

Using AI and Precision Nutrition to Support Brain Health during Aging

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Abstract

Artificial intelligence, often referred to as AI, is a branch of computer science focused on developing systems that exhibit intelligent behavior. Broadly speaking, AI researchers aim to develop technologies that can think and act in a way that mimics human cognition and decision-making [1]. The foundations of AI can be traced back to early philosophical inquiries into the nature of intelligence and thinking. However, AI is generally considered to have emerged as a formal field of study in the 1940s and 1950s. Pioneering computer scientists at the time theorized that it might be possible to extend basic computer programming concepts using logic and reasoning to develop machines capable of “thinking” like humans. Over time, the definition and goals of AI have evolved. Some theorists argued for a narrower focus on developing computing systems able to efficiently solve problems, while others aimed for a closer replication of human intelligence. Today, AI encompasses a diverse set of techniques used to enable intelligent behavior in machines. Core disciplines that contribute to modern AI research include computer science, mathematics, statistics, linguistics, psychology and cognitive science, and neuroscience. Significant AI approaches used today involve statistical classification models, machine learning, and natural language processing. Classification methods are widely applicable to problems in various domains like healthcare, such as informing diagnostic or treatment decisions based on patterns in data. Dean and Goldreich, 1998, define ML as an approach through which a computer has to learn a model by itself from the data provided but no specification on the sort of model is provided to the computer. They can then predict values for things that are different from the values used in training the models. NLP looks at two interrelated concerns, the task of training computers to understand human languages and the fact that since natural languages are so complex, they lend themselves very well to serving a number of very useful goals when used by computers.

Keywords

Artificial Intelligence (AI), Precision Nutrition, Brain Health, Aging Research, Gerontology, Cognitive Functions, Temporal Reasoning, Medication Adherence, Electronic Health Records (EHRs), Machine Learning (ML), Healthcare Technology

1. Introduction

1.1. Artificial Intelligence in Gerontology

The reduction in cognitive abilities usually complicates the adherence to regimen on medications, diets, exercises, and appointments. Although there are specific moments throughout the day when patients are prompted to move, such as rising for work or sitting down for a meal, many older people may no longer be employed or have lost their partners. Traditional reminder tools like medication organizers or notes listing follow-up appointments or instructions for monitoring physiological and cognitive signs at home rely on patients remembering to consult these tools. Patients must remember that the organizer or notes exist and what each medication is intended for. They must also recall how to complete any self-checking procedures as instructed. Unfortunately, cognitive impairment can interfere with this type of memory-based self-management, even with the aid of analog reminder systems.

However, even in the absence of the pathological cognitive decline, many patients may have difficulties in accepting and functioning within the environment that offers the vast array of the latest technologies in the sphere of the HCITL development. Making the task even more complicated, various illnesses and disorders are often prevalent in old people, which might be cured with even more and other kinds of medication. They further complicate the situation in terms of the cognitive load, which makes it even more difficult to achieve optimal scheduling of the related actions. Certain everyday tasks that may seem simple for younger individuals accustomed to technology can sometimes prove difficult for older adults without similar experiences. Members of generations who came of age prior to the widespread adoption of personal digital devices, computers, smartphones, and other networked technologies may face challenges with processes reliant on such modern tools. A lack of familiarity with personal digital appliances, computers, smart phones, and other mobile or networked information devices during formative years can potentially impact an individual's ability to incorporate such technologies into daily living as they age [2]. Some of the technological challenges as observed among the older people are also due to lack of interest or maybe due to irritation resulting from constant new releases, new interfaces, new information presentation methods and change of passwords [3].

1.2. EHRs Analysis and Associated Prediction

There are fission Federal, state, and local activities center on enhancing overall

black market as well as other areas of health care. Such initiatives are driven by the growing dependency on EHRs which were heralded to enhance the integration of patient records for better and increased collaboration across various players in the delivery of patient care. Moreover, since this data is to be captured in structured formats, and since the ultimate goal is to capture new medical data as it happens in real time, medical records may be more easily analyzed using analytics. For instance, recent works done in the University of New Mexico, and Vanderbilt point out that the future risk of type 2 diabetes mellitus can be a prediction by using ML on EHR data [4].

The authors employed ML and feature selection to build a model for predicting diabetes using data from EHRs—the process of identifying and choosing inputs relevant to the predictive model. The first reason why prediction is so essential in diabetes is due to the fact that for DM-II, clinical diagnosis could be made several years from onset of the disease which may be between 4 - 7 years and by this time some of the complications especially vascular may have already developed. Thus, we can assert that the identification of risk factors for a particular behavior should occur at a relatively early stage, which may, in turn, prevent the development of further complications and potentially lessen the rates of morbidity/mortality.

1.3. Cognitively Impaired-Reminder Systems

Advances in human-computer interaction systems driven by AI development offer potential benefits. For example, AI can enable devices to provide reminders or instructions tailored to individuals' unique needs, rather than relying solely on calendar-based triggers. Context-aware and adaptive approaches may consider additional real-time factors like changes in cognitive status from conditions such as dementia [5].

Effective reminder systems require reasoning about temporal relationships, as the timing of activities and events is crucial. Recent works have explored adaptive models using AI techniques for temporal reasoning and reinforcement learning. Unlike traditional calendars and alarms that remind based on predetermined schedules, adaptive approaches allow for flexibility by taking into account fluid contextual factors. Temporal constraint reasoning allows modeling of temporal relationships between events, including attributes like sequencing, durations, and conditional dependencies [6]. Reinforcement learning enables systems to learn mapping situations to actions through trial-and-error, with numerical rewards signaling successful task completion for machine learning algorithms [7]. Together, these techniques may facilitate development of personalized digital tools sensitive to individual circumstances like memory impairment.

2. Temporal Reasoning

2.1. Situation Recognition and Real Time Monitoring

Forecasting should be considered a critical form of discourse, an important ca-

pability of practical reason that enables intelligent action and planning in the human world, as well as in the world of artificial, cognitive or AI agents—that is, entities “capable of exhibiting intelligent behavior in complex environments, for a long periods of time” [8]. To successfully model such kinds of AI agents, reasoning about time is quite important; it isn’t simply about the time that befalls upon an agent and how long it and other agents may take to respond and act, but is also about sequences and temporal orderings of these actions. When any temporal factor influences the capability of some monitor or assist agent then deciding as to which action is best for application at that precise period means that the time constraints involved should not be over-specified as to leave no solutions or actions available, yet they also should not be underspecified with many potential solutions or actions possible. When developing agents to monitor events in real-time—such as the onset of a medical condition, gradually changing behavior indicating increasing stress levels, or potentially life-threatening situations—then timing is paramount. The suitable information or decision must be provided quickly enough to be helpful [9]. This underscores the importance for some systems to access comprehensive electronic health record data, including in real-time, in order to effectively support time-sensitive tasks like acute event response. The ability to access detailed, current patient information assists with making well-timed determinations and interventions.

