Health Analytics

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Summary
The health analytics review focuses on machine learning, natural language processing, data mining and process mining methods: their usefulness, use cases, tools and relatedness to Norwegian healthcare.

The report aims to increase the audience’s better understanding of health analytics and the methods to be utilized in improving the performance of healthcare.

Keywords
Health data, health analytics, artificial intelligence, machine learning, deep learning, data mining, process mining, natural language processing

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1. Background

Demographic trends, availability of health personnel and new treatment methods challenge the sustainability of healthcare. How can future health service be designed for more preventive, patient-centered, and cost-effective care, and reduce burden on health system? How can we utilize artificial intelligence (AI) for providing equal accessibility and quality of health services to all citizens?

Health analytics is a process of deriving insights from health data to make informed healthcare decisions. While such aspects of health analytics as the use of statistical models, data mining, and clinical decision support have existed for decades, only recent availability of enormous volume of data from various sources and increased processing power have made it readily available to support integrated decision making. Machine learning, data and process mining and natural language processing are the main topics in the report.

Data integration technologies provide completely new opportunities for advanced analytics. Health analytics has evolved from being descriptive to being predictive and prescriptive.

- **Descriptive analytics** looks at what has already happened.
- **Predictive analytics** tries to say something about what is going to happen. This involves projecting the trends and patterns in historical data and real-time data to predict, for example, the future development of health situation of a patient or patient groups in the population.
- **Prescriptive analytics** is a step further. By using medical knowledge, it can evaluate alternative treatments and find the optimal one in a given situation. Prescriptive analytics is key in personalized medicine.

HIMSS\(^1\) has developed a systematic model, the Adoption Model for Analytics Maturity\(^2\) (AMAM), used to evaluate maturity of healthcare organizations within the analytics field. On the second most advanced stage of the AMAM model, there are predictive analytics and risk stratification. Prescriptive analytics and personalized medicine are on the most advanced stage; to get to this level, genomic data must be available.

Good analyses require access to relevant high-quality data. A significant challenge for health data is its heterogeneity and complexity. The healthcare processes generate a large amount of unstructured data, such as medical images and free text. Therefore, in order to exploit the full potential of health data, the machine-learning analytics tools can be utilized. Moreover, for preserving the meaning of data, it is necessary to harmonize it with both a common data format and terminology.

The governmental white paper “One Citizen - One Record” \(^1\) promotes that “data should be available for quality improvement, health monitoring, management and research”. The Norwegian e-health strategy (2017-2022) \(^2\) has “better use of health data” as one of the strategic focus areas.

The Norwegian Directorate of e-health is developing a national health analytics platform, which will “… simplify access to health data and facilitate advanced analytics across health registries, source data, health records and other sources of health information.” It is further stated: “The Directorate of e-health aims to contribute to testing and development of new technologies in health analytics, such as artificial intelligence, machine learning, algorithms and predictive analytics.” In addition, the Norwegian Technological Council\(^3\) has its own project focusing on AI and the welfare state \(^3\).

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\(^1\) [https://www.himss.org](https://www.himss.org)
\(^2\) [http://www.himssanalytics.org/amam](http://www.himssanalytics.org/amam)
\(^3\) The Norwegian Technological Council is an independent public body that provides advice to the Norwegian Parliament and the Norwegian Government on new technologies
The implementation of large-scale e-health solutions challenges the organization of health services, including authority structures, financial systems, legal and ethical frameworks [4]. Research on the implementation of national large-scale solutions demonstrates this being a complex and time-consuming task for the sector actors [5-7]. The establishment of the National Board for e-health and national efforts to increase the sector’s capacity to implement will contribute to the dissemination of knowledge to national services [2].

Health analytics is a large and complex field. AI technology is gaining momentum in the development of future digital services and tools for interaction in healthcare. Therefore, it is important for healthcare policymakers to acquire knowledge in this field.

1.1. Project objective

The contribution of the report and the project is to improve awareness and increase knowledge and skills about health analytics, artificial intelligence and machine-learning techniques and how to utilize health analytics in improving the performance of healthcare.

1.2. Approach

Conducting research and gathering information for the report was performed as an exploratory literature study. Information search has been done through PubMed, Google Scholar, and Google. In addition, interviews with the research groups and individual researchers were conducted. A web-based survey was held among actors in natural language processing. To identify relevant publications and stakeholders, the “snowball” sampling technique has been applied. By this method, existing study subjects recruit future subjects from their acquaintances.

1.3. Organization of the report

The report chapters are machine learning, natural language processing, knowledge discovery in databases, machine-learning tools, and stakeholder mapping. Several chapters include concept basics, usefulness, and current knowledge in the field, use cases, and relatedness to the Norwegian healthcare.
2. Machine learning

The application of machine learning principles to health data can help find structure and extract meaning from such data. Together with the vast amount and variation in data being produced about people’s health, it is increasingly clear that machine learning in healthcare can contribute to improving both the efficiency and quality of medical care now and in the future.

2.1. Definition of the concept

The terms “artificial intelligence” (AI) and “machine learning” (ML) are often used interchangeably. However, they are not the same.

According to Merriam-Webster dictionary, artificial intelligence is “a branch of computer science dealing with the simulation of intelligent behavior in computers”, and “the capability of a machine to imitate intelligent human behavior” [8].

Machine learning has become a core sub-area of artificial intelligence. It is a collection of mathematical and computer science techniques for knowledge extraction, preferably actionable knowledge, from large data sets, and the use of these techniques for the construction of automated solutions for classification, prediction, and estimation problems [9]. These automated solutions are able to continuously learn and develop by themselves without being explicitly programmed.

Figure 1 shows an extended Venn diagram that illustrates the intersections between machine learning and related fields in the universe of data science, originally created by SAS Institute ([10]).

![Figure 1. Machine learning, other concepts, and their interconnections in data science universe. Source [11]](image)

Machine learning is commonly divided into the following subfields:

- supervised learning
- unsupervised learning
- semi-supervised learning
- reinforcement learning
2.1.1 Supervised learning

A learning algorithm using supervised learning receives a set of inputs along with the corresponding correct output to find errors. The analyst will choose one or several models, which generally has a number of training parameters. Based on the inputs, the training algorithm optimizes the model parameters and may update these as more data becomes available [12].

Supervised learning involves the use of labelled data. The dataset is split into three subsets: training, test and validation datasets, usually in proportion 60/20/20. A training set is used to build the model; it contains data with labelled target and predictor variables. Target variable is a variable whose values are to be modeled and predicted by other variables; predictor variables are the ones whose values will be used to predict the value of the target variable [13]. A test set is used to evaluate how well the model does with data outside the training set. The test set contains the labelled results data but they are not used when the test set data is run through the model until the end, when the labelled data are compared against the model results. The model is adjusted to minimize error on the test set. Then, a validation set is used to evaluate the adjusted model on the test phase where, again, the validation set data is run against the adjusted model and results compared to the unused labelled data.

If the model performs accurately using the training data but underperforms on new data, it is overfitting, i.e. the model describes the noise in the training set rather than the general pattern and has too high variance. If it performs poorly on both training and test data, it has too high bias (the model is
underfitting). Both overfitting and underfitting leads to poor prediction on new data sets. See Figure 3 for examples of underfitting and overfitting models.

![Figure 3. Left: Model performs poorly (underfitting). Center: Model generalizes well. Right: Model is too complex and overfitting. Source [15] ](image)

This bias-variance trade-off is central to model optimization in machine learning (Figure 4). The more parameters are added to a model, the higher the complexity of the model, the higher variance and the lower bias; the total error of the model raises. If the model has too few parameters (too simple model), variance decreases while bias increases, which also leads to a high total error of the model.

![Figure 4. Bias and variance contributing to total error. Source [16] ](image)

Various techniques based on information theory are used to balance variance and bias. Supervised learning is often used on classification and regression problems [17]. The purpose of Classification is to determine a label or category [18]. An example in healthcare is classification of dermoscopic images into malignant and benign categories. Features, such as color, border, and homogeneity of the mole are extracted from the images and used for training the ML model. Eventually the algorithm can provide decision support for classifying new images unseen by the algorithm.
Regression helps to understand how the value of the dependent variable is influenced by the changes of a selected independent variable, while keeping other independent variables constant [17]. This method is used, for example, for prediction of mental health costs [20].

There are many algorithms used for supervised learning. Logistic Regression, Decision Trees, K-Nearest Neighbors, Support Vector Machines are among them.

**Logistic Regression** [17]

Logistic regression is best suited for binary classification, i.e. datasets where output is equal to 0 or 1, and 1 denotes the default class. The method is named after the transformation function used in it, called the logistic function \( h(x) = \frac{1}{1 + e^{-x}} \).

In logistic regression, the output is in the form of probabilities of the default class. As it is a probability, the output (y-value) lies in the range of 0-1. The output is generated by log transforming the x-value, using the logistic function. A threshold is then applied to force this probability into a binary classification (i.e. if a value is less than 0.5, then output is 1).
Decision Trees [23, 24]

A decision tree is a graph that uses branching method to show each possible outcome of a decision. To train a decision tree, the training data is used to find which attribute best “splits” the training set with regards to the target. After this first split, there are two subsets that are the best at predicting if there is only the first attribute available. Then it is iterated on the second-best attribute for each subset to re-split each subset. This splitting process continues until it has been used enough attributes to satisfy the research needs.

K-Nearest Neighbors [17, 24]

The k-nearest neighbors (kNN) method can be used for both regression and classification problems, and uses the closest neighbors of a data point for prediction. For classification problem, the algorithm stores all available cases and classifies new cases by a majority vote of its k nearest neighbors. The
case being assigned to the class is most common amongst its k nearest neighbors measured by a distance function. These distance functions can be Euclidean, Manhattan, Minkowski (continuous function) and Hamming distance (categorical variables). If k is equal to one, then the case is simply assigned to the class of its nearest neighbor. For regression problem, the only difference from the discussed algorithm will be using averages of nearest neighbors rather than voting from nearest neighbors.

Support Vector Machines [24, 27]

Support Vector Machines (SVM) are binary classification algorithms. Given a set of points of two classes in N-dimensional place (where N is a number of features the data set has); SVM generates a (N-1) dimensional hyperplane that differentiates those points into two classes. For example, there are some points of two linearly separable classes in 2-dimensional space. SVM will find a straight line that differentiates points of these two classes; this line is situated between these classes and as far as possible from each one.

SVMs are able to classify both linear and nonlinear data. The idea with SVMs is that, with a high enough number of dimensions, a hyperplane separating two classes can always be found, thereby delineating data set member classes. When repeated a sufficient number of times, enough hyperplanes can be generated to separate all classes in N-dimension space.
Ensemble Methods [17, 24]

Ensemble means combining the predictions of multiple different weak machine learning models to predict on a new sample. Ensemble learning algorithms have the following advantages:

- they average out biases
- they reduce the variance (the aggregate opinion of several models is less noisy than the single opinion of one of the models)
- they are unlikely to over-fit (if individual models do not over-fit, then a combination of the predictions from each model in a simple way (average, weighted average, logistic regression) will not overfit)

Random Forest and Gradient Boosting are examples of ensemble methods.

Random Forest [23]

A random forest is the average of many decision trees, each of which is trained with a random sample of the data. Each single tree in the forest is weaker than a full decision tree, but by putting them all together, the overall performance is better due to diversity.

Figure 10. An example of SVM work. Source [28]

Figure 11. An example of how Random Forest algorithm works. Source [29]
**Gradient Boosting** [23]

Gradient boosting, like random forest, is also made from “weak” decision trees. The core difference is that in gradient boosting, the trees are trained one after another. Each subsequent tree is trained primarily with data that had been wrongly identified by previous trees. This allows gradient boost to focus on difficult cases.

![Gradient Boosted Decision Tree](image12.png)

*Figure 12. An example of gradient boosted decision tree. Source [30]*

### 2.1.2 Unsupervised learning

Unlike supervised learning, unsupervised learning is used with data sets where data is not labeled beforehand. An unsupervised learning algorithm explores raw data to find underlying structures [12].

![Unsupervised Learning](image13.png)

*Figure 13. Unsupervised machine learning. Source [14]*

The main types of unsupervised learning problems are association, clustering, and dimensionality reduction [17].

**Association** is applied to discover the probability of the co-occurrence of items in a collection. For example, if an association exists and how strong this association is [17].
Clustering groups samples such that objects within the same group (cluster) are more similar to each other than to objects in other groups (clusters) [17]. Segmentation is related to clustering. An image is divided into several sub regions/segments that are conceptually meaningful or simple for further analysis in a process. Usually the goal is to locate objects and boundaries in the images. There are various methods to do this, like clustering using K-means, compressing image to reduce texture, edge detection or Markov fields. Segmentation process is widely used in medicine for analysis of MRI, CT, X-ray, ultrasound images.

Dimensionality reduction means reducing the number of variables of a dataset while ensuring that important information is preserved [17].

K-means, Principal Component Analysis, and Topological Data Analysis are examples of unsupervised learning algorithms.

K-means [17]

K-means is an iterative algorithm that groups similar data into clusters. It calculates the centroids of k clusters and assigns a data point to that cluster having least distance between its centroid and the data point. There are four steps in the k-means algorithm. Step 1 includes a choice of k value, random assignment of each data point to any of the k clusters, and computation of cluster centroid for each of the clusters. In step 2, each point is reassigned to the closest cluster centroid. In step 3, the centroids for the new clusters are calculated. Then, steps 2 and 3 are repeated until nothing changes.

Figure 14. CT image segmentation (on the left - original CT image, in the center - CT image using threshold technique, on the right - edge-based Segmentation of CT image). Source [31]
Principal Component Analysis [17]

Principal Component Analysis (PCA) is used to make data easy to explore and visualize by reducing the number of variables. This is done by capturing the maximum variance in the data into a new coordinate system with axes called “principal components”. Each component is a linear combination of the original variables and is orthogonal to one another. Orthogonality between components indicates that the correlation between these components is zero.

