI) have become important hospital problems, several detailed models using MRI and PET are recommended. One of the first studies of the depth of understanding in the medical picture is the use of PET and MRI images to diagnose AD. Despite the fact that these pioneers in research did not use CNN, which was considered a common practice in case studies, these models eliminate the features of automatic signaling and have a high level of coverage for brain imaging. AD compared to conventional algorithms. More recently, urban simulations have used the depth of CNN simulations to separate ADs from regulators, showing great potential for classification.

An additional important application is to improve the image reconstruction and image quality. For example, CNN models were reintegrated into the reconstruction framework and performed better than conventional demonization algorithms. As a generalized approach, in-depth learning was used to address the inverse function of default sensors, including MRI and PET in terms of image modernization, resulting in a fully automated and flexible modernization framework. In addition, the correction of weight loss, a key step in the recovery of the PET image, was helped by in-depth learning maps based on learning. While CT embedded in fusion PET / CT scanners may provide less information, recent PET / MR requires synthetic CT attenuation maps. Due to the complexity of estimating the weight loss map without CT, there have been various questions regarding the quantification of PET (Xue, *et al*. 2020) [18]. From the later proposed synthesis of CT imaging based on in-depth learning using MR or PET imaging promises to address quantification issues caused by reduced correction. Deep learning is also used to increase image quality for low-dose PET images. As a result of combining image modernization algorithms with low-dose radiotherapy and correction of PET or MR-based attenuation can dramatically reduce radiation exposure in the future. Such a very low dose of PET can be used for innovative clinical purposes, including disease screening, which makes it difficult to obtain compensation for radiation risks.

Another important point to write is to promote image construction and image type. For example, NCN modules were calculated in feather daemon design and showed better performance than conventional daemon algorithms. A common denominator of almost all is the deep-rooted research of therapeutic hypotheses. Separation techniques are usually based on atomic imaging, such as CT and NMR. Because state-of-the-art clinical imaging techniques provide fusion imaging, such as PET/CT, PET/MR, and SPECT/CT, in-depth separation methods can be used to collect large quantities, such as collecting a radio tracker in clear explanatory atomic images (Brent, *et al*. 2014) [19]. The scale can be enhanced by genes of types, such as the genetically modified network (GAN). For example, pseudo-MR images were developed with AV-45 PET using GAN to measure the recording of a cortical radio tracker without MR construction (Lan, *et al*. 2020) [20].

Deep learning- based Biomarkers: Although a number of in-depth molecule formation techniques are applied to the concept of differential diagnosis, image improvement and precise comparisons, there are still many problems that need to be solved for hospitals to function (Ahmed, *et al*. 2018) [21]. One of the controversies between the in-depth study that leads to the potential for image identification and therapeutic imaging, especially molecular imaging, is the center of the imagination (Figure: 6).