2.2. Event Recognition

The description and impact of events are central to most narrative texts, including in healthcare. In this domain, AI systems aim to support timely care provision and decision-making by identifying and categorizing events based on past occurrences and current contextual factors.

However, precisely defining what constitutes an event can be complicated, as perceptions may vary depending on purpose. A key challenge in automated event recognition is how to model events such that reasoning about temporal relationships both within and between events can be performed effectively. Logic-based representation of event structures offers benefits such as formally specifying declarative structure and enabling scalable refinement supported by machine learning techniques [10].

Logical temporal modeling typically associates temporal terms with specific time points or propositions. Low-level events are identified as higher-level patterns. Representing sequential relationships via temporal constraints facilitates efficient event recognition compared to non-logical approaches. Techniques like the Chronicle Recognition System employ discrete time instances marked by chronological order and other attributes describing persistence, absence or repetition [11]. Event features can be temporal or non-temporal in nature, with temporal characteristics including instantaneous occurrence or duration as specified by constraint modeling [12]. High-level events are defined through interconnected lower-level event graphs, forming temporal constraint networks im-

portant for applications like healthcare monitoring.

2.3. AI to Support Patient Functional Independence

Improvements in life expectancies resulting from increased life spans in public health, nutrition and medicine have led to the aging of the world population (Beard *et al.*, 2012). It is also important to emphasize that many seniors continue to be active and viable members of society. However, for many people in the group, physical disabilities limit the function of even the simplest movements without help. Hence, failure to maintain independence in the later years in life should be a cause of concern. Research conducted in Britain has shown that older people in Britain are more concerned about loss of independence, 49 percent, than they are about dying, 29 percent [13].

A particular patient may experience focal motor and sensory symptoms while, at the same time, his higher brain functions may be unaffected. BMI systems aim at using preserved brain capability to supplement the losses or injuries of impaired patients, through developing two-way functional link between specific brain cells and the tools that offer motor movements and sensations [14]-[16]. For example, patients with quadriplegia due to an accident or a neurodegenerative disease may be able to regain some measure of use of their limbs, and control a motorized wheelchair or a robotic limb through a BMI that translates their brain signals [17].

3. Neural Signals Translating

3.1. Machine and Brain

Computers and peripheral devices can interface with active components of the nervous system's residual function—intact brain regions or other nerves that may include part of the affected system [18]. These systems employ certain kinds of motor or sensory motion that cause enhanced electro-coupling in the neural areas involved in these particular actions. For instance, movement of limb flexors and extensors indicates that neuron electrical activity occurs in particular areas of the cerebral motor region. While the direct correspondence between electrical conductivity in a piece of the brain and a certain action can be highly complicated and, at times, challenging to predict, scientists have designed numerous ML algorithms that approximate this functional relationship. The algorithms that were discussed earlier learn the relationships between a patient's brain signals and motor functions by adjusting their internal parameters to the optimal settings based on a training data set for which the brain signal and intended movement are already identified.

3.2. Noninvasive Body Mass Indexes

Synchronous BMIs do not physically infringe on the biological tissue while recording neuronal activity. The most frequently used noninvasive technique is electroencephalography (EEG), where electrodes are mounted on the subjects

scalp to pick up electrical voltage changes caused by neural firing in the brain [19]. Application of age-based BMI has resulted in many advanced developments: a wheelchair control [20] and control of a mobile robot. For example, Galan *et al.* in 2018 proposed EEG based system designed to let patients permanently control the movement of motorized wheelchairs. The system integrated an intelligent wheelchair capable of perceiving the user's environment, along with a basic classifier utilizing EEG signals to determine intended movement directions—left, right or forward. Some common motor behaviors, such as arm raises, occur frequently with discernible patterns of associated neural activity. Through prior exposure, algorithms may learn to quickly predict impending actions rather than relying solely on conscious steps like finger counting. The faster a system can respond, the smoother the resulting interaction. In one study where two participants mentally maneuvered a simulated wheelchair on a computer monitor from a start point to a target destination following their planned route, both achieved over 80% accuracy after just one day of training with the system. This demonstrates the potential for EEG-based control to rapidly learn intended movements.

3.3. Invasive Body Mass Indexes

However, the EEG signals obtained from the sensors placed over the scalp are preferred due to being non-invasive, portable and can be collected at any location, but these are significantly noisy [21]. Consequently, a large portion of the recent BMI work has been conducted using signals that are acquired from the motor cortex within microelectrode arrays (MEA) that are implanted onto the brain's surface [22]. These direct recordings are better than the noninvasive procedures [22]. However, to have an MEA, brain surgery is needed. Intracortical BMIs have shown that, to the surprise of non-primates, nonhuman primates as well as paralyzed humans can control computers, electronic wheelchairs, and robotic arms by imagining movement. More recent work by researchers at Battelle and Ohio State University showed that signals recorded intracortically can enable a quadriplegic subject to control a paralyzed limb typically using an external muscle stimulation cuff [23].

3.4. Computerised Diagnosis

Computer-aided diagnosis (CAD) has been an active area of research since at least the 1980s, when publications on automated medical image analysis began increasing. CAD aims to assist clinicians in diagnosis by analyzing images, identifying relevant features, segmenting regions of interest, and classifying images using various computational techniques, including machine learning [24]. Historically, CAD systems primarily analyzed images, but recent AI advances now enable incorporating other health data sources to develop more personalized diagnostic models. Even first-generation non-AI CAD systems introduced in the 1980s found clinical use by physicians [25]. Modern CAD leveraging AI can

perform early computerized screening of medical images from modalities such as CT, X-ray, MRI, PET and ultrasound to detect abnormalities indicative of conditions like cancer [25]. By fusing multi-omics data using powerful algorithms, AI-enhanced CAD systems show promise for more accurate initial risk stratification and referral prioritization.

3.5. Chest Pathology Identification

Chest X-rays contain abundant and subtle details critical for interpretation. Thus, machine learning models supporting radiologist analysis of chest radiographs warrant investigation. Deep neural networks excel at processing raw image data through multilayer feature abstraction and have proven effective for such tasks. However, deep learning typically requires vast annotated datasets, which are rare in healthcare. Despite this limitation, the promise of transferring models pre-trained on non-medical images is evident [26]. For example, a CNN pretrained on the large ImageNet dataset achieved diagnostic performance when fine-tuned on only 93 chest x-rays, demonstrating potential for leveraging non-clinical resources until medical image databases expand sufficiently for native deep learning. This shows potential for deep learning models to benefit radiology even with limited specialized data availability.

3.6. Cardiovascular Disease

It is, therefore, the age group that records the highest CVD mortality rates; approximately 66% of all recorded deaths are of patients with this disease but aged 75 years and above. According to the national statistics of 2009, men and women aged 65 years or older, the leading cause of death were diseases of the heart and cancer in both genders; stroke; and, CLRD among females and CLRD and stroke among males [27].

