

# Unveiling the Potential: Machine Learning Reshaping Nuclear Medicine Diagnostics and Treatment

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Submitted: 17/09/2023

Revised: 16/11/2023

Accepted: 28/11/2023

**Abstract:** Embarking on an exploration of the symbiotic relationship between Machine Learning (ML) and the dynamic field of Nuclear Medicine, this comprehensive overview delves into the multifaceted roles and evolving landscape of ML within this specialized domain. The narrative spans from the genesis and progressive trajectory of ML, elucidating the varying algorithms that underpin its functionality, to a discerning delineation of scenarios where each algorithm finds unique relevance and utility in the realm of nuclear medicine. This discourse pivots on an examination of the profound impact ML have already exerted on this domain, elucidating the diverse contributions that have reshaped nuclear medicine while candidly addressing the prospects and limitations that await in the future. It unearths the latent potentials and realistic constraints surrounding the integration of ML, offering a critical evaluation of its current and potential capabilities, paving the way for a holistic understanding of its applications. Amidst the plethora of applications, a focused lens is directed towards the burgeoning studies in low-dose Positron Emission Tomography (PET), disease detection, image reconstruction techniques, and the development of prognostic and outcome prediction models. These advancements, rooted in ML methodologies, mark a pivotal milestone in enhancing diagnostics and prognostics within nuclear medicine, fostering a paradigm shift in patient care and treatment. The culminating section of this discourse sets forth a clarion call to action, advocating for standardized reporting measures in study designs and outcomes. It advocates for a standardized checklist, a guiding beacon for the research community, fostering consistency and coherence in the dissemination of knowledge. Addressing the prevalent issue of variable algorithm presentation in the literature, this segment underscores the pressing need for uniformity and standardized conventions in the publication of ML-driven studies within the domain of nuclear medicine. In essence, this discourse seeks to paint a panoramic view of the vast landscape where ML converges with nuclear medicine, underscoring the need for methodical precision and unified standards in the realm of knowledge dissemination correct.

**Keywords:** algorithms; artificial intelligence; Machine Learning; atomic medicine; machine learning; semantic networks; nuclear medicine.

## 1. Introduction

At now, it seems like every conference offers a session on Artificial Intelligence or Digital Learning, and these terms are appearing more frequently in our literature. Although they are not new, AI and ML. The phrase "artificial intelligence," which was first used in 1956, describes computer programmes that can carry out tasks that would typically need Intelligence of people (e.g., visual perception or decision making). Machine learning (ML), a branch of AI, has its origins in the electronic computers of the 1950s [1] and its application to healthcare in the 1960s. [2]. In its broadest definition, machine learning Instead of depending on the explicit programming experience of the programmers, (ML) refers to procedures that are built to learn from observations and can afterwards draw statistical conclusions based on what has been learned. Like creating a precise recipe for baking a cake, a programmer traditionally specifies every facet of an algorithm, and nothing else is learned after that. ML methods integrate analogous to a novice cook using a faulty recipe to make a

cake, attributes with unknown values at the time of programming that are learned by giving the programme evidence. Based on his or her observations, the chef must choose which ingredients to utilize [3] and in what quantities. Why are there more ML approaches for diagnostic imaging now? Some of the explanations include advances in theory (better algorithms), microsystems (better hardware), and the accessibility of a vast amount of training data (i.e., big data). Additionally, areas like radiomics [4]

and radio genomics have showed a lot of potential [5]. Radio genomics is the measurement and release of mathematical signifier (sometimes referred to as traits) of picture texture, form, and different attributes that can be associated with many types of data, including histopathologic results and clinical consequences.[6] Additionally, radio genomics links radiomics traits to genetic information. These emerging domains use ML to uncover frequently undiscovered links between scientific phenomena.

## 2. Mathematical Model

A mathematical model can be used to translate input observations into outputs and to explain correlations between data. A mathematical model, for instance, a

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function that transforms input information from an image [6] into an output determination (for example, the classification of a scan as either negative or positive for amyloid deposition). [7] Choosing a model is frequently based on balancing factors such as accuracy, task fit, and practical implementation considerations. Regression issues are those where the output observation of the model is valued continuously (e.g., the deposits of amyloid), [7] whereas classification problems are those where the output observation or categories are discrete-valued. Various mathematical structures have varying degrees of intricacy or propensity for prediction.