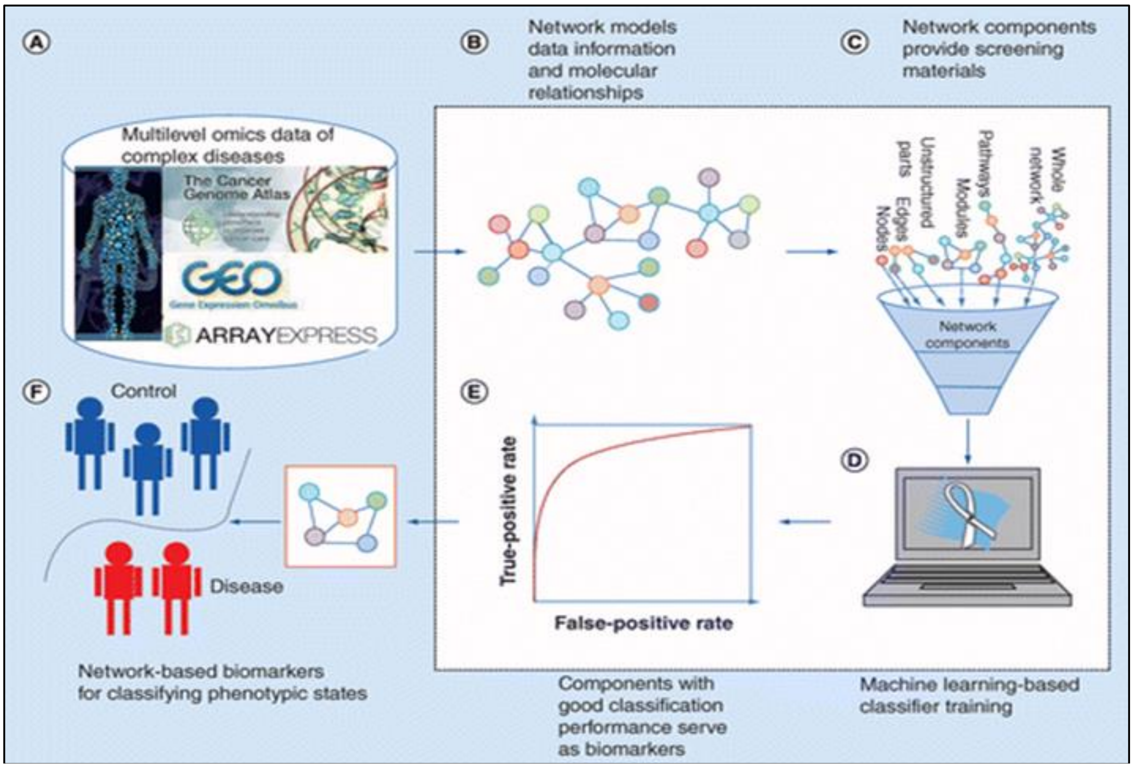

Fig 6: Deep learning-based Biomarkers

At the same time, with the image recognition function there are simple notes. Doctors often seek different types of information from medical records. They participate in predicting outcomes and treatment outcomes as well as differential diagnosis. In the narrow range of colors, contrast analysis is compared to the names of natural images; however, the number of step-by-step analyzes is not easy to separate. Due to the fact that many disorders vary in degree from general to complete illness, a low level of literature has been widely used in the study of in-depth studies with implications for medical imaging. In addition, the gold standard for diagnostic variation depends on the type of disease as well as the clinical condition. Thus, if we think critically, the ultimate goal of in-depth hospital research is not only easy to diagnose, it does not include the requirement to play an important role in the clinical program. Because imaginative molecules effectively provide molecular and pathophysiological structures in unconventional ways, in-depth study of algorithms should further emphasize the search for an objective quantitative value that can predict future outcomes and treatment outcomes. Instead of trying to recover, they wallow in their sadness and thus, experience more failure. For example, in-depth training regimens designed for Alzheimer's disease and routine studies; on the other hand, the importance of using this model was to invoke MCI studies that would quickly turn into complete depression. CNN release is moderately potential for Alzheimer's disease in a group with Alzheimer's disease and routine studies (Kanghan, *et al.* 2019) [22]. At the same time as CNN exposure to the effects of FDG and amyloid deposits in the brain was observed, these patterns may be associated with an increased biomarker of the MCI study results.

Data delivery and Legalization: While many types of in-depth research have shown surprising results in a systemic problem, such as visual acuity cystoscopy or PET brain imaging, almost all types have not been confirmed in the real-world clinical context (Dinggan Shen, *et al.* 2017) [23]. This is due to the evaluation of efficacy, as the recommended type of study is intended to be used in a clinical setting. To solve this validation problem, it is necessary to test in-depth learning styles in independent testing derived from training information and internal data validation. One of the most common methods used is to use databases located on non-standard pages. Although these types of in-depth studies operate in an external database and show a positive effect on group discrimination or predictability of clinical outcome, they can provide similar indicators in the environment of different health professionals (Martin, *et al.* 2020) [24]. Thus, the group used to develop deep forms of learning is not uncommon in clinical trials in which research involves specific conditions defined for medical conditions. The problem is that patients are in a very strong clinical setting, and medical decisions have to be made under different circumstances. For example, in-depth learning is greatly enhanced by a study group of severely disabled patients and healthy monitoring. Regular training and sedation groups include the same number of patients and system. On the other hand, in the case of a medical condition, a different diagnosis or diagnosis is made according to the symptoms and symptoms of the patients, rather than the separation into simple stages. There are many similar problems in this case of death, which focus on a more serious type of study, especially a few types of abnormal complications. The average mortality and well-being levels may differ significantly from the training group (Darren, *et al.* 2006) [25]. The problem of data transfer is a major one because we use a detailed research method to diagnose diseases in the general population (Geoffrey, *et al.* 2015) [26]. This is why in-depth research methods should be tested, even if they go beyond globalization, and it is important to use and use them properly in the clinic under certain circumstances.