Indeed, high-risk patients who are at a higher risk of having a cardiovascular event in the next two years can be identified early by evaluating the amount of calcification in the coronary arteries. Deep convolutional networks, which were AI-based on models of biological procedures, were trained on 20 low-dose chest CT images for coronary artery calcium scoring as well as detection of coronary calcification [28]. To train the network, out of 1028 LDCCS, a total of 797 scans were used, and only 231 scans were used to evaluate the performance of the network. The method's detection sensitivity, per scans of coronary calcification was 97%. 2%. The percentage of agreement by the RAS on the risk category assigned to each subject was 84.4%. In general, automatically detected incidence rate was in good concordance with manually calculated cardiovascular score.

3.7. Dementia

Alzheimer's disease is the most common cause of dementia worldwide, resulting in profound cognitive impairment more prevalent in elderly populations. Alzheimer's and other dementias currently affect one in three older adults in the

United States, costing an estimated \$236 billion in 2016 alone [29]. Globally, it was estimated that approximately 46 million people had dementia in 2015, with projections that this figure may double to over 82 million by 2050 unless effective treatments are developed [30].

Early and accurate diagnosis of Alzheimer's has been a focus of research aimed at conducting clinical trials for medications that may provide benefit in earlier disease stages. Modest progress has been made in the last three years through applying advanced machine learning techniques to incorporate new and improved MRI biomarkers and blood-based indicators for predicting cognitive decline earlier. The Alzheimer's Disease Neuroimaging Initiative (ADNI) is a seminal longitudinal study tracking cognition, function, brain structure and biomarkers in healthy elderly controls as well as Mild Cognitive Impairment and Alzheimer's disease patient groups. This work has been instrumental for developing techniques for early detection and monitoring of disease progression.

3.8. Anatomical Structures Classification

On a deeper level, for deciphering deep numerical attributes of medical images that are essential for training diagnosis and detection algorithms, sophisticated AI systems rely on annotation—labeling several organs and anatomical areas. Given the enhanced possibility of hundreds of thousands of images, manually annotating images would be laborious. However, machine learning approaches can numerically evaluate certain visual features. ML has automated organ classification by extracting image texture features into a “bag of visual words” representation [31]. Of course, the kind of document deconstruction can remain at the basic “bag of words” level; a word collection suffices to characterize a document even without considering word frequencies or order. It offers a brief, measure-based document fingerprint. This technique was generalized to “bag of visual words” for images [31], with each represented as a point in vector space containing words describing characteristics. While simple, bag-of-words modeling extracts summary information sufficient for initial medical image analysis, where fully detailed annotation remains challenging.

3.9. Macular Degeneration

The AMD disorder results in permanent vision impairment, thus being a prevalent concern amongst older persons. Apart from the two-dimensional fundus photograph, the three-dimensional imaging by OCT is used in the diagnosis of the AMD. Interpretation of the OCT volumetric is lengthy and challenging especially when it is in the initial stages where most changes may be minor. More specifically, intermediate AMD patients are likely to experience severity in their condition and hence early detection of AMD is important to prevent vision loss. In this paper, it has been revealed that there are opportunities for the usage of unsupervised ML approaches for detection of AMD. In this regard, for the development of an automated and fully-automated segmentation methodology, a

method adopting an unsupervised feature learning approach was proposed which can handle the entire image without the requirement of an accurate pre-segmentation of the retina, as described in [32].

3.10. Clinical Decision Support

Its forms reflect the collection and analysis of clinical information for diagnostic and therapeutic purposes by clinicians. Diagnostic tests, including regularly measured vital signs like blood pressure and body temperature, occasional auxiliary tests such as chest X-rays, and subjective experiences reported directly by the patient, are now complemented by an ever-growing list of data. These include genomic biomarkers and Sensors that have the ability to track endlessly different and enormous number of health indicators, data captured by mobile phones and environmental conditions among others. This has been said to have produced what has now been referred to as the “data age” of medicine [33]. But in this new age, just tapping into these data can unlock value of up to \$454 billion to the health care system in the U.S. [34] However, there is no that all these new data are without some challenges in availability. Indeed, identifying signal and noise can sometimes be challenging, on which aspect of data collection influential insights are carried and which aspects are noisy and unimportant [35]. A notable example of poor predictive performance occurred with Google Flu Trends, which failed to accurately track actual influenza cases during the 2012 winter season despite successfully forecasting prior years [36]. Undoubtedly, challenges exist in effectively capturing and leveraging vast streams of information traversing the internet or large healthcare networks. However, the potential advantages of obtaining enriched, real-time data to power clinical decision aids integrating AI-derived insights have generated significant interest and research efforts. While predictive failures can occur, continued work aims to realize faster, timelier analytics benefiting diagnosis and care through more sophisticated use of widespread digital records and online activities as new sources of epidemiological clues.

3.11. Machine Assistance in the Use of EHRs for Health Improvement

In terms of research, there are new approaches and methods connected with EHRs as well as differences in how the study of health care quality and the effectiveness of health care interventions can be done and can potentially be improved at the level of the individual patient [37]. Evidently, the abundance of precise and extensive health information could be highly complementary to the growth of AI technologies. Several problems are obvious. First, EHRs are intended to provide records to be used clinically and the requirements of research uses (for example, use in health outcomes research) conform well to the data contained in an EHR. Second, to be adopted in EHR clinical environments, AI technologies implementing corresponding systems have to achieve high accuracy and necessarily possess the ability of interpretability by healthcare providers.

Third, the majority of significant clinical data is recorded in the free-form clinician narratives or autobiographies. Machine learning is already applied in healthcare domains like EHR analysis, showing potential for even deeper integration to enhance areas like predictive analytics, personalized care, and automated reporting. Further AI development aims to optimize intelligence gained from comprehensive EHR data.

3.12. HERs-Data Source

Electronic health records (EHRs) have become widespread in U.S. healthcare. Use of the Basic with Clinician Notes standard rose substantially according to the Office of the National Coordinator, from just 4% of hospitals in 2008 to 83% in 2015. Nearly all hospitals now utilize some form of EHR. The Basic with Clinician Notes standard added functionality like physician notes/assessments and test result documentation. While more comprehensive standards incorporating actual medical images exist, far fewer hospitals currently implement them.

As such, many healthcare providers still document patient visits using less feature-rich EHR systems. Continued advancement of standards has the potential to further unlock the value of EHR data through more integrated analytics and clinical decision support. This could help address the gap between top performers leveraging comprehensive records and those with more limited documentation. Some EHR systems are EHR Enterprise systems which have data more real-time; such advanced EHR Enterprise systems are in the possession of some medical providers who offer better opportunities for enhancing the state of clinical monitoring and the options of prediction. Certainly, as has been already stated, it is relatively recent that many organizations began to implement EHR systems and therefore many patient histories are yet to be included in the EHRs.

3.13. Data from Patient History

EHR data obtained appropriately for research presents various opportunities for advanced analytics, as it includes electronic medical codes that are nearly always present as well as electronic concepts that can be derived through natural language processing, along with clinical notes from physicians and nurses that vary in structure from free-form to predefined, in addition to diverse clinical data sources such as medical images, lab results, and sensor readings, and when combined through proper techniques, this comprehensive clinical data encompassed within EHRs can be mined for relationships and utilized to develop predictive models with the goal of enhancing patient care and outcomes, while of course always adhering to strict privacy and consent standards when handling sensitive health information.