[7] Many models have so-called hyperparameters, which are pre-selected parameters that can be changed if output falls short. For instance, it might be decided initially that each amyloid brain PET result would be categorized as either positive or negative for amyloid deposition (i.e., two outcomes allowed); however, training may reveal that certain scans are ambiguous. [8] A supervised technique is ideal for using an ML algorithm to appropriately classify data into arcs and triangles because the classification scheme is established. Assigning data to categories in a situation where the categorization scheme is unknown calls for an unsupervised method. There may be two clusters of data points, according to an observer. [8] A different individual, however, may add more clusters to the data points. In the end, it could be required to make a preliminary educated guess regarding the number of categories. Potential models for each scenario are depicted in Figures 1D–1F. A straight line in Figure 1D draws a distinction between the circles and triangles. In this scenario,

[5] the mathematical model is linear, axis first  $b$ , and the machine learning system will discover both the values  $a$  and  $b$  that minimize the amount of incorrect groupings (diminishes the price factor). Because there are fewer triangles in the vicinity of the circles in Figure 1D, line 2 costs less than line 1. [9] A potent ML algorithm could change  $a$  and  $b$  to the more advantageous outcome. A linear model will invariably result in a large number of incorrect classifications in Figure 1E. In this situation, a more intricate nonlinear model may be more appropriate for this purpose.

### 3. Cost Function

How closely the model's output matches the desired outcome is determined by a cost function (also known as a loss function). The mean square error [7] or misclassification rate, for instance, may be the cost function.

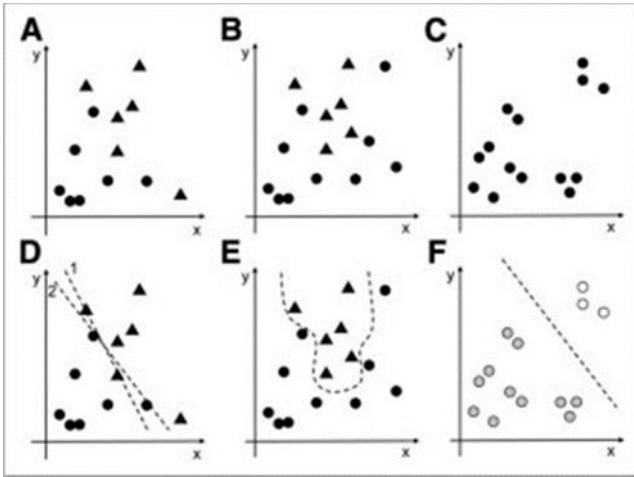
#### 3.1. Data

Utilizing data, an ML algorithm is trained. Data may consist of survival information, image measurements (like as SUVRs for a PET study on amyloid), or a mix of these and

other results. Subgroups of data are frequently established for coaching, evaluation, and assessment. Using training dataset, the trained model's efficacy is verified., the hyperparameters are adjusted using validation data, and the model is trained using training data [10]. Known outcomes are typically included in the data. For instance, a physician may have labelled all of the available amyloid PET scans as either. A positive or negative result for amyloidosis. Sometimes the conclusions are unknown. Whether the results of the scan are either amyloid-positive or -negative, [11] they may, for instance, have all the SUVRs for the ROIs. Whether the data contain known outputs separates two general algorithms in ML.