The first principal component captures the direction of the maximum variability in the data. The second principal component captures the remaining variance in the data but has variables uncorrelated with the first component. Similarly, all successive principal components capture the remaining variance while being uncorrelated with the previous component.
Topological data analysis [9]

Topological data analysis (TDA) creates topological networks from the data sets equipped with a distance function, and by the layout process obtains a shape describing the data set. A topological network consists of a set of nodes and a set of edges. There are two properties completely describing how network shapes correspond to the data.

- Each node in a network corresponds to a collection of data points, not individual data points. The collections corresponding to different nodes may overlap.
- Two nodes whose corresponding collections of data points overlap are connected by an edge.

A typical TDA pipeline consists of the following steps [34]:

1. The input is a finite set of points with a notion of distance between them.
2. A “continuous” shape is built on top of the data in order to highlight the underlying topology or geometry.
3. Topological or geometric information is extracted from the structures built on top of the data.
4. The extracted topological and geometric information provides new features of the data. They can be used to better understand the data (through visualization) or they can be combined with other kinds of features for further analysis.

2.1.3 Semi-supervised learning

Semi-supervised learning is a class of supervised tasks and techniques that makes use of unlabeled data for training: they typically require only a small amount of labeled data together with a large amount of unlabeled data [36]. Therefore, semi-supervised learning can be regarded as a combination of unsupervised and supervised learning.

Labeling data often requires a human specialist or a physical experiment (a time and cost consuming process) while unlabeled data may be more easily available. Thus, in health applications, semi-supervised learning can be effective due to the huge amounts of medical data required for research.

Figure 17. TDA visualization of clinical and billing data from total knee replacement patients. Source [35]
An example of semi-supervised learning in healthcare is its use for EHR phenotype stratification. Researchers combined denoising autoencoders (which perform dimensionality reduction enabling visualization and clustering) with random forests for classification of amyotrophic lateral sclerosis subtypes and improvement of genotype-phenotype association studies that leverage EHRs [37]. Read more about denoising autoencoders in section Autoencoders Neural Networks.

2.1.4 Reinforcement learning

Reinforcement learning is a type of machine learning algorithm that allows the machine to decide the best next action based on its current state, by learning behaviors that will maximize the reward [12]. Reinforcement learning differs from standard supervised learning because correct input/output pairs are never presented. Instead, the focus is on current performance, which involves finding a balance between exploring unknown territory and exploiting current knowledge. In other words, reinforcement algorithms usually learn optimal actions through trial and error [17].

Supervised vs Reinforcement Learning [14]

In supervised learning, a human supervisor creates a knowledge base and shares the learning with a machine. However, there are problems where the agent can perform so many different kind of sub-tasks to achieve the overall objective, so that the presence of a supervisor is impractical. For example in a chess game, creating a knowledge base can be a complicated task since the player can play tens of thousands of moves. It is imperative that in such tasks the computer learns how to manage affairs by itself. It is more feasible for the machine to learn from its own experience. Once the machine has started learning from its own experience, it can then gain knowledge from these experiences to implement in the future moves. This is the biggest and most imperative difference between the concepts of reinforcement and supervised learning. There is a certain type of mapping between the output and input in both learning types. Nevertheless, in reinforcement learning there is an exemplary reward function that lets the system know about its progress down the right path, which supervised learning does not have.
Reinforcement vs. Unsupervised Learning [14]

As mentioned before, reinforcement learning has a mapping structure that guides the machine from input to output. In unsupervised learning, the machine focuses on the underlying task of locating the patterns rather than the mapping for progressing towards the end goal. For example, if the task for the machine is to suggest an interesting news update to a user, a reinforcement-learning algorithm will look to get regular feedback from the user in question, and use this feedback to build a reputable knowledge graph of articles that the person may find interesting. An unsupervised learning algorithm will look at articles that the person has read in the past, and suggest something that matches the user’s preferences based on this.

Reinforcement learning is used, for example, for classifying lung nodules based on medical images [38]. However, use of reinforcement learning in healthcare is quite challenging due to high number of parameters that need to be tuned or initialized. Choosing the optimal values for these parameters is usually performed manually based on problem-specific characteristics, which is unreliable or sometimes even unfeasible. Moreover, it is difficult to generalize and explain both the learning process and the final solution in reinforcement learning algorithms, being a “black box” problem. Read further about algorithm/model transparency in section 2.1.6 Interpretability of machine learning algorithms.

2.1.5 Neural networks

An artificial neural network (ANN) is a computational non-linear model based on the neural structure of the brain that is able to learn to perform tasks like classification, prediction, decision-making, visualization, and others just by considering examples.

An artificial neural network consists of artificial neurons (processing elements) and is organized in three interconnected layers: input, hidden that may include more than one layer, and output (Figure 19).

If there is more than one hidden layer, the network is considered deep learning. Deep neural networks learn by adjusting the strengths of their connections to better convey input signals through multiple layers to neurons associated with the right general concepts [40]. When data is fed into a network, each artificial neuron that fires transmits signal to certain neurons in the next layer, which are likely to fire if multiple signals are received. The process filters out noise and retains only the most relevant features.
There are some popular types of deep learning ANNs as:

- **Convolutional Neural Networks**
- **Deep Autoencoders**
- **Recurrent Neural Networks**
- **Deep Belief Networks**

**Convolutional Neural Networks [41]**

Convolutional neural networks (CNN) convolves learned features with input data, and uses 2-D convolutional layers. This makes it well suited to processing 2-D data, such as images.

A CNN can have many layers where each layer learns to detect different features of an image. Filters are applied to each training image at different resolutions, and the output of each convolved image is used as the input to the next layer. The filters can start as very simple features, and increase in complexity to features that uniquely define the object as the layers progress.

CNNs eliminate the need for manual feature extraction. They work by extracting features directly from data (see Figure 20). This automated feature extraction makes CNN deep learning models highly accurate for computer vision tasks.

**Autoencoders Neural Networks [43, 44]**

An autoencoder is a neural network with three layers: an input layer, a hidden (encoding) layer, and a decoding layer. The network is trained to reconstruct its inputs, which forces the hidden layer to try to learn good representations of the inputs.

There are several types of autoencoders, but the most popular (and the basic) one is denosing autoencoder (DAE). To force the hidden layer to discover features that are more robust and prevent it from simply learning the identity, the DAE is trained to reconstruct the input from a corrupted version of it. The amount of noise to apply to the input is typically 30 percent, but in the case of very little data, the noise percent is higher.
Recurrent Neural Networks [46]

Recurring neural networks (RNN) allow for both parallel and sequential computation. An RNN is a variant of a recursive ANN in which connections between neurons make a directed cycle. It means that output depends not only on the present inputs but also on the previous step’s neuron state. RNNs process an input sequence one element at a time, maintaining in their hidden units a state vector that implicitly contains information about the history of all the past elements of the sequence. This memory allows users solve NLP problems like connected handwriting recognition or speech recognition.

Deep Belief Networks [44, 48, 49]

A deep belief network (DBN) is composed of multiple layers of latent variables (“hidden units”), with connections between the layers but not between units within each layer. When trained on a set of examples without supervision, a DBN can learn to probabilistically reconstruct its inputs. The layers then act as feature detectors. After this learning step, a DBN can be further trained with supervision to perform classification.

DBNs can be viewed as a composition of simple, unsupervised networks such as restricted Boltzmann machines or autoencoders, where each sub-network’s hidden layer serves as the visible layer for the
Boltzmann Machine is an RNN with stochastic binary units and undirected edges between units. An RBM is a Boltzmann Machine that consists of hidden layers with connections between the layers but not between units within each layer.

Neural networks are great at solving problems where the data is highly structured. However, deep learning applications are not able to explain how they came up with their predictions. This “black box” problem is quite challenging in healthcare. Doctors do not want to make medical decisions that potentially might harm the patient’s health and life without understanding the machine’s train of thought towards its recommendations.

2.1.6 Interpretability of machine learning algorithms

According to Miller [51], interpretability is the degree to which a human can understand the cause of a decision. The higher the interpretability of a model, the easier it is for someone to comprehend why certain decisions/predictions were made.

Molnar describes the following levels of interpretability [52]:

- **Algorithm transparency** *(How does the algorithm create the model?)*
  
  Algorithm transparency is about how the algorithm learns a model from the data and what kind of relationships it is capable of picking up. This is an understanding of how the algorithm works, but not of the specific model that is learned in the end and not about how single predictions are made.

- **Global, holistic model interpretability** *(How does the trained model make predictions?)*
  
  A model is called interpretable if one can comprehend the whole model at once [53]. To explain the global model output, we need the trained model, knowledge about the algorithm and the data. This level of interpretability is about understanding how the model makes the decisions, based on a holistic view of its features and each of the learned components like weights, parameters, and structures. However, it is very hard to achieve in practice.

- **Global model interpretability on a modular level** *(How do parts of the model influence predictions?)*
  
  While global model interpretability is usually out of reach, there is a better chance to understand at least some models on a modular level. In the case of linear models, the interpretable parts are the

![Figure 23. Example of a basic deep belief network for binary classification with k hidden layers. Source [50]](image-url)
weights and the distribution of the features. The weights only make sense in the context of the other features used in the model. Nevertheless, arguably the weights in a linear model still have better interpretability than the weights of a deep neural network.

- **Local interpretability for a group of prediction** (*Why did the model make specific decisions for a group of instances?*)

The model predictions for multiple instances can be explained by either using methods for global model interpretability (on a modular level) or single instance explanations. The global methods can be applied by taking the group of instances, pretending it is the complete dataset, and using the global methods on this subset. The single explanation methods can be used on each instance and listed or aggregated afterwards for the whole group.

- **Local interpretability for a single prediction** (*Why did the model make a specific decision for an instance?*)

We can also look at a single instance and examine what kind of prediction the model makes for this input, and why it made this decision. Local explanations can be more accurate compared to global explanations since locally they might depend only linearly or monotonic on some features rather than having a complex dependence on the features.

Examples of interpretable ML algorithms are linear regression, logistic regression, decision tree, KNN, naive Bayes classifier, and some others.

### 2.2. Usefulness – why do we need this technology?

There are several features that characterize healthcare data [54].

- **Much of the data is in multiple places and in different formats**
- **The data can be structured or unstructured**
- **Definitions are inconsistent/variable: evidence-based practice and new research is developing continuously**
- **The data is complex**
- **Regulatory requirements for data reuse are strict**

Machine learning algorithms allow examining patterns in heterogeneous and continuously growing healthcare data which human specialists are not capable to process in any reasonable timeframe. Factors like growing volumes and variety of available data, computational processing that is cheaper and more powerful, affordable data storage, as well as improvements of theory and computational methods make it possible to quickly and automatically produce models that can analyze bigger, more complex data and deliver faster, more accurate results.

Important benefits from machine learning within healthcare include [9]

- **reduction of administrative costs**
- **clinical decision support**
- **cutting down on fraud and abuse**
- **better care coordination**
- **improved patient wellbeing/health**

For more examples of successful machine learning application in healthcare, read *Use cases*.

However, we should also mention the challenges still to be addressed while using machine learning technologies in healthcare [55]. The challenges are as follows:
• **Data governance.** Medical data is personal and not easy to access. Many patients are not willing to share their data due to data privacy concerns. Used improperly, such data collections, both on an individual and population levels, pose a potential threat to privacy and autonomy. For more details on regulations on health data use in development of ML algorithms, please refer to section 2.3.2 Privacy concerns in machine learning.

• **Algorithm interpretability.** Algorithms are required to meet the strict regulations on patient treatment and drug development. Doctors (and patients) need to be able to understand the causal reasoning behind machine conclusions. In general, most ML methods are «black boxes» that offer little or no interpretability on how the results are produced. This might be a major problem in healthcare settings. We discussed this issue more detailed in section 2.1.6 Interpretability of machine learning algorithms.

• **Breaking down “data silos” and encouraging a “data-centric view”.** Seeing the value of sharing and integrating data is very important in medical research for improvement of patient treatment in the long term.

• **Standardizing/ streamlining electronic health records.** At present, EHRs are still messy and fragmented across systems. Structured and standardized EHRs will provide a foundation for better healthcare in general, and for personalized medicine in particular.

• **Overdiagnosis.** Healthcare is supposed to reduce illness and preventable death and improve quality of life. Active health intervention is not always good. Sometimes health services take people who do not need intervention, subject them to tests, label them as sick or at risk, provide unnecessary treatments, tell them to live differently, or insist on monitoring them regularly. These overdiagnosis interventions produce complications, reduce quality of life, or even cause premature death [56]. For ML, there is a concern that the development, particularly of patient tools may lead to overdiagnosis and worries among the population – meaning increased pressure on the healthcare system rather than the decrease that is often aimed for.

2.3. **Status of the field**

Machine learning and artificial intelligence are hot topics today in literally all areas where huge amounts of heterogeneous data are available. The underlying idea is that sophisticated methodology is needed to transform all available information into useful actions or predictions. Providing a thorough description of the knowledge in the field is challenging. Bughin et al. examine how AI is being deployed by companies that have started to use these technologies across sectors and further explored the potential of AI to become a major business disruptor [57].

2.3.1 **Reasons for ML rise**

The main reasons for machine learning to become a hot topic in many areas today are:

• **Vast amounts of data**

AI/Machine learning needs to a big amount of data in order to learn and develop itself. Nowadays, huge data sets are available for training of ML algorithms. 2.7 zettabytes of data exist in the digital universe today [58] (one zettabyte is equivalent to 44 trillion gigabytes). For comparison, in 1992–2002, about 2–5 exabytes were generated per year [59] while in 2016, 2.5 exabytes were generated per day [60].

• **Increase of computational power (GPUs)**
GPU computing is the use of a GPU (graphics processing unit) as a co-processor to accelerate CPUs for computationally and data-intensive tasks [61]. A CPU has a few cores optimized for sequential serial processing while GPU consists of hundreds of smaller cores, which together allow it to perform multiple calculations at the same time. This massively parallel architecture gives GPU its high computational performance. In the 1999-2000, computer scientists, along with researchers in fields such as medical imaging and electromagnetics, started using GPUs to accelerate a range of scientific applications [61]; from the mid-2010s, GPU computing also powers machine learning and artificial intelligence software [62].