3.14. Unstructured Text-NLP

Clinical notes are especially valuable as they contain important clinical descriptions and details that are not always fully captured or consistently represented

within billing codes, as the narrative nature of some codes could potentially lead to inconsistencies or an orientation toward institutional needs rather than patient-centered documentation as noted previously, [38] and these discrepancies coupled with the absence of specific clinical information in codes only further highlight the importance of the unstructured narrative notes which serve as a critical source of granular data like precise vital signs documented in the free-text but not included in diagnostic or billing codes required for reimbursement. Effective extraction of meaningful insights from clinical notes has relied on advancements in natural language processing techniques involving computational methods that map the human language representations within notes into standardized machine-readable formats, showing promise for more complete transformation of clinical narratives into forms suitable for subsequent predictive modeling, decision support, and other analytical applications.

However, trying to apply NLP for analyzing the clinical notes has unveiled to be a rather challenging task mainly due to the fact that clinical notes in English-speaking areas are not written in classical English and clinicians have a way of developing their own terms, abbreviations, and acronyms. Further, clinicians have many terms for one concept, and all of these terms contribute to the confusion [39]. So, there is much more data within the clinical notes than just the categorical diagnoses. As has been mentioned before, for instance, temporality in clinical narrative is crucial in establishing the sequence of events and has elicited interest in numerous studies.

3.15. Images and Sensor Data

It is also feasible for EHRs to include links or references to images as well as any other data from other forms of sensors. Interestingly, the modern techniques in handling of images and the capability of its identification has also significantly enhanced during the recent years, primarily due to the enhancements in the deep learning techniques which are form of many layered neural networks that belong to the class of statistical models of artificial intelligence and is capable of processing images at different levels of detail [40]. Among these technologies, it is worth noting that they not only enhance the image processing of machines but also perform better than people in the task of image classification. By using both image processing and NLP methods, the textual content related to the images can be mined in order to possibly determine the existence of an object or a pathology within the images, and, in fact, the existence of textual descriptions derived from images is also possible [41]. Despite the interest in applying deep learning to the problem of medical imaging, the progress has been comparatively slower compared to other domains of use due to the challenges encounters in sourcing the training data. However, it can also be noted that training these algorithms using EHR data can be beneficial due to their vast data volume. Collectively, these technologies serve as effective tools not only for aiding the radiologists in the analysis of the images but also as enabling platforms for enhancing

investigations in difficult areas like diagnosis of neurodegenerative diseases such as Parkinson's and Alzheimer's diseases.

This versatility indicates that deep learning could be integrated to process several forms of data detected through EHRs, garnered from standard tests and monitoring in the hospital or from outpatient wearable devices that are becoming progressively popular. However, an area that can certainly be considered the greatest in potential may have still remained untouched, namely, only now extensive DNA sequences are being studied with the help of deep learning approaches [42]. Just like imaging could open venues into large scale datasets to train new algorithms and discover additional genotypes for diseases, treatments and patient outcomes, evaluating health records could empower similar abilities for a broad range of areas.

3.16. Use of EHRs for Clinical Support and Treatment

On one level, there are several things that one can point to immediately when discussing EHRs and systematic review, since EHRs consist of rich, patient-specific data that can clearly be used to support systematic review, which is the foundation of evidence-based practice (EBP). Various sources argue that the highest level of evidence for EBP has always been provided by randomized controlled clinical trials. In the case of any chosen medical intervention or practice, such studies are then put together systematically in the form of a systematic review. Nevertheless, these reviews are also lengthy, time taking sometimes over a decade to disseminate into practice and do not ensure the health populations that a clinician is likely to serve in practice [43]. But EHRs are not the information gathering from directed studies; on the contrary, they provide users with the results of clinical data on numerous and heterogenic populations. Another major challenge in this type of studies is the discrepancy between the label-based information EHR contains (currently, codes like ICD-10) and the actual treatment to be investigated in the study [44]. For example, there are definitions of diabetes based on certain numbers of different lab results, but none of them may state why a certain patient is identified with diabetes ICD-10 code in their billing summary. Nevertheless, on some subjects like acute myocardial infarction, EHRs have already been demonstrated to be valuable, as they provide the regular access to the more extensive pool of subjects than it would be possible to enroll in controlled clinical trials [45]. Furthermore, in view of deep preprocessing, there are some efforts to apply deep learning for preprocessing EHRs for identifying the clinical concepts in order to reduce the “semantic gap” between research concepts and clinical concepts [46].

3.17. AI Application in Cancer Research

Cancer remains a major public health concern, currently ranking as the second leading cause of death in the United States. Projections indicate cancer may soon surpass heart disease as the primary cause of mortality in the coming years.

Available data from 2010-2012 estimates lifetime cancer risk at 43% for males and 38% for females [47]. While the overall incidence of cancer has seen little change over the last 20 years, mortality rates have dropped significantly. A 22% reduction in cancer deaths was observed between 1991 and 2011. This decline stems from factors such as fewer Americans smoking, improved prevention through screening, earlier detection, and advancements in treatment approaches.

Genomics plays an important role in several areas that are helping to reduce the burden of cancer. Advances in genomics aid prevention through risk assessment and screening. It also supports more precise detection and diagnosis. Genomic insights increasingly guide targeted treatment selection and monitoring as well. Continued progress in these domains holds promise for further improving outcomes and quality of life for those facing cancer.

3.18. Analytics and ML in Cancer Research

In an earlier approach science has recognized that DNA as the framework of life forms [48]. Before delving into the detailed application of statistical and/or ML techniques in molecular biology today and into the future, some context is needed concerning DNA and the processes and mechanisms important for its replication and function that have become critically dependent on these mathematical tools. It is therefore possible herein to discern these relationships as essential in formulating and identifying the various ways of preventing and treating specific cancers depending on the individual risk [49].

Replication of DNA. A whole copy is to be found within the nucleus of every live human cell. Cells, for instance, are known to grow and then divide after some time has elapsed. This requires that there be a duplicate copy of DNA made in the nucleus so that after division both or the new cells will contain a complete DNA set. It is in this way that most of the changes which may lead to the formation of cancer are initiated, or in other words, the natural replication process is where numerous mutations are created [50]. Molecular biologists and cell biologists, biochemists, and the broad scientific community have amassed a wealth of knowledge on the process/mechanisms by which the DNA content of the cell is translated into function. The human genome comprises 20,000 to 25,000 genes. Human genome as mentioned earlier is made up of DNA, the DNA which specifically has the instructions for building and maintaining the human body. A gene is an assigned section of DNA that contains information regarding the way a particular trait is going to be manifested. Cancer results from changes in oncogenes, tumor-suppressor genes and microRNA genes all of which result in the development of impaired cells and uncontrolled proliferation.

