



Trends of Machine Learning using Python in Nanotechnology

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ABSTRACT

The genre of nanobiotechnology has become the major area of influence in material sciences and biomedical research. As per the perking trends, amalgam of nanoscience and technology has become the right hand of contemporary world of medicine and healthcare. Machine learning (ML) is a fast-expanding medical profession that integrates computer programming and statistical analytics to tackle medical problems. Machine learning proponents praise the technology's capacity to cope with big, complicated, and divergent data sets, which are widespread in medicine, and hope that ML will considerably boost global healthcare in biomedical research, customized treatment, and computer-assisted diagnostics. The investigation of Machine Learning is considered by taking algorithms and types of learnings into account which are nowadays supported by python. Python has become one of the most amateur programming languages by users which can withstand their study and analysis. The purpose behind this article is to introspect the issues in medicine which benefit from such learning techniques, as well as to explain fundamental machine learning ideas via python. This paper shall cover all areas of utility which uses approaches of machine learning with python to boom their commercial and healthcare sectors.

Key words: Nanobiotechnology; Machine learning; python; healthcare

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INTRODUCTION

ML is a discipline that examines about computers learning from data. It was born at the interface of statistics and computer science, where the goal is to understand relationships from data. This fusion of mathematics and computer science is motivated by the computational challenges of generating statistical models from massive data sets that can contain billions or trillions of data points. There are two types of computer-assisted learning: supervised and unsupervised learning. [1,2]. The purpose of supervised learning is to anticipate a known output or target. Handwriting recognition (such as recognising drug targets) is a common supervised learning problem in machine learning competitions. Classifying pictures of objects (e.g., is this an antigen or an antibody?) and document classification (e.g., is this a clinical study regarding heart failure or a financial report?) are two further supervised learning challenges. Notably, these are all professions that a trained human can do well, which is why the computer usually tries to imitate human performance. Supervised learning is concerned with classification and prediction, which requires selecting subgroups to best characterise a given data instance. Unsupervised learning, on the other hand, has no outputs to foresee. Users are instead looking for naturally existing patterns or groups in the data. This is a more difficult task to measure, and the usefulness of such groups learnt by unsupervised learning is frequently determined by how well they perform in subsequent supervised learning tasks. Consider how unsupervised learning may be used in cardiac illness to achieve this goal, using a diverse condition like myocarditis as an example. Start with a big group of people who appear to be the same yet have unexplained acute systolic heart failure. After that, myocardial biopsies may be performed on them, and the cellular makeup of each sample can be determined by immunostaining. T lymphocytes, neutrophils, macrophages, eosinophils, and other cells would be counted, for example. Then one may look for repeated patterns in cellular composition, which could lead to the discovery of a mechanism and the development of new medicines [3,4]. A similar strategy, this time focusing on genetics, led to the discovery of an eosinophilic subtype of asthma⁷ that responds specifically to a new medication that targets the eosinophil-secreted cytokine interleukin-13.

UTILITY OF ML IN DRUGS

Medicine has not been into the skin of advancement, and in fact, is a productive area for ML. Several medical professionals are unaware with concepts of machine learning. If machine learning is embraced and utilised in research, it has the potential to improve prediction and visualisation quality. With continuous advancements in machine learning methods in medicine, researchers and doctors may find themselves falling behind as healthcare paradigms shift.

a. *Personalised medicines*

Personalized medicine offers a great opportunity to turn a "one size fits all" approach to diagnostics, pharmacological treatment, and prevention into a tailored strategy. Sure, we're all 99.9% alike, but we're also all 0.01 percent different. Because genomics gives us a window into our differences in a very specific biochemical way, it allows us to make unique predictions about disease risk, which might help someone choose a preventative approach that is right for them. Genomic medicine is a crucial component of personalised medicine. In certain situations, it also allows for the selection of the appropriate medication at the appropriate dose for the appropriate person, as opposed to the "one size fits all" approach to pharmacological therapy. Customization is possible because to the capacity of machine learning on several levels, including diagnosis, prognosis, and therapy [5,6]. Within this schema, it may be challenging for the medical professional to predict what patient clusters exist ahead of time, which is where unsupervised learning comes into play. It is not necessary to have 'solved' instances or deterministic classifications to draw relationships and predictions from data, and studies have demonstrated that previously undiscovered patient subgroups may be obtained through data questioning by an uncertain individual.

b. *Therapeutics*

As per principles of deep learning in drug discovery, addition of this ML using a simpler script like python is "revolutionary" and will be useful in prediction of toxicity, mining of genome, and application in chemo genetics. ML and deep learning techniques have improved drug discovery and pharmacokinetic prediction. In addition to pharmacological investigations, ML has been used in unique ways in the field of therapies. Using cell line mutation data, earlier known response rates, and protein-protein interactions, neural networks were utilised to predict response rates to cancer therapies with an accuracy of 85 percent [7,8]. Their utilisation of data from the Genomics of Drug Sensitivity in Cancer (GDSC) and Cancer Cell Line Encyclopaedia (CCLE) projects demonstrates the importance of bioinformatics and databases in personalized medicine.