- **Improvements of theory and methods**

In the book [63], Goodfellow et al. talk about the recent research in the ML field and the new methods that have been developed and refined in last decades. We explain just some of the improvements mentioned by Goodfellow [63].

Greedy layer-wise unsupervised pre-training is an example of how a representation learned for one task can be used for another task. It relies on a single-layer representation learning algorithm that learns latent (i.e. not directly observed) representations. Each layer is pre-trained using unsupervised learning: it takes the output of the previous layer and produces as output a new representation of the data, whose distribution is hopefully simpler. Unsupervised pre-training can also be used as initialization for other unsupervised learning algorithms, such as deep autoencoders [64], deep belief networks [65] and deep Boltzmann machines [66].

Transfer learning refers to the situation where what has been learned in one setting is exploited to improve generalization in another setting. Two extreme forms of transfer learning are one-shot learning and zero-shot learning. For one-shot learning, only one labeled example of the transfer task is given; no labeled examples are given at all for the zero-shot learning task. In one-shot learning [67], the representation learns first to cleanly separate the underlying classes. Next, during transfer learning, only one labeled example is needed to infer the label of many possible test examples that all cluster around the same point in representation space. In zero-shot learning [68-70], additional information is exploited during training. Three random variables are available for the algorithm: the traditional inputs, the traditional outputs, and an additional random variable describing the task.

In image analysis, if a group of pixels follows a highly recognizable pattern, even if that pattern does not involve extreme brightness or darkness, that pattern could be considered extremely salient. To implement such a definition of salience is to use generative adversarial networks [71]. In this approach, a generative model is trained to fool a feedforward classifier. The feedforward classifier attempts to recognize all samples from the generative model as being fake and all samples from the training set as being real. Any structured pattern that the feedforward network can recognize is highly salient.

Among other improvements, it is a synergy of minimizing prediction error with Common Task Framework (CTF). Predictive method is able to make good predictions of response outputs for future input variables. According to Donoho [72], CTF is the crucial methodology driving the success of predictive modeling. It consists of the following components:

- **A publicly available training data set** with a list of feature measurements and a class label for each observation
- **A set of enrolled competitors** whose common task is to infer a class prediction rule from the training data
- **A scoring referee**, to which competitors can submit their prediction rule. The referee runs the prediction rule against a testing dataset and objectively and automatically reports the prediction accuracy achieved by the submitted rule
Donoho [72] points out that the combination of predictive modeling and CTF is the “secret sauce” of machine learning. This statement is justified by the fact that the areas where machine learning has scored some successes are essentially the ones where CTF has been applied systematically. Since the CTF approach can and will be used in many of the healthcare applications using EHR data, it seems reasonable to assume that machine learning will play an important role in this area.

- **Rise of deep learning**

Deep learning is one of the widely used techniques for machine learning implementation. Development and refinement of such methods such recurrent neural networks and convolutional neural networks has been important for the rise of the field. As it becomes more accessible together with more data sources and more powerful GPUs available for diagnostic process, it plays an increasingly important role in medical applications. Read more about deep learning in section 2.1.5 Neural networks.

2.3.2 **Privacy concerns in machine learning**

Use of AI and ML in medical field implies use of health related data. Strict laws and regulations regulate patient health data. In the US, the Health Insurance Portability and Accountability Act (HIPAA) protects individuals’ personally identifiable healthcare information [73]. Individuals in the European Union are protected from having any data collected about them without their knowledge via the Data Protection Directive, and from 25/05/2018, via the updated General Data Protection Regulation (GDPR). Sanctions against companies that flout these regulations can include fines of up to 20 million EUR (about 200 million NOK) [74].

GDPR defines *personal data* as any information related to an identified or identifiable person. The data may be directly linked to a person (as a name, identification number or location) or indirectly (a person can be identified by a combination of one or more person-specific elements, such as physical, physiological, genetic, mental, economic, cultural or social identity) [75].

According to GDPR, *data processing* means any operation or set of operations which is performed on personal data or on sets of personal data (collection, recording, organization, structuring, storage, adaptation or alteration, retrieval, consultation, use, disclosure by transmission, dissemination or otherwise making available, alignment or combination, restriction, erasure or destruction) [75].

Machine learning deals with the GDPR rules when an ML algorithm is being developed and trained on personal data, as well as when it analyzes and/or provides decisions and recommendations about individuals.

GDPR states several principles for processing of personal data [76], such as

- principle of legality, fairness and transparency
- principle of purpose limitation
- principle of data minimization
- accuracy principle
- principle relating to data retention periods
- principle of integrity and confidentiality

The Norwegian Data Protection Authority discussed the challenges of personal data use in the development of artificial intelligence while following the GDPR principles. It is also relevant for machine learning algorithms [77].

The *fairness principle* requires all personal data to be processed with respect for the data subject’s interests; the data should be used in accordance with predefined purpose. The model must be trained using relevant and correct data and it must learn which data to emphasize/not emphasize.
Objectiveness of algorithms and models is dependent on how objective they have been developed. It also depends on how objective/non-discriminative the personal data used for training is. The model results may be incorrect if the training data is biased, or if it has no relevance to the research question.

The *purpose limitation principle* implies that the reason for processing personal data has to be clearly explained before the data is collected. The data subjects have to be fully informed about the reason of data processing, as well as if they can make a choice about whether or not to consent to it. Difficulty with development and application of ML is that it often requires many different types of personal data, in some cases also the data that has been collected for other purposes. If previously retrieved personal data is to be re-used, it should be considered whether the new purpose is compatible with the original one. If this is not the case, a new consent is required.

To develop machine-learning algorithms often takes huge amounts of personal data. However, the *principle of data minimization* requires the data used to be adequate, relevant and limited to what is necessary for achieving the purpose for which the data is processed. When developing ML, it may be difficult to define both the purpose of data processing and the data required for training the algorithm. It is often hard to predict what the algorithm will learn, as well as the purpose may be changed as the machine learns and develops. It can be also challenging to define the exact information that is relevant for development of the algorithm.

The *transparency principle* requires an open (transparent) use of personal data. Transparency is achieved by providing data subjects with clear process details and the rights to decide how information about themselves is used. However, machine learning is difficult to understand and explain. Moreover, the ML “black box” issue makes it practically impossible to explain how information is correlated inside the algorithm and how the specific decisions are made. In addition, the information about the ML algorithm often involves commercial secrets and intellectual property rights.

In the report on privacy issues in artificial intelligence [77], the Norwegian Data Protection Authority mentioned some methods for 1) reducing the need for training data, 2) upholding data protection without reducing the basic dataset, and 3) design which helps to avoid the “black box” problem.

### 2.4. Use cases

There are many examples of applications of machine learning in healthcare. We will mention some of them.

#### 2.4.1 Diagnosis in medical imaging

According to IBM researchers, medical images currently account for at least 90 percent of all medical data, making it the largest data source in the healthcare industry [78]. Machine learning and deep learning algorithms are widely used to help doctors interpret medical images. For example, Google DeepMind[^1] cooperates with the hospitals Moorfields Eye Hospital NHS Foundation Trust in England and Aravind Eye Hospital in India [79-81]. They use deep learning algorithms to detect early signs of age-related macular degeneration and diabetes retinopathy; both diseases can lead to blindness.

[^1]: https://deepmind.com/
2.4.2 Treatment queries and suggestions

Diagnosis is a very complicated process. Machines might help doctors to make the right considerations in diagnosis and treatment. Watson for Oncology (WFO) provides suggestions for treatment of cancer patients by comparing patient’s clinical data to an oncological knowledge base [82]. WFO does not diagnose, but provides treatment recommendations for patients that already have a confirmed cancer diagnosis. WFO can be used in clinical decision support, for second opinion or as support tool for multidisciplinary teams.

Another example of machine learning use for treatment suggestions is emergency medicine. Use of machine learning for development of computer-aided diagnosis (CAD) tools to address a wide variety of illnesses and trauma scenarios is the focus of ongoing research in this area. Nevertheless, most CAD tools for cardiovascular medicine have high false positive rates and do not have comprehensive validation processes, and therefore, have not received significant success [83, 84]. However, these tools can still help in diagnostics at an early stage [85].

2.4.3 Drug discovery/drug development

IBM (Watson for Drug Discovery) has been working on drug discovery for several years. They have developed several advanced machine learning tools and computational models that analyze a wide variety of data sources to improve the efficiency and effectiveness of drug discovery and development [86]. In particular, they work on drug repurposing (helping to find new use cases for existing drugs), indication expansion (helping to identify potential new indications for drugs still in various stages of a development pipeline), drug safety (helping to detect and predict a drug’s safety profiles) and personalized medicine (personalized efficacy/ safety profile predictions) [86]. Watson for Drug Discovery collaborates with the Barrow Neurological Institute and Pfizer [87].

Google in cooperation with Stanford University also investigates the drug discovery area. In particular, they analyze how the amount and diversity of screening data from a variety of diseases with very different biological processes can be used to improve the virtual drug screening predictions [88, 89]. They used totally 37.8 million data points across more than 200 distinct biological processes [89]. The research models were able to utilize data from many different experiments to increase prediction accuracy across many diseases [88].

2.4.4 Improved care for patients with multiple diagnoses

Personalized support to a patient in this category can be obtained by recognizing hidden patterns in the patient’s personal data. This can be achieved by using healthcare analytics methodologies developed over recent years based on advanced machine learning techniques, pattern recognition, patient similarity and interactive visual analytics. In the initial stage, the state space (a set of input and output features) of the patient can be learned from patients that are similar in a specific, data-driven sense. Defining similarity and learning from similar patients are important and challenging tasks, not only for state space initialization but also for assessing the patient’s state in reference to other patients. From a data set of similar patients, states that predict unwanted situations or adverse events can be inferred. It is, in particular, those states the methodology has to pinpoint since they will be used to predict unwanted and potentially life-threatening states for the patient. By this approach, hospitalization may be avoided in a large number of cases, an outcome of crucial importance for both the patient and society. The patterns and properties of the data are large and complex, and knowledge from visual analytics can be used to explore, present, and interact with the data in a meaningful and actionable way [90].
Learning from data is an important backbone for the integrated healthcare that such patients need, since the large amounts of data are not directly interpretable for a human investigator, and patterns may be subtle or arise from complex interactions of several features.

### 2.4.5 Development of clinical pathways

Clinical pathways are standardized plans of care for common diagnoses or procedures typically performed in a hospital. In collaboration with Mercy, a health system in the United States, the software provider Ayasdi[^5] used machine learning and topological data analysis to develop more than 30 new clinical pathways [35]. By comparing and analyzing Mercy’s clinical and administrative data, Ayasdi managed to identify the clinical practice patterns that lead to the best results (both in terms of economy and health outcomes). Mercy estimates that development and optimization of patient care pathways has saved between 50 and 100 million dollars over three years; at the same time, the optimized clinical pathways have improved clinical outcomes for patients [35].

### 2.4.6 Population risk management

Population risk management (prevention) programs aim to detect risk population (population level-risk stratification), improve the interventions, and lower the cost of interventions. According to Bates et al. [91], there are six potential areas within population risk management where machine learning is likely to be beneficially used:

- **High-cost patients.** Management will be much more cost-effective if interventions can be precisely tailored to a patient’s specific problems. If high-risk and low-risk patients can be identified, a better reallocation of resources can follow.

- **Readmissions.** Healthcare organizations should use algorithms to predict which patients are likely to be readmitted to the hospital, and provide them with patient-specific monitoring once they are discharged to be able to intervene if necessary.

- **Triage (assigning degrees of urgency to patients).** Use patient data to anticipate risk, and combine with routinely collected physiological measurements to make accurate assessments.

- **Decompensation (worsening of patient condition).** Continuous monitoring of multiple data streams (motion sensors, ECG, oxygen) combined with real-time alert systems.

- **Adverse events.** Similar to decompensation; applications to renal failure, infection, and adverse drug events.

- **Diseases Affecting Multiple Organ Systems.** Clinical data networks and access to history of patient visits can improve patient care.

### 2.4.6 Robotic surgery

One more example of machine learning application in healthcare is surgery assisted by robots.

The Da Vinci system is regularly used in the operating theater, optimizing many laparoscopic procedures in gynecology, urology, and general surgery [92-94].

A robotic surgical system called STAR (the Smart Tissue Autonomous Robot) is enabled to be used for soft tissue surgery. It has of tools for suturing, 3D imaging, force sensing, and submillimeter positioning. Surgeons tested STAR against manual surgery, laparoscopy, and robot-assisted surgery and found the STAR system as superior [95].

[^5]: https://www.ayasdi.com/
The UC Berkeley Centre for Automation and Learning for Medical Robotics is integrating machine learning and the Da Vinci system [96]. Researchers believe that programming a robot to operate on internal organs would be improved by allowing robots to learn for themselves. Researchers use an observational learning approach. Robots can identify different sensor conditions and represent them in terms of certain parameters. Some of the repetitive motions within an operation, including penetration, grasping, retraction, and cutting, can be combined into an algorithm to execute each subtask within the operation. The robot “learns” without being programmed: the algorithm is refined and updated based on feedback.

2.4.7 Personalized medicine (precision medicine)

Health recommendations and disease treatments can be tailored to a particular patient’s condition based on the patient’s medical history, genetic lineage, past conditions, diet, stress levels, etc., instead of data from other patients.

At present, examples of use of machine learning algorithms in precision medicine include targeted treatment for cancer patients, which targets a cancer’s specific genes and proteins that allow the cancer cells to grow and survive, and pharmacogenomics that looks at how a person’s genes affect the way the body processes and responds to drugs [97-99].

In Norway, use cases for precision medicine include treatment of rare diseases, metastatic colorectal cancer and sudden cardiac death [100].

2.4.8 Automatic treatment/recommendation

In cooperation with IBM Streams and IBM Watson Health, Medtronic developed Sugar.IQ, an app for cognitive mobile personal assistance that provides real-time actionable glucose insights and predictions for individuals with diabetes, helping to make daily diabetes management easier finds hidden patterns in user’s diabetes data [101, 102].