Vagueness and Concealed data

Issues related to data exchange and "Intangible data" among the training team can be resolved without discrimination. In the modern approach to the analysis of key concepts and their capabilities, in-depth reviews based on training and prediction of outcomes require freedom of examination due to adverse circumstances legally. In addition, clinical decisions are not made in terms of expectations of additional expectations, but there is no detailed assessment of health risks (Jutel, 2009) [27]. Reducing the incidence of fatal diseases is one of the most important factors in clinical trials and one of the most important aspects of clinical decisions that can be made on biomarkers (Thomas and Wang, 2011) [28]. Therefore, the type of in-depth study should provide variation in their resolution to determine whether the subject needs additional assessment tests.

DL numbers and estimates to measure anxiety are good examples of a controlled learning model. One way to avoid the problem of ambiguity and missing information, often unknown problems, is uncontrolled training to spot deficiencies. During in-depth analysis, such as a representative study, hidden data elements may reflect the behavior of the research center. After obtaining the distribution of the hidden element in the study data, invisible data can be selected with a definition in the hidden region. Similar to a special type, such as a conditional GAN or an automatic encoder, it enters data for a specific state; it can be used to determine the distribution of the population under certain circumstances. For example, by developing training for the type of production for frequent changes with brain aging, it is possible to build an artificial population that produces brain metabolism at all ages. This public section will be used to find unusual methods based on the age data in this image. This type of misdiagnosis can prevent a problem associated with a serious learning process on a variety of issues.

Data Labeling: Sustainable learning is an important approach to solving the practical problems of image data labels. Identifying image data can be time consuming and labor intensive, especially for medical images. The trainer should interpret the photo or make a clinical decision. The diagnosis of “gold status” often requires a definition of clinical follow-up which requires advanced screening by the medical registry. The ethical issues associated with extensive data collection and labeling are inevitable. Limiting the data to such records, overloading them, and making detailed analysis programs more difficult is a major drawback. In addition, various nuclear and molecular imaging data are used for clinical purposes in combination with imaging techniques, making them difficult to obtain using many markers (Figure: 7).