#### 3.2. Supervised and Unsupervised Learning

The algorithms in ML that are trained using predetermined results are referred to as supervised learning. [12] For instance, an ML algorithm could predict neurologic consequences based on earlier SUVR/ROI data. Neurological findings and combination's. Supervised algorithms, in a sense, establish a mathematical structure's unknown parameters. Based on training data with the intention of forecasting results for future test results Typical supervised machine learning algorithms. [13] Neural networks that use artificial neural networks, forests, and support vector machines using linear regression are shown here. (ANNs). Unsupervised learning describes machine learning techniques that use training data with unknowable results. These algorithms frequently resolve issues as figuring out how to data compaction (lowering the variety of attributes required to predict an outcome) or seeing trends in the data (e.g., clustering amyloid PET into amyloid-positive or -negative without prior understanding of the PET scan's category). [11] Unsupervised machine learning (ML) methods include decomposition of singular values, analysis of primary components, and grouping. Theoretically, Figure 1 demonstrates these ideas. The data points in Figures-1A and 1B are divided into shapes and spheres. There is no categorization of the data points in Fig.1C. A overseen strategy is advised if the goal is to properly train an ML system. [12] to classify data into rounds and triangular and the classification algorithm is assigning data to categories in a situation where the categorization scheme is unknown calls for an unsupervised method. There may be two clusters of data points, according to an observer. Different user, however, may as well add more clusters to the data points. In the end, [13] it could be required to make a preliminary educated guess regarding the number of categories. Potential models for each scenario are depicted in Figures 1D–1F. A straight line in Figure 1D draws a distinction between the circles and triangles. In this scenario, the mathematical model is linear, and the machine learning system must discover the total values that [14] minimize the variety of incorrect categories (reduces the expense factor).



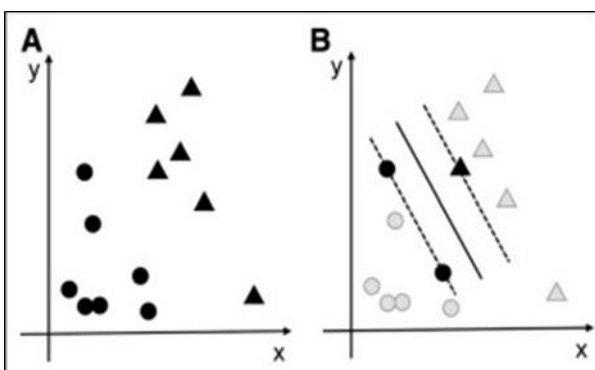
**Fig. 1.** Tasks ML. input measurements in (A and B)

### 3.3. Common ML Algorithms

There are numerous ML algorithms mostly with created assistance developed in various programming languages [6]. (e.g., as libraries, toolkits, or packages). The ideal approach to employ frequently relies the complexity of the statistical model, the task, and the data (The quantity of inclusions and operations such as addition that must be made). These algorithms vary greatly from one another. [15]

### 3.4. Naïve Bayes Classification and Linear Regression

The automated Bayes classification method technique that categorizes traits which adhere to an easily understood probabilistic model (For instance, a multivariate regression or Normal distribution.) and assumes that the qualities are unrelated to one another (allowing for mathematical solutions). [10] The distribution's properties, such as the average for each class, as well as the deviation of the attributes, [13] are known as hyper-parameters. In order to classify something, features are examined, and the method improves a probabilistic functional category is determined. Low computational costs are involved. For instance, Mehta et al- retrospective's [11] investigation utilized a



**Fig. 2.** Illustration of support vector machine

multinomial naïve Bayes classifier to forecast 90Y radioembolization response characteristics. The use of 22 training scenarios, 8 test cases, and the precision for predicting the reaction was probably around 80%.

Regression line offers the most optimal system. simply to the dataset among n-dimensional classifications (thus the linearity). [13] regression, which is a supervised technique for regression issues with n-dimensional constant datasets characteristics. Total mean square difference between actual results and those predicted by the model is used to define the cost function. [14] The cost of computing is little.

