Machine learning tools in training of medical staff

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Abstract: *A key challenge in the field of healthcare is the integration of artificial intelligence methods and tools to support the activities of physicians in decision-making processes. The analysis of medical data is essential for understanding the disease, monitoring and predicting the development of the disease. The report examines Machine Learning techniques that are used to analyze the effectiveness of various treatments, extract and interpret complex, multidimensional data from medical studies to improve diagnostic and prognostic accuracy. Algorithms based on Deep Learning reveal hidden patterns and dependencies and offer predictions that support medical staff in their activities and assessment. Approaches for combining heterogeneous data are considered in order to improve the effectiveness of the models. The work involves the design of an intelligent application that can assist medical staff and improve their training and integration into the work environment.*

Keywords: Artificial Intelligence, artificial neural networks, deep learning.

1. The field of deep learning in medicine

In recent years, deep learning models have shown great potential in the field of medicine. Deep Neural Networks (DNNs) are a type of neural network consisting of multiple layers that process and transform input data, improving the accuracy of the models in solving complex tasks. DNNs are the basis for many modern technologies. Potential applications include bioinformatics and medical language processing (Mamoshina et al., 2016) for automated drug discovery or for navigating the vast unstructured data available in the scientific literature. In recent years, deep neural networks have revolutionized many areas of machine learning. Today, they are the basis for groundbreaking advances in medical diagnostics, feature extraction from magnetic resonance imaging (MRI) images, and their analysis in combination with many other data to identify patterns that predict molecular changes.

Convolutional Neural Networks (CNNs) are a type of neural network, primarily used in image processing, that use filters to extract important features from data. They achieve pattern recognition by exploiting spatial dependencies and hierarchical representations of data, which distinguishes them from traditional artificial neural networks. Their adaptability and efficiency define the latest advances in Deep Learning, making them a major factor in modern AI. Their main

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property is that they can detect features in images, such as brightness, dark spots or a specific color, contours at different orientations, patterns, etc. Artificial neural networks are difficult to train to detect similar features based on pixels in the input data, because in different images the features may be present in different locations, orientations and sizes (McCorduck et al., 1977). Convolutional neurons are typically placed in the lowest layers of a multilayer neural network, where they process the raw input pixels. They can be trained from large amounts of unlabeled data (images without labels). The underlying neurons (such as the perceptron neuron) are placed in the higher layers, which process the output data from the lowest layers, and are trained using supervised machine learning techniques and an error backpropagation algorithm.

Other architectures, such as *Recurrent Neural Networks (RNNs),* which incorporate feedback loops and *Long Short-Term Memory (LSTM),* are being investigated for their ability to recognize temporal dependencies and patterns in medical imaging data with successive measurements (Prasad et al., 2024). RNNs are a type of neural network that processes sequences of data, text, or speech, using internal states to remember information from previous steps. They are recurrent because they perform the same operation on each successive input. *LSTMs* are a specialized type of recurrent neural network that can remember information for long periods. They consist of a memory cell, an input gate, an output gate, and a forget gate. The memory cell stores values for arbitrary time intervals, the forget gates filter and discard some of the input information for each iteration, and the output gate decides which information from the current state will comprise the final output. Selectivity in the output allows LSTMs to maintain useful, long-term relationships and make predictions at current and future time steps. These neural networks are capable of learning complex patterns in multidimensional, time-varying data. Therefore, they are applied to identify anomalies based on the difference between the model's prediction and the actual observed values.

Ian Goodfellow of Google Brain proposes a combination of two neural networks. They compete with each other, with one trained to generate images from the training data. The other “adversarial network” has the task of separating the images generated by the first network from the real images (the training data). A system of this type, called a *generative adversarial network (GAN)*, trains both models in parallel. As the generative network improves, the adversarial model also improves, and the cycle continues until the generated images become very similar to the real images.

Modular neural networks (MNNs) divide complex tasks into smaller and independent sub-modules that can be trained in parallel. The use of modular architectures for medical imaging allows for high accuracy in tasks such as tumor detection and anomaly classification. Modular networks can process different data sources – such as computed tomography and magnetic resonance imaging (MRI) – with high efficiency. (Hu et al., 2024) emphasize that combining different modules in neural networks improves the recognition of spatio-temporal features of images, which is especially useful in neurological diseases such as Alzheimer's.

An advantage of the modular architecture is the possibility of training specialized modules for different sub-tasks. Guebsi and Chokmani demonstrate how networks can be applied to accurately recognize heart and lung diseases by dividing the diagnostic process into separate components (Gabsi & Hedi, 2024). An advantage of MNN is the easier interpretation of the models, with modular structures providing clear dependencies between input data and predictions, which is important for clinical applications (Shin et al., 2024,).