3.19. Cancer Research Connection with ML Examples

Machine learning approaches have been widely applied to study cancer risks, progression, and prognosis. For instance, support vector machines (SVMs), de-

cision trees, and naïve Bayes classifiers were once used to analyze 98 marker single nucleotide polymorphisms (SNPs) across 45 breast cancer genes in 174 patients and controls. [51] Three SNPs were found to indicate high breast cancer risk. SVMs produced the best results, accurately classifying 69% of patients and controls. The involvement of SNPs across different chromosomes supports the notion that cancer arises through additive effects of weak risk alleles.

In machine learning, models are classified as supervised, unsupervised, or semi-supervised based on the availability of “response variables” (e.g. patient class) during training. Supervised learning uses fully labeled data, while unsupervised learning has no labels. Semi-supervised techniques leverage some labeled examples alongside unlabeled data, assuming unlabeled observations provide useful structural information. For the SNP study, patient class labels comprised the response variables, and SNP genotypes served as explanatory variables to train classification models and predict cancer risk. Further refinement of machine learning algorithms may continue improving risk assessment).

3.20. Smart Medication Development and Optimization

Some of the recent points most useful in medication delivery include; Target drug delivery for cancer patient; where medication is delivered directly to the tumor [52]. AI is also being employed to determine the best ways to deliver the drugs as well. For instance, while administering the drugs, it becomes hard to establish the right concentration of the particular drug and the period of time it will be effective in curbing the disease at the same time reducing side effects.

In this regard, an example of applying the proposed ML methods to solve this problem in the context of infectious diseases was presented in vitro experiments with *Giardia lamblia*, a protozoan parasite [53]. With only four combinations of concentrations of the drug and states of pathogens, they achieved 73 percent accuracy of the effectiveness of a particular dose of the drug and with nine, the rate of accuracy was over 97 percent of the actual results. This is rather a useful method for the given task because it needs very little supervision from the physicians, and can be adjusted to shift in the pathogens' population.

3.21. Smart Drug Development

The information available on the impact of chemical entities has been ascending steeply due to HTS and HCS. So many compounds to think of when screening for the desired target makes it very impractical to make complete sense of the data without very many experiments. For instance, if there are only twenty compounds to account for, then attempting each compound in isolation and then with every other compound would mean over a million experiments (precisely 2 to power twenty or 1,048,576 experiments). However, there is also inter-individual variability, that is, the reaction can vary given the circumstances such as age, diseases, genetic predisposition, and even the place in which the drug is used, which adds to the possible outcomes. Current practice demands

that a scientist selects a subset of experiments to be run, which he/she believes are likely to deliver maximum information with minimal cost. This process comes with several drawbacks; for instance, the scientists are unable to make predictions when there exist potential interaction complications.

Active learning approaches for drug development seek to maximize the information gained from each experimental trial. As described by [54], active learning methods first construct a predictive model incorporating relevant interaction terms based on existing data. This model relates variables like perturbagen, target, and cell type to an outcome of interest, such as phenotype.

Rather than randomly selecting new experimental conditions, the active learning model is utilized to strategically choose trials that have the potential to most improve model predictions where current uncertainty exists. For example, if the model response is highly variable for certain untested perturbagen-target-cell type combinations, those experiments may be prioritized to refine that area of the model. Experiments expected to confirm existing predictions are deprioritized.

This aims to enhance the model's ability to predict phenotypic responses to new chemical-target-cell contexts using the smallest number of additional experiments. Advanced these methods by integrating AI techniques to further automate the experiment selection and conduct of optimization trials [55]. Their automated, robotic pipeline required far fewer experimental iterations than a traditional manual trial-and-error approach to map chemical-protein interaction effects.

By leveraging predictive models to strategically select the most informative new experiments, active learning seeks to accelerate target evaluation and drug discovery. Automating these processes through integrated AI and robotics also aims to minimize human involvement and associated costs. However, further research is still needed to fully realize these time and resource efficiencies at scale for real-world drug development programs. Continued technological progress holds promise to increasingly streamline the optimization of potential new therapies.

3.22. Literature Knowledge Extraction Using AI

Major fields in aging are expanding equally at an alarming rate and as a result, there appears to be tremendous pressure of evaluating distinct, sometimes even opposite findings and conclusion made in the literature. This is no longer sufficient for meeting knowledge needs tomorrow: precisely because ordinary document retrieval has been so powerfully addressed by the Google, National Library of Medicine, and others for ordinary documents. It is here that big-picture thinking really fails: Often what is required is not a “document” per se, but those assertions and claims and pieces of data that may be linked; rendering these may require other contextual or explanatory knowledges found in the texts identified in an earlier stage, and which may not be easily seen as associated with the orig-

inally given documents.

Language itself, the conduit of human knowledge and intelligence, was among the first subjects of AI endeavor, which subsumes NLP. While it has been possible to formulate ideas of language understanding and generation since the mid-century, the technical realization of natural language interaction has become possible only recently due to the limitations of computational power. With regard to situation-specific, large-scale, complex written documents, however, we have only been able to somewhat peer into the idea of humanlike reasoning of passages.

3.23. Computational Linguistics

Computational linguistics is an area of study that has established two main approaches for understanding language: statistical and knowledge-based methods. [56] Machine learning plays a role in both, and effectiveness may rely on aspects of each. Statistical techniques focus on inferring patterns and associations between linguistic elements like words, phrases, concepts, and topics based on their distributions and relationships across language samples. This supports tasks such as topic modeling to determine a document's implicit and explicit "aboutness" or related concepts.

Knowledge-based approaches leverage formal representations of expertise regarding a topic's logical structures and conceptual details. This guides identification of nuanced semantic features that may be difficult to discern through statistical analyses alone. While both incorporate machine learning techniques, statistical computational linguistics analyzes top-down probabilistic patterns while knowledge-based methods apply bottom-up domain-specific understandings. Integrating aspects of each may unlock complementary insights relative to their individual strengths and limitations. Continued research refining these methodologies promises to further advance capabilities for language interpretation across domains.

4. Extracting Knowledge

In the context of the study of aging, geriatrics, and gerontology, certain sub-languages may be employed in the textual sources that report results for describing and analyzing the details of the various fields of research within the domain. Semantically-driven methods involve the identification and utilization of knowledge about a certain topic, typically expressed by the use of on-time domain ontologies. An ontology in this context is an "abstract specification of what entities there are in a certain domain of discourse, whereby what is referred to here is the formal definition of the types of entities, their attributes, and their relations" [57]. The primary benefit of ontologies when it comes to comprehending scientific literature is that ontologies can also determine the logical properties of various types of entities described in the body of the literature in that particular field. I was able to show that by converting all contextual knowledge into an on-

tology, appropriate knowledge base is created which can be used to answer questions regarding the research itself and by using such type of queries that may incorporate inferential problem solving—specifically deductive one.