### 3.5. Hierarchical Clustering

A well-liked machine learning approach for classification and regression analysis is called a Support Vector Machine (SVM). They function by identifying the ideal decision border that divides the various data classes [22]. An SVM looks for a hyperplane in a binary classification problem that optimizes the margin between the two classes. The margin is the separation between the hyperplane and each class's nearest points. In addition to decreasing the misclassification error, the SVM seeks to identify the hyperplane that optimizes this distance. SVMs can still be employed even if the data cannot be separated linearly by translating it into a higher-dimensional space using a process known as the kernel trick. Finding non-linear decision boundaries that can better separate the data is made possible as a result. [8]. SVMs are superior to other machine learning algorithms in a number of ways. They work well in high-dimensional spaces, use little memory, and are theoretically sound according to the max-margin principle. They are also capable of handling tiny and medium-sized datasets with ease. They are less prone to overfitting than other algorithms and are able to handle non-linear decision boundaries through the use of kernel functions the difficulty of deciphering the model's decision-making process and the sensitivity to the selection [24] of the kernel function and hyperparameters are two drawbacks of SVMs.

### 3.6. Resolution

An unsupervised clustering algorithm is hierarchical clustering. By pairing and clustering the closest surrounding data points until there are no more free data points, hierarchical clustering searches for data commonalities.[15] A dendrogram is the name given to the resulting structure. For instance, Tsujikawa et al. suggested linked findings on induced neurotoxicity PET in individuals with cervical cancer using a dendrogram [16].

### 3.7. Random Forest

A machine learning approach called Random Forest can be applied to both classification and regression applications. It is an ensemble learning technique that creates several decision trees during training, then combines their predictions during testing to produce a final result. [17] The method selects a random selection of features and cases to create each tree in the forest (These subsets' sizes can be thought of as hyperparameters.) In our example, the available ROIs are used to randomly select the subset of

instances and the subset of features. [18] and the clinical values from amyloid PET scans, respectively. For the left pile of cases, the left branch is produced, and for the right pile, the right branch is created. The property and attribute value that, according to accuracy of classification, most effectively distinguishes the cases in the subset into a left stack and a right heap is initially identified before each tree is formed iteratively. The tree's endpoints, which can also be classes, are reached and serve as [12] the outputs when a pile only contains examples that belong to a single class (for example, all negative or all positive cases) (for classification problems). They are all distinct since each tree deals with a certain collection of data. Fresh data are provided to each tree for classification after the forest has been built; the decision is determined by the majority of the trees. [19]

### 3.8. ANN's

ANNs can solve classification or regression problems and are typically (but not always) supervised. ANNs go through data in stages (called layers). [20] The micro functional units, or neurons, at each layer transmit the outputs to the neurons at the level below after they process the input data. The weighted summation of the inputs and a bias are typically used to start a neuron's calculation. After that, the result undergoes a nonlinear transformation. An algorithm called backpropagation is employed for training [17] (learning weights' values). The most efficient but also computationally intensive ML techniques are often ANNs. Each cell in a layer is usually linked to just about every neuron in the layer above it, which boosts computation time. Together, DNNs and CNNs have enabled the current ML boom (in fact, The bulk of ANNs used today are both deep and multilayer, and there is no distinction between the two in the literature. Compared to more conventional ML techniques, deep learning often requires less human input during the training process. [18] Deep learning is unfortunately more difficult and typically involves a lot of training data to work well. For instance, more than a million annotated photos were utilized in the ImageNet challenge [13]. It is frequently challenging to obtain such a huge number of training samples in medical imaging.

### 4. Considerable Issues and Discussion

Which ML algorithm to select or the rationale behind a particular algorithm's use in a publication are two issues that can be difficult. There are Several algorithms that actually need massive databases [17] particularly when splitting up them into groupings for coaching, verification, and certification). To start, each machine learning (ML) method focuses on a certain task (such as classification, regression, dimensionality reduction, or any, other strategies, such as data augmentation, have been developed to address this issue. Potential biases in datasets are one danger. ANNs were accidentally tricked by seemingly unimportant factors

like lighting conditions in the early days of machine learning! [20] The conclusion is that when subgroups are too small, even the most merciful Machine learning algorithms and the best augmentation techniques will fall short.