Neural networks can be built based on fuzzy logic, as it better corresponds to the inaccuracies and ambiguities registered in the real world. In (Sotirov, et al., 2025), a hybrid deep learning framework is proposed, which combines convolutional neural networks with intuitionistic fuzzy estimates. The goal is to improve the accuracy, sensitivity and robustness of pneumonia detection in pediatric chest X-rays. Inception v3, one of the neural network architectures specifically designed for image processing, is applied. It was developed by Google and is part of the Inception model series, the structure of which is shown in Figure 1 (Sotirov et al., 2025).

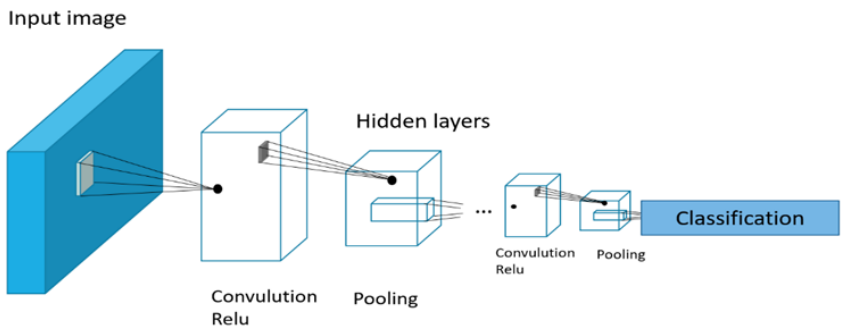

Figure 1. CNN Inseption V3 neural networks

2. ML techniques for medical data analysis

Researchers are focused on developing models that can extract and interpret complex, multidimensional data, with the goal of improving diagnostic and prognostic accuracy (Ahsan et al., 2022). The process of data analysis depends on a number of factors, including data availability, data quality, preprocessing techniques, as well as algorithms that are applied.

Machine learning techniques, such as Random Forests (RF) and Support Vector Machines (SVM), as well as deep learning architectures such as Convolutional Neural Networks (CNNs), are essential for automated medical data analysis.

Support vector machines (SVMs) are powerful machine learning algorithms that are widely used in medicine for image classification, text data, and bioinformatics, due to their ability to handle multidimensional and complex data (Rodríguez-Pérez & Bajorath, 2022). SVMs work by finding an optimal hyperplane that separates data into different classes while maximizing the distance between them, in order to achieve the best separation. This distance (margin) is the distance between the hyperplane and the closest points of each class, known as support vectors. By maximizing this margin, SVM improves the model's ability to generalize, making it effective for classifying new, unknown data. SVMs are particularly effective at handling high-dimensional data and can model both linear and nonlinear relationships. This flexibility makes SVMs a valuable tool for complex biomedical applications, such as genomic classification or visualization (Miteva, 2024).

The limited availability of large, annotated datasets poses a challenge for training and validating ML models. Many existing biomedical datasets are small and lack sufficient diversity, which can lead to problems with overfitting and poor generalization (Massimo et al., 2024). Ensuring transparency and developing models that not only demonstrate high accuracy but also provide interpretable explanations for their predictions further complicates the problem (Ibomoiye et al., 2024).

Medical imaging data analysis is important in understanding diseases, monitoring their progression, and predicting clinical outcomes (Mengfang et al., 2023). Typically, genetic analysis of cancer requires surgical intervention to extract a tissue sample and is time-consuming to analyze. A reliable method for predicting the genetic features of cancer through imaging, such as magnetic resonance imaging, could provide faster diagnosis in certain cases (Saeed, et al., 2022). It could guide the specialist towards more precise and personalized treatment, improving the accuracy of patient prognosis.

Integrating multimodal data (e.g., combining radiomic features with genomic and clinical data) offers much richer capabilities, but introduces additional complexity. For ML models to successfully integrate these heterogeneous data types, precise data preprocessing, extraction of relevant features, and use of sophisticated model architectures are required (Miteva, 2024).

3. Multimodal data integration

Traditional machine learning models struggle to integrate different types of data that differ in structure and scale (e.g., medical images and genomic sequences). Integration of diverse multimodal data is a growing area of research, such as combining MRI data with genetic, clinical, and even environmental data. This integration is expected to improve prediction accuracy by allowing models to capture a wider range of features and achieve higher accuracy. Various data fusion techniques and ensemble methods are being explored to improve model performance (Xu et al., 2024). Image preprocessing plays a key role in improving data quality, helping to reduce noise and correct parts of images (Trojani et al., 2024).

Ensemble method in machine learning is a powerful approach that combines the predictions of multiple models to improve the overall performance, often surpassing the capabilities of each individual model separately (Opitz & Maclin, 1999). The following approaches to data integration are considered:

- *Early integration* - combining raw data before modeling, usually performing fusion of data from sensors and other sources. Early sensor-level fusion methods include Random Forest, SVM, Bayesian Inference, Fuzzy Logic, Artificial Neural Networks, Dempster–Shafer, etc. For example: the integration of different data, such as combining MRI data (radiomic data), with genetic, clinical and even environmental data is expected to improve the accuracy of predictions and create a robust and generalized model from heterogeneous data sources.