Artificial Pancreas (AP) systems aim to simulate the function of the physiological pancreas and serve as an external automatic glucose regulation system in Type 1 Diabetes (T1D) patients. AP combines a continuous glucose monitor, a continuous subcutaneous insulin infusion pump and a control algorithm that closes the loop between the two devices and optimizes the insulin infusion rate. Daskalaki et al. developed an algorithm for optimization of insulin infusion for personalized glucose regulation [103]. The algorithm optimizes the daily basal insulin rate and insulin/carbohydrate ratio for each patient based on the patient’s glucose profile. Insulin-to-glucose transfer information is linked to patient-specific characteristics related to total daily insulin needs and insulin sensitivity. The algorithm was evaluated using an FDA-accepted T1D simulator on a large patient database and showed comparable or superior results.

In the future, there will be even more autonomous treatment that would adjust, for example, a patient’s dose of painkillers or antibiotics by tracking data about their blood, diet, sleep, and stress. However, the legal constraints of giving that much power and responsibility to the machines are not trivial, and it will take a long time to prove their viability and safety.
2.4.9 Performance improvement

At present, ORRECO\textsuperscript{6} and Under Armour\textsuperscript{7} use IBM Watson cognitive technology to map structured and unstructured data from athlete biomarkers, performance, diet, sleep, weather and travel plans against findings from volumes of worldwide scientific research \cite{104, 105}.

Health-promoting apps can be used not only for athletic performance. Machine learning may also be implemented to track, for example, worker performance or their stress levels at work \cite{106}. However, there are strong ethical concerns around “augmenting” human physical and especially mental abilities.

2.5. How does this relate to Norway and the needs in Norwegian healthcare?

The core idea in health analytics is to learn from the observational data gathered by care delivery network, so that the quality of care iteratively improves in all parts of the healthcare system \cite{107}. Gaining insight from the observed data is crucial. Consequently, various types of data analysis become important ingredients in successful systems. In Norway, where One Citizen - One Record is a future goal, it becomes crucial to use all existing patient record information to improve treatments and, thereby, care.

Norway, as most European countries, is facing an increasing number of elderly and a larger population of chronic patients. In the future, we need to improve our health service’s reactive response. This corresponds to identifying the optimal diagnostic and treatment options available. Secondly, we need to proactively avoid that people become ill by predicting future illness and mitigating the effects of these events when they occur \cite{84}. Both these areas are established research fields and use cases for ML.

Norway has specific advantages when it comes to health data analysis. Among them are

- A number health and quality registries with high-quality population-wide data.
- Early digitization of the healthcare sector, which has led to a large base of legacy data.
- A uniform, single-payer healthcare system, which means that life-long data on much of the population exists, albeit difficult to access.
- Personal ID numbers that identify all citizens throughout all levels of care and throughout life.

To get an overview of the activity of research within machine learning in medicine in Norway, we did a short review using “machine learning Norway” as keywords in Pubmed. The review shows that ML has active research groups at all major universities and university hospitals in Norway. We found 75 research papers published by Norwegian researchers. The majority of the papers have been published during the last 5 years with the number of papers increasing in 2016 and 2017. Compared to international trends, ML research in medicine in Norway is a slow starter, but is now gaining speed. Popular research areas are image analysis, especially fMRI images, support vector machines and neural networks. Only a few papers focus on natural language processing of clinical text. This area should be given increased attention and research funding as the majority of clinical documentation is currently stored as text. The review shows evidence of established competence and skills and, therefore, also a capacity to increase the use of ML in medicine in Norway. Further details about this review is given in the Appendix.

\textsuperscript{6} https://orreco.com/
\textsuperscript{7} http://www.uabiz.com/
To move the use of ML in medicine from the research labs to functional healthcare systems, two core needs must be addressed:

1. **Standardization of clinical information models**
2. **Access to clinical data**

Without a standardized way of recording and storing clinical data, machine learning, along with optimal diagnosis, treatment and prediction of future needs, will hardly reach mainstream medicine in Norway. Using different clinical information models to store medical data in the e-health system across the hospitals and health institutions in Norway, will partition the datasets in ways that will hinder standardized ways of reusing the data. This has been the main barrier for use of decisions support system is clinical practice so far [108], and will be a barrier for broad use of ML and AI in Norway. In addition, the success of the Common Task Framework, explained above, illustrates this point. If the datasets are partitioned, we may not be able to conclude on the performance of ML and AI tools, as the base data used by the algorithms will be different. Partitioned datasets will also block ML applications from finding optimal diagnosis and treatment, and prediction of future needs, since comparison across health institutions and health regions may become impossible. Likewise, without being able to use data from all types of health institutions, major parts of the medical history of patients will be missing and can consequently not be used to support diagnosis, selection of treatment or prediction of future needs. Currently the only approach in Norway that may satisfy both these requirements is the research infrastructure being developed by the Norwegian primary care research network called PraksisNett8. This research infrastructure plans to use openEHR archetypes to represent clinical data and use privacy-preserving computations on distributed health data [65] to provide access to data from all types of health institutions. Using health data where it is stored, within the health institutions, is the only way, in the near future, to provide access to all available data about the Norwegian patients. To expand the possibilities for distributed statistical computations, more funding should be dedicated to increasing the computational capabilities. An important future research area is therefore federated ML approaches.

Finally, it should be mentioned that an important decision Norwegian center for e-health research has to make concerns what types of information should be included in the developed healthcare tools. At this stage, it seems obvious that unstructured and structured text should be included. Clearly, as our review shows, image information is important in medicine and will be included in the patient journal. Because of this, images also seem like a natural ingredient in the healthcare tools developed at NSE and it is therefore recommended to include deep learning as a research area, since these methods seem to make headway in many application areas where information is provided in terms of images. This implies knowledge in deep convolutional networks to be required in future use cases.

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8 [http://www.uib.no/praksisnett](http://www.uib.no/praksisnett)
3. Natural Language Processing (NLP)

3.1. Definition of the concept

Humans use natural language for most communication. Natural Language Processing (NLP) is sometimes broadly defined as automatic processing of human language. Today, alternative terms such as Language Engineering or Language Technology are also commonly used. Since human language can be expressed in text and speech, speech recognition and text mining are both sometimes cited when discussing NLP.

NLP is often mentioned together with machine learning (ML), deep learning (DL) and artificial intelligence (AI), as some of the most promising technology for analysing big data. As with many new sub-concepts, it is sometimes difficult to understand the relationships with well-established concepts, and how they all fit together.

Figure 24 illustrates how NLP is placed within these technologies. A Venn diagram is an appropriate illustration since there are significant overlaps. In addition to ML and NLP, AI includes a wider array of subfields such as reasoning, computer vision and robotics. DL is a subfield of ML, and they both represent one of the major statistical approaches to NLP. The other major approach to NLP is rule-based; regular expressions, for example, which are non-statistical and somewhat less sophisticated, but for some tasks, can yield state-of-the-art performance [109].

A related term, computational linguistics, is usually thought of as involving basic linguistic research, while NLP is an applied form of language technology. Some NLP methods use very little linguistics, and view text as a bag-of-words.

More advanced methods will seek to derive meaning based on the syntax and semantics of the text. For instance, word sense disambiguation, where the same word can be used in different contexts and the problem is to determine the context of current use.

Natural language understanding (NLU) is another sub-field associated with NLP. NLU involves computers actually comprehending text articles or speech, and this is considered to be a complex task and generally difficult to achieve, for example, paraphrasing.
It should already be clear that NLP is a complex mix of linguistics, computer science, statistics and usually specialized domains such as healthcare, medicine, human computer interaction and cognitive sciences. As a result, there exists several variants of how NLP, computational linguistics, NLU and natural language generation (NLG) are related.

3.1.1 Tasks NLP can be used for [110]

1. **Information extraction** - one of the most common applications of NLP in biomedicine is to identify entities such as patients, places, dates, drug names, diagnosis, symptoms (named entity recognition - NER) from clinical text. Additionally, an important task is to determine the relations among the entities, regardless of how they are located in the text (reference resolution).
2. **Question answering (QA)** - some uses in healthcare include mental health where patients seek information or help using chat robots (chatbot).
3. **Text summarization** - when clinicians use an electronic health record during treatment, text summarization can draw from different sources of patient information, and summarise the results. Readability assessment and simplification are important elements to evaluating text.
4. **Text generation** - natural language text can be generated from sources that may be not human readable.
5. **Machine translation** - converts text between languages (e.g. Norwegian to Spanish)
6. **Sentiment analysis and emotion detection** - is sometimes used to gauge positive and negative attitudes towards certain products or services, for example, using user comments from online social media. In healthcare, pharmaceutical companies can get feedback on their drugs based sentiment analysis of online content.

3.1.2 Example of NLP pipeline

The example in Figure 25 shows how a transcript of the physician’s notes that is in natural language can be converted to structured data by extracting entity names such as tobacco, drug names, quantities and dates. A typical process can start with recognising sentence boundaries and morphological processing such as determining the base forms of words (lemmatization or stemming), abbreviations, spelling and part-of-speech tagging. Text is checked against grammar rules in syntactical parsing, and then the meaning is interpreted by resolving entity names, negation, ambiguity, relations, etc. The final step, discourse processing, will depend on the task at hand, such as the tasks described in the preceding subsection.
There is generally an explosion of digital data that could be useful for clinicians, patients and researchers, but manually sifting and synthesizing the data is nearly impossible. Computers are not able to efficiently process much of this text because the text is in natural human language and unstructured. Abbot Analytics reports an estimated 80% of electronic data is free-text, citing research from reputable firms such as HP, IBM, Gartner and Teradata. In terms of clinical applications, it is estimated up to 40% of the information in EHRs are clinical notes in unstructured text form. Healthcare practice and care processes result in narrative reports; clinical, nursing, radiology, discharge notes, etc. It is well-known that there are risks of error when manually re-coding clinical narratives to structured forms or terminology. Clinical text can contain spelling errors, abbreviations, acronyms, ambiguous and uncertain statements, synonyms, homonyms, etc.

NLP can be used to structure and quality check data that has been input; checking for errors of both omission and commission and conflicting information. This structured organization makes further analysis and computation easier. Therefore, this ability of NLP to structure and summarize text is expected to speed up scientific discovery.

NLP has been a constantly evolving field, with research developing interesting new insights into how natural language can be processed by computers. Language is complex, and computers are machines that lack a human world view. Therefore, human communication peculiarities such as metaphors, irony and sarcasm will test the limits of what NLP can do. Even humans sometimes to do not quite understand sarcasm and personal interpretation of metaphors can be based on human experience. Sometimes meaning can be derived from human gestures, slurs and emphasis and the wider environment. Therefore, the amounts of data needed to build a knowledge model for processing all these factors is conceivably very large, but research continues to push knowledge boundaries.

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3.2. What is the knowledge in the field?

3.2.1 Seminal work

Scholarly activities within NLP date back to the 1940-50s, especially after WWII when interest in artificial intelligence began to grow. Arguably, one of the most influential seminal works was Allan Turing’s 1950 paper title “Computing Machinery and Intelligence” [114], where he proposed what is today called the Turing Test, by asking the question “can machines think?”. The core of the Turing Test was to determine whether machine intelligence can be indistinguishable from that of a human.

Excitement during these formative years generated high expectations for AI in popular culture, resulting in films such as the 1968 “2001: A Space Odyssey” where a computer was able to intelligently interact with people. The expectation was that, by the turn of the millennium, AI would be ubiquitous and there would be artificial general intelligence, that is, ‘machines show a human-like flexibility in solving unfamiliar problems’ [115].

One early example is the ELIZA system [116] that could talk to people about their psychological problems. The system could carry on a conversation based on probing the user, similar to psychotherapy methods. Users who tested the system had generally positive feedback. In hindsight, although scientific research seemed to have come very far by the turn of the millennium, it still lagged initial expectations from the 1960s. While significant progress has been made in the last decade or so, the Turing Test, relevant today as it was half a century ago, still appears elusive. AI is once again on focus in popular culture because of a combination of factors such as the increase in digital literacy and digital data systems, computing power and the Internet.

3.2.2 Current activities and expected future trends

AI personal assistant products such as Amazon’s Alexa and iPhone’s Siri are becoming standard in many digital devices. Services such as voice-commands in ambient systems are part of many products shipped today. The question of whether we are near achieving artificial general intelligence is widely contested, and disagreements among scholars are apparent. Some scholars like Andrew Ng (see Harvard Business Review article10) are optimistic, and believe machines can take over some of the distinctly human jobs, while other scholars like Markus have more tempered expectations [115].

Figure 26 contains an excerpt from our conversation with Mitsuku11, one of the Loebner prize award-winning chat robots. The conversation interrogates Mitsuku about why she was happy when earlier in the conversation she had said she was a “machine of metal and wires”, without human emotions. The conversation has its quirks, but it somewhat emulates human conversation, arguably a much further step from ELIZA, who could only respond with unspecific, open-ended questions. However, the conversation seems to lack continuity or the “red thread”. The robot does not seem to keep the context of the conversation. It feels like a “question-response” or “statement-response” system, therefore the conversation seems too contrived.

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11 http://www.mitsuku.com/
The learning techniques are becoming more and more sophisticated (like Hanson Robotics’s Sophia, a humanoid robot\[^{12}\]); so perhaps in the near future, it may be difficult to tell apart the conversation between a human and a robot, thus achieving the Turing test.

In healthcare, however, much of NLP-related work is based on clinical and biomedical text. As more of patient data is becoming digital, the methods for using the data for patient treatment directly and for secondary use are also evolving. Chat robots are also present in healthcare applications, especially in mental healthcare (see the NFR-funded project in the next section).

To date, however, no credible effect studies have been conducted, and much of the work is still exploratory. While research on clinical NLP methods is still in its infancy, the evidence points to promising results in areas such as diagnostic surveillance [117], identifying cohorts [118], quality assessment and patient safety [119], among others.