Machine Learning (ML) has remarkably contributed to the evolution of nuclear medicine, fundamentally reshaping diagnostic and therapeutic approaches. ML's impact in this domain is multifaceted, revolutionizing diagnostics through advanced imaging techniques. ML algorithms, particularly in Positron Emission Tomography (PET) and Single-Photon Emission Computed Tomography (SPECT), have enabled superior image reconstructions, offering clearer and more precise visualizations. Moreover, ML innovations have substantially reduced radiation exposure in these imaging processes, presenting low-dose imaging solutions without compromising diagnostic accuracy, thereby ensuring safer protocols for patients. The application of ML algorithms, including support vector machines and neural networks, has significantly enhanced [25] disease detection and classification. By deciphering intricate data patterns, these algorithms empower early disease detection and classification, critical for timely interventions. Moreover, ML's predictive prowess has led to the development of prognosis models and outcome predictions, allowing for personalized treatment strategies tailored to individual patient needs, improving overall patient care. Furthermore, ML has spurred research and development, propelling the discovery of new biomarkers and innovative imaging methodologies. Collectively, these contributions underscore ML's pivotal role in enhancing the precision and efficacy of nuclear medicine, promising a future of more accurate diagnostics and tailored therapeutic [23] interventions for improved patient outcomes.

### 5. Future Scope

The future scope of Machine Learning (ML) in the context of nuclear medicine and medical imaging holds tremendous promise yet is confronted by certain challenges that warrant attention for advancement. While ML applications in medical imaging are still relatively nascent, the fusion of hybrid imaging, particularly PET/MR, presents an ideal terrain for ML due to its capacity to gather diverse data concurrently. However, limitations persist, primarily the requirement for vast, high-quality medical databases to ensure the accuracy and reliability of ML-driven findings. Thrall et al. (2018) [22] proposed the establishment of global and national image sharing networks, reference databases for evaluating AI programs, and standardized practices for refining and validating advanced testing protocols, all of which could significantly bolster ML in medical imaging. Additionally, as ML becomes more pervasive in nuclear medicine, several pertinent issues surface, including individual patient responsibilities, data privacy, ethical considerations, and the necessity for

unbiased procedures [23]. The process for assessing algorithms and their applicability to wider patient populations with differing data availability remains a critical concern that demands resolution for the broader integration of ML technologies. Addressing these challenges will be crucial for the successful proliferation and responsible deployment of ML in medical imaging and nuclear medicine. However, the comprehensive exploration and resolution of these complexities lie beyond the scope of this study and necessitate focused research and collaborative efforts for further development in the field.

## 6. Conclusion

This article serves as an introductory exploration of the intersection between Machine Learning (ML) and nuclear medicine, offering a comprehensive insight into the developmental trajectory of ML, a discussion on prevalent algorithms, and practical examples illustrating their applications within nuclear medicine. Delving into the existing contributions of ML in this specialized field, it scrutinizes the prospects and constraints shaping the future landscape of nuclear medicine. An extraordinary breakthrough appears imminent in the medical application of nuclear medicine, particularly with the rising popularity [26] of Artificial Neural Networks (ANNs) and the emergence of novel algorithmic families specifically tailored for nuclear medicine applications. The growing momentum in shared picture databases is poised to enhance the availability of expansive datasets essential for training, testing, and validation purposes. Nonetheless, unresolved issues loom large, notably pertaining to data ownership, deidentification, and the ethical considerations surrounding data privacy. Amidst this, the standardized reporting of ML algorithm metrics emerges as a crucial necessity for establishing a collective understanding of the current status quo. The study also envisions recommendations for data collection methodologies that can construct infographics, elucidating the most suitable machine learning techniques for varied applications within nuclear medicine. It anticipates providing comprehensive insights into the operational scope of ANNs, their diverse therapeutic applications, and envisions potential future directions for this evolving synergy between ML and nuclear medicine. This informative study paves the way for understanding the intricate interplay between ML and nuclear medicine, aiming to shape future advancements and foster responsible integration within this specialized domain.

### Author contributions

**Pankaj Pathak:** Conceptualization, Methodology, Samaya Pillai: Data curation, Writing-Original draft preparation, Amrit Kuchroo: Visualization, Investigation, Writing-Reviewing and Editing.

### Conflicts of interest

The authors declare no conflicts of interest.

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