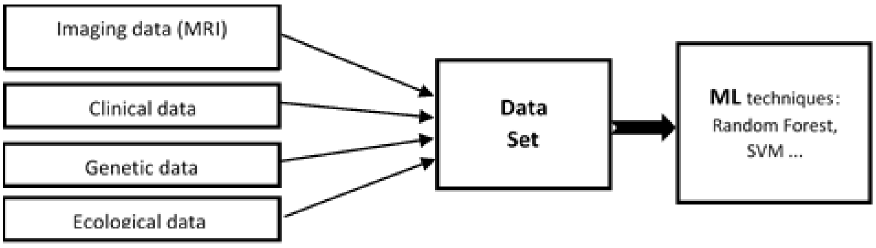

Figure 2. Early sensor data fusion scheme (early sensor-level fusion)

- *Inter-functional integration* - merging data from features, combining features extracted from different data types. Early Fusion from Features methods can be: Principal Component Analysis (PCA), Singular Value Decomposition (SVD), Multidimensional Scaling (MDS), Deep Learning, etc.

By merging features, ML models can be improved, Figure 3 shows a diagram in which data sources are initially processed to extract the characteristic features that describe them. The most significant of them are then selected, which will be used to create models through regression and/or classification. The results can be used in decision-making processes.

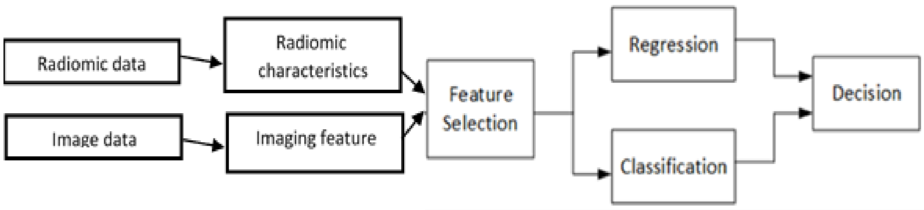

Figure 3. Data merge scheme from functions (Early feature fusion)

- *Late integration* - Late fusion is divided into Late Fusion from Scores and Late Fusion from Decisions. These methods can effectively reduce the error and provide a more accurate final forecast.

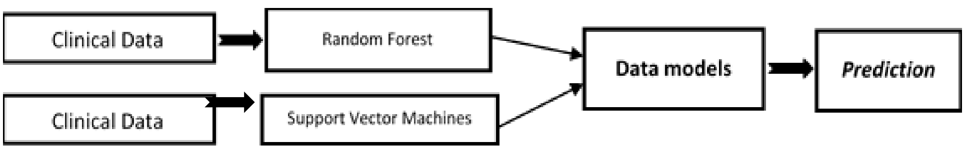

Figure 4. Scheme for late merging of results (Late Fusion from Scores)

An example of late decision merging is performing a combination of outputs, through techniques such as majority voting for classification tasks or averaging for regression tasks.

According to a comparative study of methods from different algorithms conducted in (Pereira et al., 2024), ensembles not only improve prognostic accuracy, but also increase the model's robustness to noise and bias, which supports more reliable clinical decision-making.

4. Intelligent application to support the training and adaptation of medical staff

The integration of ML techniques in various areas of medical practice allows for earlier and more accurate diagnosis, precise treatment planning, and effective disease monitoring. Algorithms based on Deep Learning analyze large volumes of data, reveal hidden patterns and dependencies beyond human perception, and offer predictions that rival expert judgment. The approaches considered for interpreting heterogeneous and multimodal data from medical examinations and other sources are related to the task of improving the effectiveness and performance of ML models, their diagnostic and prognostic accuracy.

The report provides an overview of various models and approaches to machine learning in medicine as part of a dissertation study related to the possibilities for integrating artificial intelligence methods and tools to support medical staff in their training and assessment in decision-making processes. The work involves the design and development of an intelligent application to support the activities and adaptation of staff, providing access to targeted resources, guidelines, and recommendations for work, depending on the context of the tasks they perform. The hypothesis is that such an approach can significantly assist medical staff and improve their education and integration into the work environment.

The conceptual framework of the application combines a model of knowledge domains, which will be represented through ontologies for the application domain, a set of technologies supporting knowledge management, and intelligent assistants that implement key functionalities of the system (such as summarization, categorization, and search). This conceptual framework is intended to serve as the basis for building a flexible space in which different approaches and technological options for extracting new knowledge and improving navigation in semantic repositories can be explored and validated. At this stage of the work, basic functional requirements are extracted from the analysis of technological solutions in the field of medicine, which enrich the set of approaches and methods, and can be used in the development of such an application. According to the delegated rights of the user, the system should redirect him to the various knowledge domains, provide access to documentation, provide tools for knowledge analysis, summarized information, and recommendations for effective use.

The knowledge, skills and experience of medical staff to use the technological potential are essential. In this new work environment, a new type of medical literacy is needed - understanding data, algorithms, working with software. The connection between technology and medicine is becoming stronger and well-prepared medical staff is a guarantee of success and prosperity.

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