### 3.3. Use cases

There are several cases of research projects and commercial attempts within the NLP field in Norway. The number of initiatives from start-ups as well as large companies, though difficult to ascertain, seems very large. For example, Orbit Systems AS is a Norwegian start-up that uses NLP to develop products that can summarize content such as the weather, sports or finance. They also develop chat robots for finance, medicine and general internet commerce. Orbit Systems AS names Santander as one of their customers for chat robots, and perhaps this indicates the maturity of the technology, but market penetration of any of these products is difficult to assess. Other companies in this space include Schibsted Media Group, IBM Norge and Vivit AS, to name a few.

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3.3.1 Norway research and development cases

The research council of Norway (NFR) has funded a number of projects that work with NLP and machine learning. The Language Technology Group at the University of Oslo partnered with NRK and Schibsted in an NFR-funded project to develop sentiment analysis tools for Norwegian text. Sentiment analysis aims to assess the general attitude or feelings portrayed in vast amounts of texts. This can be useful in business to get opinions of customers towards a service or product, or to extract thematic issues raised in the text.

BigMed is another project funded by NFR that uses NLP methods for large-scale phenotype extraction from electronic health records (EHR). This means NLP can be used to process unstructured data in EHR as an additional source of information about patients. Their stated aim is to “identify and address the barriers to Precision Medicine in Norway”\(^{13}\). This aim is in line with the world trends towards precision medicine, defined as “an emerging approach for disease treatment and prevention that takes into account individual variability in genes, environment, and lifestyle for each person”\(^{14}\).

The project Social Health Bots from SINTEF is also funded by NFR to investigate online chatting robots in mental health. The consortium include University of Oslo, Oslo University Hospital, University of Agder, and they report that “the core idea of Social Health Bots is that online chatbots will lower the threshold for young people to ask for information and help concerning mental health issues and, thereby, strengthen their access to trustworthy informational support and also provide a gateway to more extensive support”\(^{15}\). Other recently-funded projects with NLP elements are IDDEAS and Evicare.

3.4. How does NLP relate to the needs in Norwegian healthcare?

While there are notable research groups dealing with NLP in Norway, for example the Language Technology Group at the Department of Informatics at University of Oslo, very few deal with the healthcare aspects of NLP. The Information Systems group at the Department of Computer Science at NTNU is one such national actor, visible for its application of NLP in the healthcare domain. We therefore sought the opinion of these leading institutions in Norway, to assess possible important implications of NLP for healthcare in Norway.

3.4.1 Eliciting expert opinion using the Delphi Method

The Delphi method is often used for technology foresight [120], especially for new and promising technology whose benefits or harms are still unclear. While the Delphi method has its limitations, like difficulty identifying the experts, significant benefits have also been reported. There is no statistical significance analysis, but the method involves at least two rounds of gathering expert opinion anonymously. In the second and subsequent rounds, the experts get to see the summary of the forecast gathered from the previous round.

We conducted a survey of leading researchers in the field of NLP in Norway. The goal was to solicit opinions of experts and strategic thinkers regarding important developments relevant to achieving eHealth strategy goals. Developmental work and research within NLP should yield economic and social benefits and be well-aligned with national direction for e-health and overall healthcare sector defined in a white paper “One Citizen – One Record” [1].

\(^{13}\) https://bigmed.no/

\(^{14}\) https://ghr.nlm.nih.gov/primer/precisionmedicine/definition

\(^{15}\) https://www.sintef.no/en/projects/socialhealthbots/
We identified 22 experts in general computing and clinical sciences who have demonstrable interest in NLP, representing opinion from leading research institutions in Norway. Some of the experts are part of our collaboration network. This process of gathering insights from thought leaders also strengthens NSE’s collaboration systems, as suggested in the literature [120].

The questions were few, but open and unstructured, designed to elicit visionary and quotable expert statements:

1. What three challenges or knowledge gaps are specific to Norwegian language technology?
2. What three broad applications of NLP in healthcare do you consider promising?
3. What Norwegian universities, research labs or commercial companies are leading R&D in the field?

Original:
1. Hvilke tre utfordringer eller kunnskapshull er det for språkteknologi i Norge?
2. Hvilke tre applikasjoner av språkteknologi i helsevesenet anser du er lovende?
3. Hvilke norske universiteter, forskningsgrupper eller selskaper leder FoU på feltet?

3.4.2 Results from expert opinion survey

Seven experts (approximately 30% response rate) responded to the short survey. Leading groups in language technology research and development (sorted by mode, based on 25 institutions cited by respondents):

- UiO: Language Technology Group
- NTNU: Institutt for datateknologi og informatikk
- UIT: Giellatekno/Divvun
- UiO: Tekstlaboratoriet
- NTNU: inst. for elektroniske systemer
- UiA: Center for Artificial Intelligence Research
- IBM (med Ahus, CapGemini på Watson)
- UiB: Language Models and Resources (LaMoRe)
- Schibsted Media Group
- Anzyz Technologies AS
- Vivit AS

According to the survey of experts, some of the most promising areas of research and developed were (the first two were the most cited):

- Textual analysis is currently not adapted for the language of the health service, for example, for use in data mining through text analysis of journals or as background for through-wide association studies
- Speech recognition and speech-driven software (both understanding and producing speech), dictation and reading - functioning but still inadequate (could be useful for different patient groups, for example, Dementia and mental health). There’s also need to support both for Norwegian and for the Sami language, all dialects
- Anonymization and patient privacy
- Concept-based search
- Model-based interpretation of symptom development over time
- Automatic, interactive structuring / coding based on free text input.

Survey results suggest there is some consensus regarding EHR data re-use as the most promising area. Experts also note the difficulties with anonymization and preserving the privacy of patients. Current regulations require that patient data can only be accessed for specific research purpose and not kept
for secondary or general exploratory work. The second frequently cited area was speech technology, with possible uses in dementia care and mental health, where systems could actively interact with patients.

Some of the greatest challenges and knowledge-gaps cited by the respondents include the following:

- **Research at universities is aimed at publications, not usable systems.** There are also weak study programs in language technology and too few students who graduate in language technology. Lack of focus on Norwegian language technology for clinical NLP.
- **Lack of resources in the form of manually annotated text corpora.** Norwegian speaking resources are not open to developers. Lack of access to clinical texts. There is **text-to-speech (TTS)** for north Sami, but not for southern and Lule Sami. There is no automatic speech recognition for any Sami language. There are major shortcomings in Sami corpus resources, both current and older texts. Syntactic analysis for Southern and Lule Sami is too bad.
- **There is insufficient cooperation between the academic community and partners from business and public administration.** Lack of industry and sector expertise and understanding of opportunities and limitations.
- **Clinicians’ lack of satisfaction with speech recognition in healthcare.** Some believe that “structured journal” and process / package-oriented documentation is effective and expressive enough in clinical work and documentation for the future. Language technology suitable for capturing pathways, temporality and richness in clinical language requires long-term efforts in robust domain-specific research groups over time.
- **Scanned documentation, speech and handwritten documentation add complexity, limiting the achievable precision.**
- **Lack of support schemes for smaller language technology projects (such as annotation projects).**

What we can surmise from the reported challenges is that, education programs will have a great impact on the future developments of NLP in healthcare. Since AI is dominating popular culture, it is conceivable that university programs will continue to restructure in favour of AI and NLP-related research, as new demand from young researchers increase.

Another challenge is that creating annotated corpora can be time consuming, but a properly annotated corpus can spur an enormous amount of wide-ranging research. Experts report that securing funding for small annotation projects is a challenge in itself, but some experts suggested that increasing private-public collaboration can help establish the basic resources. It was further noted that there were multiple challenges for minority languages such as northern Sami, southern Sami and Lule Sami. While some resources have been developed such as text-to-speech technology for northern Sami, disparities among minority languages exists, for example, syntactic analyses for southern and Lule Sami are still very poor.

### 3.5. Tools and Resources

It is difficult to have an overview of all the NLP resources available today, but we discuss one important resource developed by Nordisk Språkteknologi Holding AS (NST). This was a Norwegian language technology a company in Voss that went bankrupt in 2003. They had developed a language bank for Norwegian language technology, and according to Språkrådet, these resources were subsequently purchased by Språkrådet, together with University of Bergen, University of Oslo, NTNU and IBM Norge AS.
Some of the resources that have now been made public through The National Library of Norway\textsuperscript{16} include Bokmål text corpora and lexicons, with synonym networks and word disambiguation tools.

There are several other key language technology resources such as the Norwegian dependency treebank [121] and the Oslo-Bergen Tagger\textsuperscript{17}. Brat\textsuperscript{18} is an open tool for annotating text. In terms of programming interfaces for machine learning algorithms, tools such as the Natural Language Toolkit (NLTK) or Google’s Tensorflow have been used. There are dozens of institutions that developed custom software for mining clinical text, such as cTAKES, and some of them have since been put on the public domain.

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\textsuperscript{16} \url{https://www.nb.no/sprakbanken/#ticketsfrom?lang=en&query=alle&tokens=&from=1&size=12&collection=sbr}

\textsuperscript{17} \url{http://www.tekstlab.uio.no/obt-ny/}

\textsuperscript{18} \url{http://brat.nlplab.org/}
4. Knowledge discovery in databases (data mining and process mining)

4.1. Definition of the concept

“Knowledge discovery in databases” [122], “knowledge discovery and data mining”19 (both titles are abbreviated as KDD in literature) is a process of discovering patterns in large datasets by employing computational techniques. KDD maps large quantities of low-level data into other forms, which may be more compact, more abstract or more useful [122]. It is an interdisciplinary field combining tools from statistics, computer science, artificial intelligence as well as data collection and storage technologies [123], [61].

Parallel development of advanced data analysis methods resulted in several concepts, which are often associated with KDD, for instance, data mining, pattern recognition and machine learning. In literature, KDD is referred to as the overall process of knowledge discovery in large datasets (data preparation, data selection, data cleaning, mining and interpretation of the results), while data mining is the core step in this complex process. It deals with algorithms and techniques for data discovery and, therefore, often attracts more attention than the other steps in KDD [122]. KDD/data mining uses machine learning (ML) algorithms for explaining a phenomenon of interest by discovering patterns in existing data, however, it does not put much emphasis on predictive side of ML. In many cases, all these concepts are highly interrelated, which may explain the confusion between these terms in literature.

KDD emerged together with the increasing amounts of transactional data being stored on computer systems and lacking human resources to analyse them in a reasonable timeframe. It is commonly used in research, marketing, investment, finance, manufacturing, communications and other fields. One of the early applications of data mining on transactional data, which is still of vital importance, is detection of credit card fraud. Analysis of payments over time provides insight into money spending patterns of an individual (paying by card in Norway for several years), while unusual event (payment in Somalia) hints about misuse of the credit card and can be refused by the credit card company to protect the financial funds of an individual [123], [61].

Fayyad et al. divided the process of KDD into 9 steps [122], [124] (Figure 27):

1. Developing the understanding of application domain and relevant prior knowledge. It helps establishing the goal for the overall KDD process.
2. Creation of a target dataset by selecting relevant data in a potentially bigger dataset.
3. Data cleaning and pre-processing. It includes noise removal and handling of missing data.
4. Data reduction and projection. Selection of features to represent data and reduction of dimensionality.
5. Matching the goals of KDD process (identified in step 1) to data mining algorithms. Depending on a specific case, data mining can be assigned to one of the six classes of tasks, using different algorithms:
   5.1. Anomaly detection – identification of unusual data records, requiring additional attention.
   5.2. Association rule learning – identification of relations between variables.
   5.3. Clustering – grouping data records, which are in some way similar, without knowing the criteria of similarity or group characteristics in advance.
   5.4. Classification – assigning data records to predefined groups based on certain criteria.
   5.5. Regression – finding the function, which models the relationship between data variables with the least error.

19 http://www.kdd.org
5.6. **Summarization** – combination of variables into a more compact representation [122].

6. **Choosing data mining algorithm(s).**

7. **Data mining.**

8. **Interpretation of the discovered patterns. It often involves visualisation techniques.**

9. **Consolidating discovered knowledge, documenting or reporting it to the interested parties** [122], [124].

Interpretation and evaluation of the discovered patterns is of key importance in KDD process. Data mining algorithms may discover patterns in training datasets, which look significant, however, they cannot be reproduced in a wider dataset. This refers to overfitting problem [125]. Overfitting occurs when analytical models reach high performance in training datasets, while performance declines significantly when validating the model using the data unseen by the algorithm. In simple terms, the algorithm “learns” the data it was trained on and fails to demonstrate the same performance in a wider/new dataset (discussed in Chapter 2). It could also refer to data dredging – presentation of significant patterns in data without considering hypothesis on underlying causality [126]. In other words, it is not uncommon to discover relationships between variables, which occurred randomly and cannot be explained, however, is statistically significant (Figure 28). According to Fayyad et al., “… if one searches long enough in any dataset (even randomly generated data), one can find patterns that appear to be statistically significant, but, in fact, are not”. 

*Figure 27. Overview of steps in KDD. Source [122]*
A relatively new branch of KDD is process mining. Process mining uses data mining principles to infer knowledge from event logs. It puts major emphasis on making the discovered patterns understandable for the end user, while data mining often prioritizes accuracy of the algorithms rather than clarity and usefulness of the results. Even though the overall principals in data and process mining may be similar, most data mining techniques are not process centric and cannot be reused. Process models are often more complex, including concurrent sub processes, and should not be compared with data mining constructs as decision trees or association rules [127]. Process mining is often associated with business intelligence tools, as highlighted in Figure 29.

An event log is an input to the process mining algorithms. It is a collection of events, happening in time, which are a part of a bigger process. An example of such event could be patient contact with a GP, blood test order or a new medication prescription. Every documented interaction with healthcare services is an event of a different granularity. Analysis of such events in a scope of a single patient would represent patient pathway through health services, while on a group level it could identify trends in care processes, highlight bottlenecks, help estimating waiting times, etc. Events are often
created automatically by health information systems (HIS) or can be obtained applying transformations on EHR data [128]. Depending on the granularity of the events, processes of various levels of detail could be identified and analysed [129].