Depending on the design of the semantic tagging output, the knowledge derived from literature can be captured in the form of a graph, where interconnections and viz., sections 2 and 3, overlooks. Knowledge graph-based approaches to computational linguistics provide researchers with a networked view of language that facilitates examining relationships between concepts as well as potential knowledge gaps within literature corpora. [58] Rather than solely utilizing such tools for traditional literature reviews summarizing findings from large bodies of texts, the capability of knowledge graphs to link encoded elements of published evidence through logical inferences opens up new opportunities. By systematically connecting reported results across an extensive knowledge base, it may enable an integrative process of deriving presently undisclosed hypothetical conclusions for advancing initial discovery beyond conventional structured literature reviews. The chaining of logical inferences across many supported research findings could aid hypothesis generation by surfacing relationships not explicitly stated within individual sources. This method therefore presents an exploratory analysis technique with prospective value for accelerated knowledge discovery through leveraging the prospective reasoning of knowledge graphs over significant language data.

5. Access and Affordability

Access and affordability are major concerns regarding the use of AI and machine learning technologies in elderly healthcare. As the costs of developing and implementing these new tools are significant, it is important to consider how the financial burden will be distributed and who will be responsible for covering the costs. For aging populations, many of whom live on fixed incomes, out-of-pocket costs could act as a barrier to accessing important diagnostic and treatment approaches enabled by AI. Ensuring equity of access across different communities will be vital so that geographic and socioeconomic disparities in care are not exacerbated.

However, with proper planning, AI and digital health solutions also hold promise for expanding access to specialized care. Technologies like telehealth could help bridge geographic gaps by allowing elderly patients to connect with top specialists regardless of physical location. Remote patient monitoring through wearable devices and home health sensors has the potential to improve outcomes and quality of life for seniors living with multiple chronic conditions. But realizing this promise requires overcoming infrastructure barriers like limited broadband access in some areas. It also necessitates strict privacy and security measures to protect sensitive health data and build trust among elderly populations. Addressing issues of cost, access, and data protection proactively can help ensure that AI and ML benefit healthy aging in an equitable and socially inclu-

sive manner.

6. Conclusion

Here we have provided and explicated some of the impacts that AI could have on the health and quality of life of the elderly. AI technologies are relatively young but are developing and have vast potential in one way or another in elderly care for instance in medication alerts or any other care scheduling and administration to acceleration and coordination for medication development and usage or even computational algorithms to deliver accurate doses of the same depending on the specific individual for the elderly. For clinical providers, the potential of AI in this role is a valuable opportunity for algorithms to effectively mine large amounts of data, as well as to seek out new information, improve decision support systems, and help physicians diagnose diseases and manage patients' records from multiple disparate systems. Remaining an important field of future research and development, brain-machine interfaces have the promise to return motor functionality to older adults with neurological deficits. Similarly, as adjunct "thinkers" to those who suffer from cognitive disorders or their carers there is another rather active branch of work across the field: AI cognitive agents. Despite the current state of affairs still containing many questions that need to be faced in the future years (see Chapter 1), these technologies seem to progress year after year and, as such, bring some promises that one day, these tools could become clinically feasible—at least—and, maybe, even standard—to offer some degree of control and autonomy to impaired individuals. However, the biggest obstacles to turning these efforts to the next level for utilization in the context of an aging society are not related to certainly not in scientific, engineering or medical potential but rather how to bring these into safe, sustainable, ready-to-use stability in practice.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

- [1] McCorduck, P. (2004) *Machines Who Think: A Personal Inquiry into the History and Prospects of Artificial Intelligence*. A K Peters/CRC Press.
- [2] Campbell, O. (2015) *Designing for the Elderly: Ways Older People Use Digital Technology Differently*.
<https://www.smashingmagazine.com/2015/02/designing-digital-technology-for-the-elderly>
- [3] Hougham, G.W., Rahimi, A.M., McClelland, B.A., McMillan, N.J., Schwemmer, M.A., Friedenber, D.A., Bellay, J., Landgraf, A.J. and Osborne, T.F. (2017) Artificial Intelligence and Its Potential to Improve the Health of Older Adults. In: Chau, D. and Osborne, T.F., Eds., *Using Technology to Improve Care of Older Adults*, Springer Berlin Heidelberg. <https://doi.org/10.1891/9780826142436.0012>

- [4] Mani, S., Chen, Y., Elasy, T., Clayton, W. and Denny, J. (2012) Type 2 Diabetes Risk Forecasting from EMR Data Using Machine Learning. *AMIA Annual Symposium Proceedings*, **2012**, 606-615.
- [5] Rudary, M., Singh, S. and Pollack, M. (2004) Adaptive Cognitive Orthotics: Combining Reinforcement Learning and Constraint-Based Temporal Reasoning. *ICML'04: Proceedings of the Twenty-First International Conference on Machine Learning*, Banff, 4-8 July 2004, 91. <https://doi.org/10.1145/1015330.1015411>
<https://web.eecs.umich.edu/~baveja/Papers/rlcogorthdist.pdf>
- [6] Fernández-Leal, Á., Moret-Bonillo, V. and Mosqueira-Rey, E. (2009) Causal Temporal Constraint Networks for Representing Temporal Knowledge. *Expert Systems with Applications*, **36**, 27-42. <https://doi.org/10.1016/j.eswa.2007.09.044>
- [7] Lee, D., Seo, H. and Jung, M.W. (2012) Neural Basis of Reinforcement Learning and Decision Making. *Annual Review of Neuroscience*, **35**, 287-308. <https://doi.org/10.1146/annurev-neuro-062111-150512>
- [8] Langley, P. (2006) Cognitive Architectures and General Intelligent Systems. *AI Magazine*, **27**, 33-44.
- [9] Chakravarty, S. and Shahar, Y. (1999) Specification and Detection of Periodic Patterns in Clinical Data. <https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=09fa7bc19f7efdc bd74b96062cda6cf529f578c0>
- [10] Artikis, A., Georgios, P., François, P. and Anastasios, S. (2010) Logic-Based Representation, Reasoning and Machine Learning for Event Recognition. *Proceedings of the Fourth ACM International Conference on Distributed Event-Based Systems*, Cambridge, 12-15 July 2010, 282-293. <https://doi.org/10.1145/1827418.1827471>
- [11] Dousson, C. and Le Maigat, P. (2007) Chronicle Recognition Improvement Using Temporal Focusing and Hierarchization. <https://www.ijcai.org/Proceedings/07/Papers/050.pdf>
- [12] Dechter, R., Meiri, I. and Pearl, J. (1991) Temporal Constraint Networks. *Artificial Intelligence*, **49**, 61-95. [https://doi.org/10.1016/0004-3702\(91\)90006-6](https://doi.org/10.1016/0004-3702(91)90006-6)
- [13] Christensen, K., Doblhammer, G., Rau, R. and Vaupel, J.W. (2009) Ageing Populations: The Challenges Ahead. *The Lancet*, **374**, 1196-1208. [https://doi.org/10.1016/S0140-6736\(09\)61460-4](https://doi.org/10.1016/S0140-6736(09)61460-4)
- [14] Aflalo, T., Kellis, S., Klaes, C., Lee, B., Shi, Y., Pejsa, K., Andersen, R.A., *et al.* (2015) Decoding Motor Imagery from the Posterior Parietal Cortex of a Tetraplegic Human. *Science*, **348**, 906-910. <https://doi.org/10.1126/science.aaa5417>
- [15] Bansal, A.K., Truccolo, W., Vargas-Irwin, C.E. and Donoghue, J.P. (2012) Decoding 3D Reach and Grasp from Hybrid Signals in Motor and Premotor Cortices: Spikes, Multiunit Activity, and Local Field Potentials. *Journal of Neurophysiology*, **107**, 1337-1355. <https://doi.org/10.1152/jn.00781.2011>
- [16] Chapin, J.K., Moxon, K.A., Markowitz, R.S. and Nicolelis, M.A.L. (1999) Real-Time Control of a Robot Arm Using Simultaneously Recorded Neurons in the Motor Cortex. *Nature Neuroscience*, **2**, 664-670. <https://doi.org/10.1038/10223>
- [17] Ramli, R., Arof, H., Ibrahim, F., Mokhtar, N. and Idris, M.Y.I. (2015) Using Finite State Machine and a Hybrid of EEG Signal and EOG Artifacts for an Asynchronous Wheelchair Navigation. *Expert Systems with Applications*, **42**, 2451-2463. <https://doi.org/10.1016/j.eswa.2014.10.052>
- [18] Lebedev, M.A. and Nicolelis, M.A.L. (2017) Brain-Machine Interfaces: From Basic Science to Neuroprostheses and Neurorehabilitation. *Physiological Reviews*, **97**, 767-837. <https://doi.org/10.1152/physrev.00027.2016>