Surgeries

In surgery, ML has mostly been used in two areas: robots and decision assistance. Researchers present a rapid overview of current surgical robotics research and accomplishments, including autonomous endoscopic guidance and knot tying, performing fundamental tasks with human-like performance, and revealing unique operating procedures that are superior to current practice. Many clinicians are familiar with subset and decision aids, which have been around for a long time and are often utilized online. Similar to medicine and diagnostics, machine learning decision support systems are becoming more frequent in detecting clinical candidates, feasible post-operative problems, making diagnoses, and providing result forecasts [9,10]. Using smartphone images of iatrogenically induced tissue ischemia, researchers developed a prophetic algorithm using k-nearest neighbor (a pattern recognition and regression machine learning approach) that could detect or measure its venous or arterial occlusion and may be able to distinguish between occlusion (venous, arterial, and mixed vascular) with a sensitivity (94 %) and specificity (98 %) using smartphone pictures of the subject's fingers.

In Cancer Research and Hematology Studies

Hematology, oncology, and histopathology, like radiology, are data-intensive professions, with current practice including massive data sets obtained from clinical examinations, computerized medical records, radiographic images, histological images, and genetic information, among other sources. Furthermore, most patients are progressively being included in databases to track their therapy response. As a result, these specialties have complex multi-dimensional datasets with many layers of interconnectivity, necessitating the use of a more flexible and scalable tool due to the large size and diverse types of data (genetic, proteomic, clinical, biochemical, temporal, demographic, therapeutics, continuous, nominal, categorical, binary, etc.). The benefits of radiological image processing have been applied to histology images, with several studies illustrating how this skill may be used in new ways. Image analysis software was used by the researchers to supplement the collection of lung cancer images, providing new variables for an ML software programme. The computer was able to generate classifiers that could automatically distinguish tumour cells and predict long-term survival, and the researchers anticipated that similar

techniques may be used to other cell types and contribute to precision oncology. They achieved this by developing fully automated image segmentation software to locate nuclei and cytoplasm in 2,187 histopathological specimens (i.e. benign, squamous cell, and adenocarcinoma cases) and then profiling 9,880 quantitative parameters from each image. They next employed a variety of machine learning algorithms (support vector machine, naive Bayes, and random forest) to accurately predict survival outcomes that outperformed those predicted by traditional pathologic evaluation based on tumor stage and grade [11]. Many research imply that ML techniques outperform expert-based or statistical systems in terms of prediction accuracy in cancer, indicating a shift toward artificial neural networks. With bigger, linked datasets, the potential predictive ability and individualization of treatment decisions grows, and it is vital that these databases are preserved and enhanced in the future.

APPLICATION IN NANOMATERIALS

The rage of construction of nanomaterials in this era is the most happening topic for researchers (**Fig.1**). The requirement has been so high that it has resulted in the development of numerous computational/theoretical subjects, such as computational chemistry and biology, which have grown increasingly common with the fast growth in computer power over the previous decade or two. Nanomaterial characteristics are significantly difficult to predict than those of conventional materials due to quantum phenomena at such small sizes, hence machine-learning approaches are being used. Various networking strategies backed by my ML have been used to study and optimize the numerous diverse traits and properties imaginable at the nanoscale: Artificial Neural Networks, deep neural networks, and generative adversarial networks. These results may be analyzed and used to come up with the best potential answer for creating a new nanomaterial or optimizing an existing nanomaterial. It's similar to a more sophisticated version of computational chemistry/biology that may be used to materials with unusual characteristics and phenomena [12]. To mention a few, such approaches have been used to develop and optimize a variety of nanomaterials, including 2D materials, 2D material heterostructures, nanoscale catalysts, nanophotonic materials, and 1D materials.