Van der Aalst classified process mining techniques into three categories (Figure 29):

1. **Process discovery** – creation of a computational model based on event logs. Event logs are fed to the mining algorithms, which produce visual process models.
2. **Conformance check** – validation of the intended process model against actual event logs. It could as well be called a “reality check”, measuring to what extent processes used when designing and implementing the system are followed in reality.
3. **Model enhancement** – use of domain knowledge or log information not captured by the algorithm to improve or extend the model, for instance, visualize bottlenecks, throughput times, frequencies, etc. [130], [127].

Processes in healthcare are known for being unstable, complicated and often disconnected from the planned processes. Theoretical care models often do not reflect actual processes in healthcare institutions [128]. Many of the processes are person specific, tuned by personal practices and other external conditions, which may not be known to the outsiders. Inferring real processes from data is a way of getting an up to date insight into the actual organization of healthcare at a preferred level of granularity (patient, doctor, health institutions, healthcare system, society, etc.).

Process mining can provide knowledge on several perspectives:

- **Control-flow perspective**. It focuses on order of activities and identification of possible paths. Results are often expressed in Petri nets, UML or other business process notation.
- **Organizational perspective**. It emphasizes resources mentioned in log statements, map connections between actors (people, systems, departments, etc.). It structures processes into social network visualizations.
- **Case perspective** looks into a specific path in the process attributed to certain cases.
- **Time perspective** is linked to durations and frequencies of events to identify bottlenecks, monitor utilization or predict delays [127].

Process mining puts major emphasis on explainability of the discovered patterns. Therefore, an easily interpretable visual representation is of key importance when presenting findings to the user. A typical output of process mining tools is a graph representation of concepts and relations (Figure 30). Time and throughput perspectives can typically be overlaid on the discovered processes for a more detailed analysis.
Talking about data in healthcare, it is important to remember the characteristics of big data, formulated by Demchenko et al. Big data is characterized by five Vs [131]:

- **Volume** – the most distinctive feature characterizing the size and amount of data.
- **Velocity** – the speed of data collection.
- **Variety** – structured, unstructured, semi structured, mixed data.
- **Veracity** – consistency (statistical reliability) and trustworthiness of data.
- **Value** – added value that the collected data can bring to the intended process [131].

Not all medical data could be characterized as big data, according to the 5 Vs criteria provided by Demchenko et al. Data in a size of petabytes (10^{15} bytes) or more may be still rare in healthcare. However, health data suffers from many big data problems, such as high variety, limited reliability and varying value. McKinsey Global Institute estimated, that data mining of health data can save healthcare industry up to $450 billion every year in the United States alone [132]. Reports suggest that healthcare system in the US had generated more than 150 exabytes (10^{18} bytes) of data by 2011 [133]. It does not mean that all this data is equally relevant, important or useful for providing better care. KDD be the only way of transforming such amounts of data into useful information for the healthcare services.

Potential of KDD in healthcare is enormous. It helps transforming current reactive system into an agile Learning Healthcare System (LHS) [134], where care data is treated as a major asset enabling fast knowledge generation and adoption in practice. The concept of LHS appeared in literature in 2007 to address the shortcomings of Evidence Based Medicine [135]. LHS promotes fast progression of research knowledge into clinical practice, pays major attention to personalised care and facilitates public engagement of patients and clinicians for evidence production and dissemination. Interest in this new healthcare paradigm has been global, however, stories of successfully adopting it are few [136]. Data generated in routine care is the main driver of the entire paradigm, making KDD/data mining in medical data one of the key technologies rendering successful transformation of reactive and inert healthcare systems into agile, adaptive and patient centred LHSs.
4.3. What is the knowledge in the field?

Mining medical data is an important research direction, continuously attracting more attention of data scientists. Regardless of data access and patient privacy concerns, the number of publications in the field is increasing. Data mining initiatives in healthcare has already been summarised in several reviews [133], [137], [138], providing an overview of progress in the field. In this section, we refrain from analysing the results of the selected data mining projects. Instead, we look into a big picture of mining health data to sketch the direction research is taking, rather than reporting on achievements of specific groups.

It is difficult to provide a systematic outlook over the increasing number of publications reporting KDD/data mining activities in medical domain. It was acknowledged by Herland et al., who introduced some organization in literature by categorising data mining initiatives in healthcare according to the data these projects were using. The review divided publications into four levels:

- **Micro level (molecules)** uses data gathered at a molecular level and typically employs gene expression data to answer clinically important questions on health outcomes.
- **Tissue level.** Examples of publications assigned to tissue level include brain-connectivity map development as well as predictive health outcome research based on medical imaging.
- **Patient level** contains publications on mortality risk estimations, readmission predictions and similar tasks using historical or real-time data.
- **Population level** health related data (for instance coming from social media) used for outbreak monitoring, patient advice and support [133].

It is important to note, that the list of research topics belonging to every level is not meant to be complete. It only provides several examples illustrating the differences between levels, which were characterised by different research questions and mining algorithms. This paper discussed many research projects, traditionally using data from a single level to answer the questions researchers were interested in. Integration of data from several or even all levels is suggested as a currently lacking future work for data mining research. Combination of data from various levels may give better understanding of relations between diseases and treatments, genomic information and influence on public health trends. It would provide a more holistic picture of the entire healthcare system, rather than relatively narrow focused single-layer projects [133].

Another review analysed KDD related publications from MedLine, following the 9-step process proposed by Fayyad et al. and summarised in previous section. It concluded that clinical data miners are mostly interested in three perspectives: understanding clinical data, assisting healthcare professionals and developing data analysis methodology suitable for medical data. In addition, the paper provided a systematic overview of more detailed mining purposes (exploration, visualization, quality assessment and evaluation, prognostic evaluation, diagnostic assistance, quality of care, information retrieval, natural language processing, image analysis and data mining methodology evaluation), data types used in the process, mining functions and algorithms as well as a summary of evaluation metrics used by the researchers to verify the results [137].

Process mining is a relatively young discipline, represented by a limited number of publications in the scientific community. Numbers of published research papers are increasing every year, together with the share of reported process mining initiatives in healthcare. In year 2015, approximately 10% of publications in the field of process mining were using data from healthcare systems following an increasing trend over the years [128]. Process mining in healthcare is already summarised in several literature reviews, however, a systematic review in the field is lacking.
Literature reviews suggest that most of the process mining research uses oncology and surgery as use cases, followed by radiotherapy, stroke treatment and cardiology. There is sufficient interest of researchers to identify processes in other patient groups, pointing out the multidisciplinary application of the approach [129]. The studies are guided by 5 major research questions:

1. What are the most followed paths and what exceptional paths are followed?
2. Are there differences in care paths between patient groups?
3. Do we comply with internal/external guidelines?
4. Where are the bottlenecks of the process?
5. What are the roles and social relationships between actors in the processes [129], [128]?

These questions summarize the interest of researchers performing process mining activities in healthcare. Looking at the process mining techniques defined by Van der Aalst, most of the studies focus on process discovery (60%), while conformance checks and process advancement are represented in 21% and 16% of publications included in the review [129], [128]. Mining techniques are primarily applied in the control-flow perspective. Countries leading the research in process mining in healthcare are the Netherlands, Belgium and Germany.

4.4. Use cases

In this section, we refrain from analysing selected and relatively narrow use cases. Instead, we look into categories of problems, which could be addressed by KDD/data mining techniques. Koh and Tan [139] divided applications of KDD/data mining in healthcare into four major groups:

- **Evaluation of treatment effectiveness.** One of the drawbacks of Evidence Based Medicine is overstandardization of treatment options to algorithmic rules, which rarely correspond to the needs of a specific patient [135]. KDD/data mining techniques can be used for evaluating the outcomes of various treatments for a very specific patient group. Instead of delivering standard treatment, patient care plans could be tuned based on historical data of other patients, which are very similar in demographics, care history and other factors. Applying such techniques in a large scale relatively big populations of patients suffering from rare conditions can be identified and used in clinical decision-making process.

- **Management of healthcare.** This group of applications consists of numerous use cases, ranging from organization of internal processes in healthcare institutions (resource planning, identification of bottlenecks and process optimization) to identification of at-risk patients enabling proactive care.

- **Customer relationship management.** This group of use cases is well known for the commercial organizations, while it was not of such high importance in healthcare. However, the potential to analyze service consumption patterns of individuals, their preferences and individual needs is highly significant. These applications could suggest whether a specific patient is likely to adhere to prescribed treatment or whether preventive care is likely to have impact on the individual health outcomes in the future. A link to patients establishes a feedback mechanism, enabling continuous improvement of care practices and service delivery.

- **Detection of fraud and abuse** – this class of applications focus on detecting abnormal behavior in data. It could highlight cases of health system abuse, for instance, unnecessary laboratory tests or examinations. Moreover, it can provide quality control in care delivery process, for instance, detect inappropriate/incorrect prescriptions or referrals [139]. It could as well help monitoring the use of healthcare systems and identify users characterized by suspicious behavior. This class of applications is important for intrusion detection in computer system and is highly relevant considering the increasing numbers of health data breaches worldwide.

These groups make it easier to define use cases of KDD/data mining in healthcare in a relatively structured manner.
4.5. How does this relate to Norway and the needs in Norwegian healthcare?

KDD/data mining provides a set of techniques for secondary use of health data accumulated in healthcare institutions. These techniques may be applied in numerous use cases aiming to enhance healthcare services for populations, to improve individual patient experience and to reduce per capita costs of care (triple aim for healthcare) [140]. It is important to note that KDD/data mining are tools enabling secondary use of health data. Like any other tools, they do not guarantee that their use will automatically lead to the expected outcomes. However, experience from industries, which successfully employed KDD/data mining techniques in their processes hints major underexploited potential.

Improving secondary use of health data is in the agendas of many developed countries. Norway is no exception. Increasing and simplifying the use of health data for quality control, monitoring, management and research is highlighted as one of the three focus areas of government vision for future health sector, One Citizen – One Record [1]. This goal was later specified in more detail by the Directorate of e-health in the national strategy for e-health 2017-2022 [9]. These and several other strategic documents emphasize the importance of methods for advanced data analysis in future healthcare.
5. Tools

5.1. Definition of the concept

Tools are a big part when working with machine-learning algorithms. At a low level, the tools execute
the algorithms described in the Machine learning chapter. At a higher level, the tools support scien-
tists and developers by providing built-in algorithms, integration, data cleaning, optimization, scaling,
validation, benchmarking, A/B-testing\textsuperscript{20}, as well as deployment of the application into production as a
service.

Machine learning, natural language processing and knowledge data discovery are interrelated fields,
therefore the used tools are interchangeable.

This chapter focuses on describing the tools that help scientists to extract knowledge without specifying
how each service can be built by leveraging existing knowledge. Additionally, the chapter de-
scribes tools in the form of software services, libraries, frameworks, and hardware.

5.2. Usefulness – Why do we need this?

Knowing the relevant tools, their maturity and capabilities is important for implementing new ser-
vice, but also for being objective about what services are practically feasible.

The algorithms are only one part of data science. The tools can aid developers in several ways by
providing help with benchmarking, visualization and more. Maturity and functionality of the tools are
important for assessing how feasible it is to implement a new service. We have identified the follow-
ing decisive factors for selecting a tool for implementing machine-learning algorithms.

- **Programming language support** – it is important if the tool can use the developer’s pre-
dered programming language such as Python, R or Java.
- **License cost** - the organization must be able to afford the tool, and the license must be com-
patible with the organization.
- **Available support** - for some applications, support is not mandatory, but for production envi-
ronments in, for example, health services, good vendor support is indispensable.
- **Community** - an active community, conferences, and forums are good resources for getting
started and getting support while using ML tools.
- **Scalability** - when the software needs to be moved to a production environment, it should be
able to efficiently process huge data sets.
- **Integration** – it is important whether the tool can be seamlessly integrated with existing sys-
tems.
- **Data access & data cleaning** – the data has to be efficiently pre-processed before feeding
the algorithms.

Hardware has also a major impact on running the ML-applications. Current advances in available
computational resources have made machine learning, and deep learning, successful. ML and AI are
primary drivers for development of hardware both in powerful specialized hardware such as TPU
\textsuperscript{[141]}, NNP [142] and GPUs [143], and less powerful and resource-constrained devices such as mobile
phones and IoT (Internet of Things)\textsuperscript{21} gadgets (including tiny computers [144], mobile phones [145,
146] and even cameras [147, 148]).

\textsuperscript{20} A/B testing (also known as split testing or bucket testing) is a method of comparing two versions of an application against each other to
determine which one performs better.

\textsuperscript{21} IoT is a concept of connecting any device with an on and off switch to the Internet (and/or to each other)
5.3. What is the knowledge in the field?

Numerous ML tools are available, and new tools are being developed and released frequently. While writing this report, several new services have been released by large companies such as Amazon and Google [149]. Several of the existing machine-learning frameworks have also released new versions. Table 1 presents an overview of important properties of some of the most popular tools used for data science.

Table 1. Overview of available ML tools

<table>
<thead>
<tr>
<th>Name</th>
<th>Company</th>
<th>License</th>
<th>Enterprise Support</th>
<th>Main field or goal</th>
<th>Programming language support</th>
<th>Platform</th>
<th>Processor support</th>
</tr>
</thead>
<tbody>
<tr>
<td>H2O</td>
<td>H2O.ai</td>
<td>Apache 2</td>
<td>Yes</td>
<td>Machine learning</td>
<td>Java Scala R Python REST Web UI</td>
<td>JVM Hadoop Spark AWS Azure Linux Windows macOS</td>
<td>CPU GPU TPU</td>
</tr>
<tr>
<td>TensorFlow</td>
<td>Google</td>
<td>Apache 2</td>
<td>Community</td>
<td>Deep learning</td>
<td>Python Java C Go R</td>
<td>Linux Windows macOS Android iOS Google Compute Engine AWS Azure</td>
<td>CPU GPU TPU</td>
</tr>
<tr>
<td>Azure ML Studio</td>
<td>Microsoft</td>
<td>Commercial</td>
<td>Yes</td>
<td>Machine learning</td>
<td>GUI</td>
<td>Azure</td>
<td></td>
</tr>
<tr>
<td>SageMaker</td>
<td>Amazon</td>
<td>Commercial</td>
<td>Yes</td>
<td>Machine learning</td>
<td>Python R Scala Java</td>
<td>AWS</td>
<td></td>
</tr>
<tr>
<td>MXNet</td>
<td>Apache</td>
<td>Apache 2</td>
<td>Community</td>
<td>Deep learning</td>
<td>Python Scala R</td>
<td>Linux macOS Windows</td>
<td>CPU GPU</td>
</tr>
</tbody>
</table>
### 5.3.1. Programming language

Relatively straightforward to use a framework that provides support for a programming language and a platform familiar to the user. Python and R seem to be the most supported languages by the ML tools. For those with no previous programming experience, selecting one of the point-and-click solutions will probably be the best option.