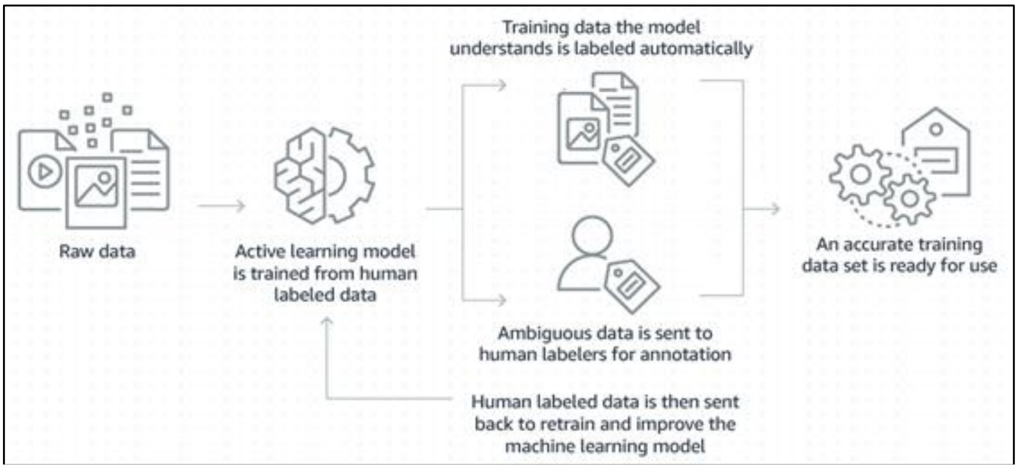

Fig 7: Data Labeling

One way to tackle this tagging problem is to find your own medical imaging data (Marc, *et al.* 2017) [29]. Collecting heterogeneous imaging data for clinical research is relatively easy. Typical features can be obtained using routine clinical data and unsupported training methods. Typical features are visualized using the dimensional method to make it easier to understand the definition of a large image data model. In addition, features from unsustainable studies can be transferred to relatively small datasets that contain both tags and images. This retraining allows you to create a robust model of deep learning, even if the good data score is relatively small. Flexible applications for supervised learning and transfer learning can be extended to semi-supervised learning. As mentioned above, regularly retrieved databases are relatively easy to retrieve and can be labeled as clinical outcomes or diagnostics, from small data to large unsigned data. Despite the small labeled samples, the combination of detailed analytical techniques uses unlabeled data to find characteristic representatives of the small labeled samples. Larger datasets for gene expression can be used without PET data to develop models for predicting FDG uptake. There are various clinical datasets as "large unlabeled data and small labeled data", and detailed learning models that can improve performance through unsustainable research and unlabeled data are the future of molecular imaging and medical data.

An easy way to solve a signal problem is to use a data structure similar to the data model. For example, clinical imaging data, including study reports, include the results of interpretations by native English speakers (Akib, *et al.* 2020) [31]. Although these reports are generally unstructured, they contain a lot of information about detection defects, areas of pain, visual clues, and even abnormalities. Extracting data from clinical images and literature provides an effective way to develop more detailed modeling of these changes over time based on actual clinical data. In addition, self-study of visual expression using analysis of semantic basis applicable to conventional visual expression will learn medical visual expression and evaluate data analysis.

Studying image models and investigating technical issues can be a data-driven biomarker-driven approach without prior knowledge. Self-monitoring training is one of the future aspects of a data-driven approach that can be used as a test report or use inside information to run age and gender model data.

Data Synchronization and Data Renewal

The most unexpected issue that has not come up before is the data structure. Different types of nuclear imaging are used in the clinical field. There are several types of markers that can be used for clinical purposes (Hussein & Habib, 2020) [33]. In addition, agencies have to demonstrate the correct image protocol so they can reduce the reliability of dipper learning models if they want to be implemented for multiple agencies. (Figure: 8).

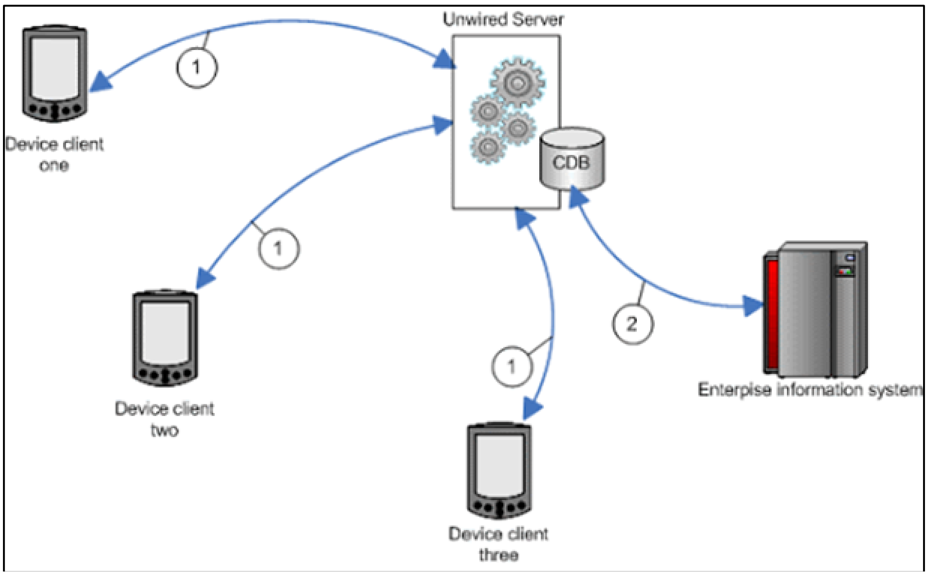

Fig 8: Data Synchronization and Data Refresh

Abnormal analyzer types and different shape textures associated with the algorithm structure can affect deep analysis performance. In addition, the dispersion of the observer is the dynamics of time, and photography at different times influences the acquisition of biomarkers of deep analysis. Recently, depth analysis has been used to analyze the kinetics of dynamic shape images; On the other hand, most of the image documents obtained in the clinic are real-time images that require a large-scale connection. Unity issues cause audience differences at similar atomic levels. For example, many radiotherapists are available to provide information about amyloid accumulation in the brain, such as 11C-PIB, 18F-Florbetapir, 18F-Florbetaben and 18F-Flutemetamol. This PET image shows similar results but different statistical results. Although ancient amyloid sizes can be determined by linear correction, there is a great need for in-depth study models for the use of imaging documents with different markers (Figure: 9).