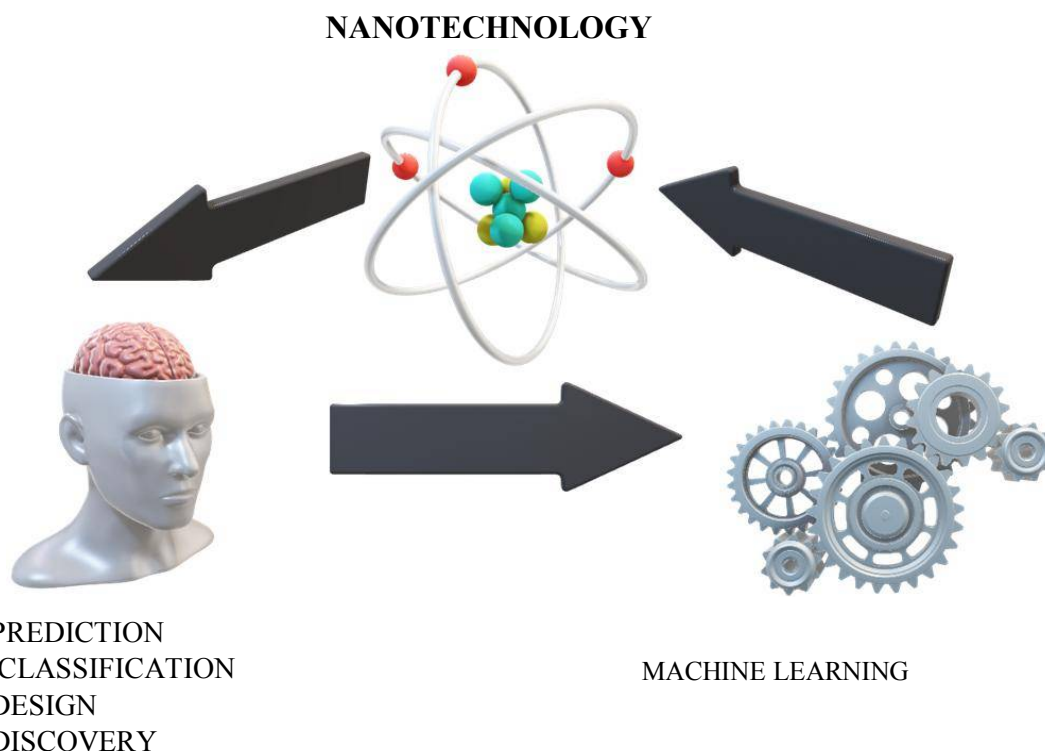


Fig.1. Applications of Nanotechnology

FUTURE PERSPECTIVE OF MACHINE LEARNING IN MEDICINE

The potential applications and accuracy of ML are somewhat exaggerated, but the work done so far gives a glimpse of the actual application related to digital imaging systems including medical data base or its records, and linked with testing of several parameters related to human healthcare in hospitals. The results are widely adopted. The flow of data (clinical) may be available to researchers is increasing or

enhanced in terms of its quantity and quality. The algorithmic baselines of ML can support the study of various drug targets and help scientists decide the best approach. Over fitting, under fitting and best fitting models encompass all areas of research and help opt best idea commercially. The future research hopes to design artificial brain using nanotechnology and making a machine that learns function as brain. Deep learning and big data are the major demand of various sectors in all alone. Management of data and results of research can be maintained using these approaches. The data of bioinformatics and HGP can be maintained via big data. The use of ML to healthcare data has resulted in a number of intriguing and perhaps game-changing innovations [13]. While some clinicians, such as radiologists, are equally optimistic and concerned about how machine learning will affect their field of expertise, pessimists are pessimists, many of the work will be redundant if the current trajectory of success continues and thus replaces the next as an extension [14, 15].

CONCLUSION

Continuing the fusion of computer science along with statistics, ML not only represents the next wave of improvements in today's healthcare, but is already used in a variety of healthcare disciplines with great success in real-world applications. The transition to large-scale applications and integration into standard clinical practice is inevitable, and the problem may be when. In this study, we took up machine learning theory, examined the most common ML algorithms used in medicine, and looked to the future. Machine learning with a view to personalized treatment is more likely to produce computer-aided medical assistants than autonomous "doctors", but the concept of "deep learning" hospitals is completely theoretical. Instead, we are actively building and integrating databases to support this process. In short, physicians should be familiar with this core concepts and indicators of machine learning and understand its applications and correlate with Artificial intelligence and machine learning into modern medicine.

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