### 5.3.2. Scalability

All tools displayed at table 1 have support for scaling-up and running on both CPU and GPU, as well as on clusters if needed. However, there are still differences in performance of the tools, which can be critical for particular use cases.

### 5.3.3. Enterprise support

On the production phase, an enterprise support for the service can be a requirement. For some of the frameworks listed in Table 1, the enterprise support is provided by the back-end organization; for others – it is supported through third parties.
5.3.4. Installation and ease of getting started
All the presented tools in Table 1 are easy to install, but some of them are less involved than others. For example, H2O can be installed and run by downloading one binary file, while Keras, another high-level framework, requires also installing a back-end such as TensorFlow, Theano or CNTK.

An alternative to locally installed software is to use a cloud provider to get access to either a machine-learning-as-a-service solution or a virtual data science workstation. All cloud providers offer time- and resource-limited free trials.

Extensive documentation, examples, tutorials, and active community are available for all of these tools. However, as the ML field is continuously developing, these resources quickly become outdated.

5.3.5. License
Several tools are developed under free and open-source licenses that makes them free to use, modify and share. All of these frameworks have active communities making it easy to get help, in addition to proper tutorials and getting-started guides.

As mentioned earlier, Keras depends on other back-ends to function. These back-ends tools can be used as standalone products. H2O is also able to use TensorFlow and other back-end systems apart from its own default implementation.

TensorFlow is used by cloud providers. Amazon and others companies provide this and other tools as software services, either as is or modified to suit a particular service. Having many tools sharing the underlying technologies is heavily motivated by the free and open-source licenses making this practically feasible. This also means the tools can be improved by many contributors which allows some products to focus on usability, data cleaning, visualization and other challenges, while the underlying algorithms are being developed and maintained by others.

Some products are only provided as closed-source products or software-as-a-service solutions, or have premium functionalities that are closed source and only provided to paying customers. H2O is given for free with the Apache 2 license, but has a premium closed-source component called Driverless AI.

5.3.6. Impact on IT infrastructure
Several presented tools are provided both as local installations and as software-as-a-service hosted by cloud providers, therefore a user has flexibility selecting a platform for running the tools. However, machine learning requires substantial computational resources, in particular for deep-learning applications. This can become expensive and affect an organization’s IT infrastructure Organizations have the option to rent the resources for buying and maintaining processing clusters from a cloud provider. This requires the data to be uploaded to the cloud, which can be restricted from privacy and security perspectives. For an organization already storing its data in the cloud, any of these services are feasible. However, integration with existing services would be easier.

5.3.7. Interoperability between models
Lack of interoperability the models produced by the different frameworks should be taken into consideration when building a new service.

Developers planning to use Inference deployment on edge device such as a mobile phone should ensure the mobile phone is able to use the model. This can be limited both by software and hardware resources. If it is not possible to do the inference on the edge device, one option is to provide the inference as a service. That would imply the relevant input data from the phone to be transferred to the inference service. Privacy concerns and network availability can lead to challenges [150]. Latency may also be reduced by doing on-device inference instead of using a remote service. This can be used, for example, for swifter replies from a virtual assistant [151].
Microsoft and Facebook have initiated an open-source project named Open Neural Network Exchange (ONNX) that will provide “a shared model representation for interoperability and innovation in the AI framework ecosystem” [152]. The project has later been joined by Amazon, AMD, ARM, Huawei, IBM, Intel, Qualcomm and Nvidia [153, 154]. This is an attempt to solve the issues of interoperability between the resulting models.

Currently ONNX supports conversions between the models from Caffe2, CNTK, MXNet, and PyTorch, and more are coming.

Microsoft recently announced that Windows devices would support natively running ONNX models accelerated in hardware [155].

5.3.8. Hardware dedicated to machine learning
As computational capacity became more available, scientists discovered that using hardware at ML tasks often resulted in higher quality models and more precise outcomes. This discovery has led to a boom of hardware development targeting ML applications, particularly in the field of deep neural networks. Google’s Tensor Processing Unit (TPU) is one example of the specialized hardware. While the TensorFlow is flexible to be run on a variety of hardware platforms, Google pushed the boundaries of efficiently processing TensorFlow programs by designing dedicated hardware. However, TPU is not as versatile as a CPU or a GPU. Google has made a cluster of TPUs available to the research community for computationally expensive research on neural networks [156]. The TPU played a critical role being the learning and inference platform when DeepMind recently achieved great success with their AlphaGo Zero project [157].

In addition to Google, Intel, Nvidia and Amazon have made efforts to process efficiently complex neural networks; some of these are commercially available. Popular smart phones are starting to include dedicated hardware to perform on-device neural network calculations efficiently.

5.4. Use cases
This section presents machine-learning tools used in NLP and KDD. The tools are grouped for getting a practical experience and understanding their maturity.

H2O represents a full-fledged machine-learning framework with a possibility of local installations. Other alternatives for this type of tools are RapidMiner and Keras.

Amazon, IBM, Google, and Microsoft provide machine-learning-as-a-service. Microsoft Azure is selected for testing.

Gate Developer exemplifies NLP tools. There are other NLP tools as OpenNLP, CoreNLP and more.

To represent a tool for building deep-learning networks, TensorFlow was chosen. Other alternatives here are MXNet and Coffee.

5.4.1. TensorFlow
TensorFlow is a programming library targeting the neural networks. It can be applied to other tasks, but its core structures and handling of data maps directly to neural networks. Neural networks are computationally expensive and have to be programmed in a lower level language. It evolved from Google’s initial efforts in this field and was released as an open-source project in 2015.

The research community as well as many other open and closed software efforts have embraced TensorFlow. Programming a new neural network and training new models in TensorFlow requires using Python; the resulting models can be used on several different programming languages and platforms, including mobile platforms. In addition, a crafted network can be scheduled to run on CPUs, GPUs or even TPUs without changing the application. After producing a model, TensorFlow Server can manage
and provide inference services for clients. Multiple models and versions of the same model can be served at the same time, helping A/B testing and experimental deployments.

**Installation & use**

The basic installation of TensorFlow with CPU support is simple; it becomes more difficult when adding GPU support. It is possible to rent cloud instances for CPU or GPU processing, or even buy pre-configured workstations.

As neural networks are difficult for humans to understand, Google provides a visualization tool that integrates with TensorFlow. *TensorFlow’s TensorBoard* allows the scientist to evaluate the neural network’s configuration and performance with a number of standard graph visualizations.

TensorFlow maintains a repository of models implemented in the framework [158]. *TensorFlow’s Community Models* contain tutorial style models, as well as a research section.

### 5.4.2. H2O.ai

H2O.ai is a machine-learning framework based on free and open software. They aim to provide open, fast AI to the enterprise.

H2O is available on several platforms. It provides relatively easy ways of scaling-up and a REST interface, and integrates with many different data sources and the most important programming environments such as R, Python and Java/Scala.

**Installation & use**

H2O can be downloaded as a single self-contained binary file in .jar format. The only requirement is the Java runtime environment. The H2O Flow interface and REST interface are included in this file. R library or Python module has to be installed to connect through their bindings.

In addition to the bindings and REST interface, there is also H2O Flow a graphical user interface based on Jupyter/IPython. Being a tool for creating interactive scientific notebooks, it integrates markup language, source code and visualization in the same document.

H2O Flow also provides a point-and-click experience where no programming is required. Jupyter widgets allow importing data files, cleaning and transforming data, benchmarking multiple machine-learning algorithms, as well as providing insight into resource usage at the H2O instance and visualization of the results of the computations.

The resulting models are represented as Java classes that can be downloaded and used in any JVM.

### 5.4.3. Microsoft Azure

Microsoft Azure is a cloud platform providing software-as-a-service, platform-as-a-service and infrastructure-as-a-service. For an organization already storing its data in the Azure cloud, it is a natural choice to use the Azure platform for machine learning. It provides a large portfolio of machine-learning services as well as other data-science tools.

**Installation & use**

There are three different tools to get started with machine learning in Azure: Machine Learning studio, Machine Learning services, and Data science virtual machine. Each of these are described below, and all require the user to sign up for an Azure account (a trial period of 30 days including about $200 in credits is available).

*Machine Learning Studio* is machine-learning-as-a-service, and everything runs in the cloud. A web-based, graphical drag-and-drop user interface that lets the user create an Experiment represented as a flow chart is provided. Different resources can populate the flow chart, and an output from one re-
source can be the input to another just by drawing lines between them. There are pre-configured machine-learning algorithms, scoring, data splitting, and testing and evaluation resources. It is also possible to add Python or R scripts to the flow in addition to numerous other resources available such as language detection, deep learning, data transformation, and others.

Due to the tight integration with the Azure platform, it is even possible to add a web-service resource to the flow chart that can be deployed to production using the same graphical interface, requiring no programming.

A user can have several projects and experiments held in a Workspace. A key functionality of a Workspace is to invite other people to a Workspace to collaborate on a set of projects and experiments.

In addition to the Studio’s Flow-Chart interface, there is also a separate Notebook component. It is based on Jupyter, the same free and open-source technology that is used for H2O Flow. Microsoft has taken this idea further and created a free-hosted Jupyter notebook service [159].

*Machine Learning Services* is a collection of native applications and cloud services. It has Workspaces, Projects and Experiments as the Machine Learning Studio; the drag-and-drop user interface is replaced by the Workbench desktop application along with its command-line utility. This can be installed on a Windows or macOS workstation.

The Workbench application offers great possibilities for customizing. One of these customizations is the compute target attributes of an experiment. By changing an experiment’s compute target, it is possible to run first on a local computer, and then move to a Docker container on a remote computer or a cluster.

Workbench allows for data cleaning and benchmarking different algorithms to select the best models. The Workbench tracks the steps during the algorithm’s running, so that it is easy to go back and try different approaches, as well as re-running the same procedures on other datasets. The feature set is similar to the H2O Flow web interface, and Azure integrates with open-source frameworks such as TensorFlow, Caffe and CTLK. The application integrates very tightly with the rest of the Azure services. This means that when a model is considered good enough, it can be promoted to a production model, and then easily be used in other Azure services, making it very easy to, for example, create an Azure web service that can run inference using the model.

Workbench has an integration with PROSE, machine learning for data cleaning [160].

*Data Science Virtual Machine* is a virtual machine pre-configured with pre-installed relevant machine-learning tools such as TensorFlow, Caffe, CTLK and others. The Azure Workbench is currently not pre-installed, but the installer is downloaded and ready to run on the Windows version.

The user can specify what kind of virtual machine has to be installed, including several Windows and GNU/Linux versions, being platform-as-a-service.

Azure is a well-established platform with many users, and Microsoft is a large corporate actor. This means that there are many courses, tutorials and a large community for Azure.

### 5.4.4. Gate Developer

Gate Developer is a product part of the Gate tools portfolio. It is a text analytics platform with a wide range of tools from developing environments, collaboration tools, including a wiki to Gate as a cloud service solution [161].

Gate Developer is a development environment that provides a rich set of graphical, interactive tools for the creation, measurement and maintenance of software components for processing human language [162]. The Gate Developer user interface is not self-explanatory, and there is no first-time tutorial available when launching the application. However, at its web pages, Gate has provided a screen-
cast tutorial that describes the user interface, including Language resources, Processing resources, Datastores and Applications, and its functionality.

**Installation & use**

The installation of Gate Developer is straightforward, and it is available on Windows, macOS and Linux. The first thing to do after installation is to import documents.

Gate calls the original document a source document, and a working document - a Gate document. When importing a source document, it is possible to specify it as a plain document or a markup document. A markup document is either an html or an xml file. While importing a markup document, all markup is removed, and the document is automatically annotated using the tags from the original markup. This sort of automatic data processing can be a huge time-saver and makes simple NLP annotation tasks much quicker. For the plain document type, no such automatic processing is available.

Gate documents are stored in memory as language resources, but can be persisted to a data storage for later retrieval and saving working memory. The data storage also serves as a shared repository for all the Gate community. Several documents can be stored as a collection called a Document Corpus.

For working on corpus document, a process resource must be added. The process resources perform tokenizing, annotations or dictionary lookups of a text.

Process resources are implemented as plugins, making it possible to easily extend the functionality of Gate Developer. The plugin architecture is quite powerful, allowing for changes in the graphical user interface. Plugins can also be shared with the community.

Each of these process resources can be run individually to experiment and tweak the attributes and annotation schemas, being even more useful if they are combined in a Gate Application. In a Gate Application, the process resources are organized as an execution pipeline where the output of one resource is input to the next. The Gate Application can be run within the Gate Developer or be exported as a compressed file and included in Gate Teamwork.

5.5. How does this relate to Norwegian healthcare?

Research projects using health data are subject to laws and regulations with strong requirements for privacy and security. Use of these tools in accordance with the required regulations is able due to the capability of the tools to be installed on the same machine where the data is located, independently of a platform. However, there are restrictions on what kind of cloud-based solutions to use with regard to where the data is stored physically, as clouds can move across country boarders.

Data in Norway is distributed across institutions and data sharing is difficult. This limits the usefulness of the traditional machine-learning tools, where the training data is expected to exist in a single data center. Even if each health organization could install the required hardware and software locally, the results of utilizing machine learning will be limited by the amount of data available in that organization.

Norway has many high-quality health registries, which are currently being consolidated in the national health analytics platform; there is an ambition to provide there an infrastructure to run machine learning [163]. This will require the relevant software and hardware resources to be available on the platform.