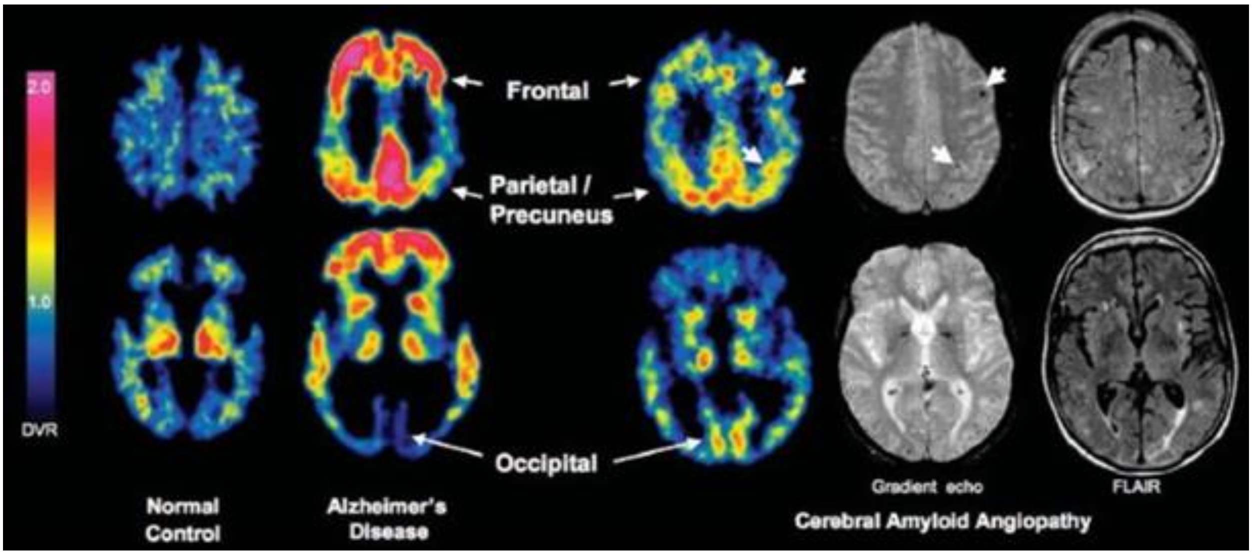

Fig 9: PET imaging of classical amyloidal quantification

Conclusion

In this analysis, traditional depth analysis models developed for molecular imaging are presented in a few words according to their purpose. Because the molecular image involves a number of molecular changes in pathophysiology, accurate and balanced measurement is a key clinical step. This amount of information refers to clinical decision and decision assessment and differential diagnosis. Therefore, instead of direct diagnostic classification, we should focus on reproducing biomarkers by capturing the molecular information used by the image using in-depth analysis. It can contribute to therapeutic approaches that require diagnosis and a combination of treatment using the same molecular targets.

In-depth study models summarize patients' power and status values. Models should be clinically validated in a clinical setting with passive data, rather than limited data sets. These problems include the circulation of various data, invisible data and uncertainty of decisions. Unsupported studies, followed by studies, can form a collection of detailed study models with small examples. Given the specificity of the medical field and the scope of molecular imaging objectives, it is crucial to extend the model of in-depth study to meet specific clinical objectives, and the result will be a relevant biological indicator needed to make a clinical decision. A proven biomarker for a clinical molecular image can be used to monitor disease status based on the information used. Treatment plans, including dosage and schedule, as well as treatment modalities, can be modified to predict the patient's condition at the individual level using imaging data. Uncontrolled data and unsupported studies promise to make clinically applicable models for in-depth study. This will be done manually to significantly address the difficulties posed by the learning tutorials taught by most in-depth visual data learning models.

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