- [19] Biasiucci, A., Franceschiello, B. and Murray, M.M. (2019) Electroencephalography. *Current Biology*, **29**, 80-85. <https://doi.org/10.1016/j.cub.2018.11.052>
- [20] Tariq, M., Trivailo, P.M. and Simic, M. (2018) EEG-Based BCI Control Schemes for Lower-Limb Assistive-Robots. *Frontiers in Human Neuroscience*, **12**, Article 312. <https://doi.org/10.3389/fnhum.2018.00312>
- [21] Rashid, M., Sulaiman, N.P.P., Abdul Majeed, A., Musa, R.M., Nasir, A.F., Bari, B.S. and Khatun, S. (2020) Current Status, Challenges, and Possible Solutions of EEG-Based Brain-Computer Interface: A Comprehensive Review. *Frontiers in Neurorobotics*, **14**, Article 25. <https://doi.org/10.3389/fnbot.2020.00025>
- [22] Kao, J.C., Stavisky, S.D., Sussillo, D., Nuyujukian, P. and Shenoy, K.V. (2014) Information Systems Opportunities in Brain-Machine Interface Decoders. *Proceedings of the IEEE*, **102**, 666-682. <https://doi.org/10.1109/JPROC.2014.2307357>
- [23] Friedenberg, D.A., Schwemmer, M.A., Landgraf, A.J., Annetta, N.V., Bockbrader, M.A., Bouton, C.E., Zhang, M., Rezai, A.R., Mysiw, W.J., Bresler, H.S. and Sharma, G. (2017) Neuroprosthetic-Enabled Control of Graded Arm Muscle Contraction in a Paralyzed Human. *Scientific Reports*, **7**, Article No. 8386. <https://doi.org/10.1038/s41598-017-08120-9>
- [24] Doi, K. (2007) Computer-Aided Diagnosis in Medical Imaging: Historical Review, Current Status and Future Potential. *Computerized Medical Imaging and Graphics*, **31**, 198-211. <https://doi.org/10.1016/j.compmedimag.2007.02.002>
- [25] Suzuki, K. (2012) A Review of Computer-Aided Diagnosis in Thoracic and Colonic Imaging. *Quantitative Imaging in Medicine and Surgery*, **2**, 163-176.
- [26] Bar, Y., Diamant, I., Wolf, L. and Greenspan, H. (2015) Deep Learning with Non-Medical Training Used for Chest Pathology Identification. *Medical Imaging 2015: Computer-Aided Diagnosis*, Orlando, **9414**, Article ID: 94140V. <https://doi.org/10.1117/12.2083124>
- [27] Roger, V.L., Go, A.S., Lloyd-Jones, D.M., Adams, R.J., Berry, J.D., Brown, T.M., Carnethon, M.R., Dai, S., De Simone, G., Ford, E.S., *et al.* (2011) Heart Disease and Stroke Statistics—2011 Update: A Report from the American Heart Association. *Circulation*, **123**, e18-e209. <https://doi.org/10.1161/CIR.0b013e3182009701>
- [28] Lessmann, N., Išgum, I., Setio, A.A.A., De Vos, B.D., Ciompi, F., *et al.* (2016) Deep Convolutional Neural Networks for Automatic Coronary Calcium Scoring in a Screening Study with Low-Dose Chest CT. *Medical Imaging 2016: Computer-Aided Diagnosis*, **9785**, Article ID: 978511. <https://doi.org/10.1117/12.2216978>
- [29] Alzheimer's Association (2016) 2016 Alzheimer's Disease Facts and Figures. *Alzheimer's Association Report*, **12**, 459-509. <https://doi.org/10.1016/j.alz.2016.03.001>
- [30] Alzheimer's Association (2023) 2023 Alzheimer's Disease Facts and Figures. *Alzheimer's Association Report*, **19**, 1598-1695. <https://doi.org/10.1002/alz.13016>
- [31] Alfonso, O., Foncubierta-Rodríguez, A., Depeursinge, A. and Müller, H. (2015) Texture Classification of Anatomical Structures in CT Using a Context-Free Machine Learning Approach. *Medical Imaging 2015: Computer-Aided Diagnosis*, **9414**, 94140W.
- [32] Agurto, C., Nemeth, S., Zamora, G., M. Vahtel, Soliz, P. and Barriga, S. (2016) Comprehensive Eye Evaluation Algorithm. *Medical Imaging 2015: Computer-Aided Diagnosis*, **9785**, Article ID: 978518.
- [33] Business Report: Data-Driven Health Care (2014) MIT Technology Review. <https://www.technologyreview.com/business-report/data-driven-health-care>
- [34] Tanwar, R. Balamurugan, S., Saini, R.K., Bharti, V. and Chithaluru, P. (2022) Advanced Healthcare Systems: Empowering Physicians with IoT-Enabled Technolo-

- gies. John Wiley & Sons. <https://doi.org/10.1002/9781119769293>
- [35] Wang, Y. (2017) Education Policy Research in the Big Data Era: Methodological Frontiers, Misconceptions, and Challenges. *Education Policy Analysis Archives*, **25**, 1-24. <https://doi.org/10.14507/epaa.25.3037>
 - [36] Butler, D. (2013) When Google Got Flu Wrong. *Nature*, **494**, 155-156. <https://doi.org/10.1038/494155a>
 - [37] Ehrenstein, V., Kharrazi, H., Lehmann, H. and Taylor, C.O. (2019) Obtaining Data from Electronic Health Records. In: Gliklich, R.E., Leavy, M.B. and Dreyer, N.A., Eds., *Tools and Technologies for Registry Interoperability, Registries for Evaluating Patient Outcomes: A User's Guide, 3rd Edition, Addendum 2*, Agency for Healthcare Research and Quality. <https://www.ncbi.nlm.nih.gov/books/NBK551878/>
 - [38] Stead, W.W., Denny, J.C., Giuse, D., Lorenzi, N.M., Brown, S.H., Johnson, K.B. and Rosenbloom, S.T. (2010) Generating Clinical Notes for Electronic Health Record Systems. *Applied Clinical Informatics*, **1**, 232-243. <https://doi.org/10.4338/ACI-2010-03-RA-0019>
 - [39] Mowery, D.L., South, B.R., Christensen, L., Leng, J., Peltonen, L.-M., Salanterä, S., Suominen, H., Martinez, D., Velupillai, S., Elhadad, N., Savova, G., Pradhan, S. and Chapman, W.W. (2016) Normalizing Acronyms and Abbreviations to Aid Patient Understanding of Clinical Texts: ShARe/CLEF eHealth Challenge 2013, Task 2. *Journal of Biomedical Semantics*, **7**, Article No. 43. <https://doi.org/10.1186/s13326-016-0084-y>
 - [40] Taye, M.M. (2023) Understanding of Machine Learning with Deep Learning: Architectures, Workflow, Applications and Future Directions. *Computers*, **12**, Article 91. <https://doi.org/10.3390/computers12050091>
 - [41] Chen, L., Li, S., Bai, Q., Yang, J., Jiang, S. and Miao, Y. (2021) Review of Image Classification Algorithms Based on Convolutional Neural Networks. *Remote Sensing*, **13**, Article 4712. <https://doi.org/10.3390/rs13224712>
 - [42] Alipanahi, B., Delong, A., Weirauch, M.T. and Frey, B.J. (2015) Predicting the Sequence Specificities of DNA-and RNA-Binding Proteins by Deep Learning. *Nature Biotechnology*, **33**, 831-838. <https://doi.org/10.1038/nbt.3300>
 - [43] Morris, Z.S., Wooding, S. and Grant, J. (2011) The Answer Is 17 Years, What Is the Question: Understanding Time Lags in Translational Research. *Journal of the Royal Society of Medicine*, **104**, 510-520. <https://doi.org/10.1258/jrsm.2011.110180>
 - [44] Elizabeth, W.T. and Stoddart, J.M. (2012) Rethinking Information Delivery: Using a Natural Language Processing Application for Point-of-Care Data Discovery. *Journal of the Medical Library Association*, **100**, 113-120. <https://doi.org/10.3163/1536-5050.100.2.009>
 - [45] Tsai, C.H., Eghdam, A., Davoody, N., Wright, G., Flowerday, S. and Koch, S. (2020) Effects of Electronic Health Record Implementation and Barriers to Adoption and Use: A Scoping Review and Qualitative Analysis of the Content. *Life*, **10**, Article 327. <https://doi.org/10.3390/life10120327>
 - [46] Berge, G.T., Granmo, O.-C., Tveit, T.O., Ruthjersen, A.L. and Sharma, J. (2023) Combining Unsupervised, Supervised and Rule-Based Learning: The Case of Detecting Patient Allergies in Electronic Health Records. *BMC Medical Informatics and Decision Making*, **23**, Article No. 188. <https://doi.org/10.1186/s12911-023-02271-8>
 - [47] Siegel, R.L., Miller, K.D., Fuchs, H.E. and Jemal, A. (2022) Cancer Statistics, 2022. *CA: A Cancer Journal for Clinicians*, **72**, 7-33. <https://doi.org/10.3322/caac.21708>
 - [48] Brownell, L. (2021) DNA: From Blueprint to Blank Slate.

- <https://wyss.harvard.edu/news/dna-from-blueprint-to-blank-slate/>
- [49] Balmain, A., Gray, J. and Ponder, B. (2003) The Genetics and Genomics of Cancer. *Nature Genetics*, **33**, 238-244. <https://doi.org/10.1038/ng1107>
 - [50] Kourou, K., Exarchos, T.P., Exarchos, K.P., Karamouzis, M.V. and Fotiadis, D.I. (2015) Machine Learning Applications in Cancer Prognosis and Prediction. *Computational and Structural Biotechnology Journal*, **13**, 8-17. <https://doi.org/10.1016/j.csbj.2014.11.005>
 - [51] Hajiloo, M., Damavandi, B., HooshSadat, M., Sangi, F., Mackey, J.R., Cass, C.E., Greiner, R. and Damaraju, S. (2013) Breast Cancer Prediction Using Genome Wide Single Nucleotide Polymorphism Data. *BMC Bioinformatics*, **14**, Article No. S3. <https://doi.org/10.1186/1471-2105-14-S13-S3>
 - [52] Mills, J.K. and Needham, D. (1999) Targeted Drug Delivery. *Expert Opinion on Therapeutic Patents*, **9**, 1499-1513. <https://doi.org/10.1517/13543776.9.11.1499>
 - [53] Li, Y., Lenaghan, S.C. and Zhang, M. (2012) A Data-Driven Predictive Approach for Drug Delivery Using Machine Learning Techniques. *PLOS ONE*, **7**, e31724. <https://doi.org/10.1371/journal.pone.0031724>
 - [54] Murphy, R.F. (2011) An Active Role for Machine Learning in Drug Development. *Nature Chemical Biology*, **7**, 327-330. <https://doi.org/10.1038/nchembio.576>
 - [55] Naik, A.W., Kangas, J.D., Sullivan, D.P. and Murphy, R.F. (2016) Active Machine Learning-Driven Experimentation to Determine Compound Effects on Protein Patterns. *eLife*, **5**, e10047. <https://doi.org/10.7554/eLife.10047>
 - [56] Cohen, K.B. and Demner-Fushman, D. (2014) Biomedical Natural Language Processing. John Benjamins Publishing Company.
 - [57] Guarino, N. (2009). Handbook on Ontologies. Springer Berlin Heidelberg.
 - [58] Gubiani, D., Petric, I., Fabbretti, E. and Urbančič, T. (2015) Mining Scientific Literature about Ageing to Support Better Understanding and Treatment of Degenerative Diseases. *Conference on Data Mining and Data Warehouses*, Lubljana, October 2015, 3. https://www.researchgate.net/publication/281816321_Mining_scientific_literature_about_ageing_to_support_better_understanding_and_treatment_of_degenerative_diseases

Index of Abbreviation

AI—Artificial Intelligence
 BMI—Brain-Machine Interface
 EHR—Electronic Health Record
 ML—Machine Learning
 NLP—Natural Language Processing
 CAD—Computer-Aided Diagnosis
 CVD – Cardio-Vascular Disease
 SNP—Single Nucleotide Polymorphism
 SVM—Support Vector Machine
 OCT—Optical Coherence Tomography
 AMD—Age-Related Macular Degeneration
 EEG—Electroencephalography
 MEA—Microelectrode Arrays