Another approach for performing machine-learning and deep-learning analysis in such a distributed environment as the Norwegian healthcare sector is to use federated learning, which enables machines to collaboratively learn a shared prediction model while keeping all the training data locally. This topic has not been covered in this chapter since there are no present tools capable of doing this out of the box. Tools for running secure and privacy-preserving machine-learning data analysis across
institutions nationally, would greatly improve the potential of exploiting of machine learning in Norway given the current laws and regulations.
6. Stakeholder mapping

We have identified stakeholders in the field of health analytics in Norway and Sweden.

Research groups in Norway, including Sweden are performing studies using deep learning networks for medical image analysis. At Karolinska Institutet, Danderyd hospital researchers tested if deep learning networks could be trained to identify fractures in orthopedic radiographs. The study findings support that deep learning methods are capable of performing at human level. At Radiumhospitalet in Oslo the DoMore! project in their search for improvements in cancer treatment use concepts as image analysis or more specific deep learning, texture analysis, quantification of DNA for transferring the complex thinking and decision-making currently based on visual observation to an digital process with objective and reproducible algorithms. The combination of digital pathology and laboratory automation will reduce human error and remove subjective and time-consuming analysis. Patients with lung, colorectal and prostate cancer will experience these gains by more precise diagnosis and more targeted treatment resulting in fewer cases of overtreatment and thus a better quality of life.

There are fewer research institutions identified in the stakeholder mapping working for the use of genomic data, and to collect data by using smartphones and sensor watches. Structured and unstructured data from electronic health records are included in many of the studies performed by the identified actors. Additionally there are researchers who combine data from different data sources.

There are many exciting research initiatives in cancer and cardiology, and within gastrointestinal surgery, mental health, pain, allergy, diabetes, orthopedics, anesthesia, and a large research project in ultrasound.

6.1. Background, methodology, limitations and categorization

Methodology

The stakeholders are not chosen by their publications - the information is mostly gathered through their website and by performing interviews with few selected researchers. The identified stakeholders perform research within health where advanced statistical and mathematical machine learning algorithms are used as methods.

There are weaknesses in the mapping since websites are used as sources and there is a chance that the institutions websites are outdated. There is also a risk that the mapping is missing key stakeholders.

Categorization of stakeholders

The mapping divides stakeholders into the following categories:

- University
- Research center
- University hospital/Hospital
- Private foundation
- Consortium
- Enterprise group

Private operated businesses are not included in the mapping because of time constraints in the project. Be aware of that there is a possibility that important stakeholders are not included in our mapping.
6.2. Norwegian stakeholders and initiatives

**BigInsight**

**Website:** [https://www.biginsight.no/](https://www.biginsight.no/)

**Location:** Oslo, Norway

**Category:** Consortium

**About**

BigInsight is a research-based innovation center funded by Norwegian Research Council and the 15 public, private and research consortium partners. Their objective is to work with statistics and machine learning for performing predictions and decision [164]. The consortium aims for developing new statistical tools for performing analytics of high dimensional and complex data [6] and the objectives are to work with personal marketing, personalized health and patient safety, personalized fraud detection, sensor systems and forecasting power systems [7].

The consortium consists of the following partners: Norwegian Computing Center (Norsk Regnesentral), University of Oslo, University of Bergen, ABB, DNB, DNV GL; Gjensidige, Hydro, Telenor, NAV, Skatteetaten, Oslo University Hospital, Norwegian Institute for Public Health, Cancer Registry of Norway, Statistics Norway [165].

**Methodology used in health specialties**

In their personalized health and patient safety innovation objective the researchers work on developing new mathematical, statistical and computational methodology for improving treatment predictions for patients with breast cancer. Additionally they develop methods to predict synergy between drugs or the effect of the drug combination with data from cancer cell lines. Develop models for predicting cancer drug sensitivity with large-scale in vitro drug screening [166].

**Methodology specialties**

Methodologies and techniques used in different projects (not only within personal health and patient safety) are clustering, focused inference, functional data analysis, graphical models, hierarchical Bayesian models, data integration, model comparison and model improvement, multiple testing, multivariate dependence and copula models, extreme value theory, non-parametric Bayes, non-stationary and non-linear stochastic processes and time series, sequential inference, stochastic geometry and space time models, subsampling and data thinning [167].

**Researchers involved in patient safety projects**

Principal investigator Magne Thoresen, professor at University of Oslo, Faculty of Medicine, Institute of Basic Medical Science and co-Principal investigator Clara Cecilie Gunther from Norwegian Computing Center [166].

**Publications**

Publications linked at BigInsight website: [https://www.biginsight.no/press-on-big-insight/](https://www.biginsight.no/press-on-big-insight/)

**BigMed, The Intervention Centre, Oslo University Hospital**

**Website:** [https://bigmed.no/about](https://bigmed.no/about)

**Location:** Oslo, Norway

**Category:** Hospital
About

The BigMed project at the Intervention Centre at Oslo University Hospital work for advancing precision medicine and big data analytics in healthcare by testing and integrating ICT solutions to enhance the implementation of clinical precision medicine within diseases as metastatic colorectal cancer, sudden cardiac death and rare diseases. The project is an ICT Lighthouse project funded by The Research Council of Norway, and it is a consortium with partners from the industry organizations, patient associations, universities, and hospitals [168]. BigMed as a project work on defining the barriers for adopting precision medicine in Norway, in addition to expand partner ecosystem for precision medicine [169]. For investigating the barriers to implement precision medicine they have convened a series of workshops with stakeholders where they identified six key category barriers to the widespread adoption of precision medicine: legal and regulatory, organizational, financial and political, competence and knowledge and technological [168].

Content health area specialties
Metastatic colorectal cancer, sudden cardiac death and rare diseases [168].

Methodology specialties

The BigMed partners and collaborators methodology focuses are applied statistics, machine learning methodology and algorithms for extracting understanding from clinical and genomic data and make predictions of future events/conditions. Biomarker discovery, patient safety monitoring based on electronic health records, natural language processing, sequencing technologies, artificial intelligence, big data, computer architecture, computer graphics, computer security, databases, human computer interaction, information systems, operating systems and software engineering [168].

Partners and collaborators

DIPS, DNV GL, Norwegian Armed Forces, Joint medical Services, IBM, Karolinska Institutet/SciLifeLab, Kunskapsforlaget, The Norwegian Heart and Lung Patient Organization (LHL), Norway Health Tech, Norwegian Cancer Society (Kreftforeningen), Faculty of Information Technology and Electrical Engineering, Department of Computer Science at the Norwegian University of Science and Technology (NTNU), Department of Medical Genetics at the Oslo University Hospital (OUS), Institute for Cancer Research, Department of Tumour Biology at the OUS, the Interventional centre at the OUS, Hospital-legal department at the OUS, ICT at the OUS, OCBE at the OUS, PubGene, Sykehuspartner, The Norwegian Association for Children with Congenital Heart Disease (Foreningen for hjertesyke barn), The Faculty of Law at the University of Oslo (UiO), Institute of Health and Society at the UiO, Services for Sensitive Data (TSD) at the UiO, Department of Informatics at the UiO, Department of Informatics, Language Technology Group (LTG) at the UiO, Department of Informatics, Logic and Intelligent Data (LogID) at the UiO [168].

Publications


INTROMAT (introducing personalized treatment of mental health problems using adaptive technology)


Location: Bergen and Oslo, Norway
Category: Consortium

About

INTROMAT at Haukeland University Hospital is a lighthouse project funded by the Norwegian Research Council. The project is working on integrating innovative technologies and psychological treatments. The INTROMAT project is working for improving public mental health with innovative ICT [170]. INTROMAT partners are: Atensi, BTQ, Bryggen Research, CheckWare, Explorable, Helse Bergen – Haukeland universitetssykehus, Helse Vest IKT, Høgskulen på Vestlandet, IBM, imatis, ModumBad, Psyktools, University of Oslo and University of Bergen [171].

Methodology used in health specialties

The goal is to develop five personalized digital health services: relapse prevention for bipolar disorder, cognitive training in ADHD, job-focused treatment for depression in adults, early intervention and treatment for social anxiety disorder in adolescents and psycho-social support for women recovering from gynecological cancer [172].

Professor Jim Tørresen at Robotics and Intelligence Systems (ROBIN) research group at Department of Informatics at the University of Oslo [173] is leader for work package one on developing patient monitoring and support systems [174]. The research is about what specific features are being significant for human behavior and mental health, as well as research and prototype a flexible system for modelling and prediction of behavior and develop a support system for effective mental health improvement. Data is collected using smartphones and sensor watches from the patient for modelling behavior including emotional state for prediction. They apply machine-learning methods to phone calls speech data and other sensor data collected with smartphones and wearable devices to predict mental states such as depression in bipolar disorder patients. Additionally they apply state of the art machine learning techniques to develop effective mechanisms for predicting upcoming negative periods as early as possible. Data collected are from speech, motion, heartbeat, phone usage, etc.

Researchers

Professor Jim Tørresen at Robotics and Intelligence Systems (ROBIN) research group at Department of Informatics at the University of Oslo [173], Associate professor Tine Nordgreen at Department of Clinical Psychology, Faculty of Psychology at University of Bergen [175] and other researchers are listed on the website.

Norwegian Computing Center - Norsk Regnesentral, Statistical Analysis, Machine Learning, and Image Analysis (SAMBA) department

Website: https://www.nr.no/en/about-main

Location: Oslo, Norway

Category: Private foundation

About

Norwegian Computing Center (NR) research areas are methodological and the research fields are statistical modelling, information technology, remote sensing and image analysis. The center application areas are oil and gas, bank and finance, climate and environment, industry and energy, health and private and public services [176].

Methodology specialties
The SAMBA department at NR have a broad knowledge in a variety of methods used in different research areas for various industries. They have theoretical and practical knowledge in the field of statistics, machine learning, and image analysis [177] and are working towards developing specialized deep learning solutions [178]. The pattern recognition group are working with understanding needs for deep learning solutions for solving problems for various industries and medical applications, additionally within analysis of remote sensing images. The group collaborate with the machine learning team at the University of Tromsø [177].

Researchers

Chief Research Scientist Line Ekvil, research director SAMBA Andre Teigland, other researchers are listed on their website [179].

Norwegian University of Science and Technology (NTNU), Faculty of Medicine and Health Science, Department of Circulation and Medical Imaging (ISB) with affiliated centers K.G. Jebsen Center for Exercise in Medicine (CERG), Centre for Innovative Ultrasound Solutions (CIUS), Operating Room of the Future, The Medical Simulation Centre and Norwegian Centre for Minimally Invasive Guided Therapy and Medical Technologies (NorMIT)

Website: https://www.ntnu.edu/isb/department-of-circulation-and-medical-imaging
Location: Trondheim, Norway
Category: University

About

The Department of circulation and medical imaging perform research within ultrasound, MRI, exercise, the circulatory system, anesthetics and emergency medicine [180]. With a total of around 200 employees [181] the department has approximately 80 PhD candidates. The department hosts the K.G. Jebsen Center for Exercise in Medicine (CERG) and the Centre for Innovative Ultrasound Solutions (CIUS) [182]. By exploiting synergies across disciplines as healthcare, maritime, and oil and gas CIUS work for improving patient care through leveraging ultrasound technology as well as imaging by performing research within transducer design, acoustics and image formation, Doppler and deformation imaging, as well as image analysis and visualization [183]. At CIUS, there are nine work packages where the fourth work package covers image processing, analysis and visualization. One of the goals for this work package is to develop an automatic real-time 3D segmentation of all heart chambers, in addition to develop real-time image analysis for providing information for optimizing image acquisition [184]

Methodology used in health specialties

Researchers at the CIUS have designed a neural network for automatic detection of blood vessels in real-time from ultrasound images [185].

Automatic blood vessel detection may be helpful in medical applications for detecting deep vein thrombosis, anesthesia guidance and for catheter placement. The deep convolutional neural network method determine the vessels position and size in real-time. By validating dataset of carotid artery the accuracy of the findings demonstrate that the method can generalize to blood vessels to various parts of the body [186].

Methodology specialties

Machine learning, deep learning, convolutional neural networks, image segmentation, Parallel and GPU processing etc. [187].

Researchers
Postdoctoral researcher Erik Smistad employed at NTNU, CIUS and SINTEF Medical Technology [187], Professor Lasse Løvstakken, NTNU, Department of Circulation and Medical Imaging [188], he is also head of work package four: Imaging processing, analysis and visualization in the CIUS project [184].

Norwegian University of Science and Technology (NTNU), Department of Computer Science, Faculty of Informatics Technology and Electrical Engineering

Website: https://www.ntnu.edu/idi
Location: Trondheim, Norway
Category: University

About

The department of Computer Science lead research in artificial intelligence, big data, computer architecture, computer graphics, computer science, databases, human computer interaction, information systems, operating systems, etc. [189]. In 2016, a Telenor-NTNU AI-lab was established for conducting research in artificial intelligence, machine learning and big data analytics [190].

Methodology used in health specialties

The EU Horizon 2020 research project Selfback work towards improving self-management of non-specific low back pain by the use of data, app development and artificial intelligence [191]. In the ExiBiDa project funded by the Norwegian Research Council, FRIPRO research program they focus on data dimensions containing spatiotemporal-textual contents. Techniques as efficient algorithms and index structures are developed for processing spatiotemporal-textual queries on data, where textual social media data is an example [192]. Researchers have also assessed the user satisfaction on search-based and content-based approaches when finding the most relevant guidelines and recommendation to clinicians, also known as clinical decision support system which is a health information technology system [193].

Methodology specialties

Machine learning, health informatics, knowledge-based systems [194], artificial intelligence, big data, database systems, data mining, text mining [195].

Researchers

Associate professor Øystein Nytrø, associate professor and leader of the data and artificial intelligence (DARY) group Heri Ramampiaro and professor Kjetil Nørvåg. The list of all staff members can be found here.

Oslo University Hospital, Division of Cancer Medicine, Norwegian Radium Hospital, Institute for Cancer Genetics and Informatics (ICGI)

Website: http://icgi.no/
Animation videos: https://www.youtube.com/user/medicalinformatics
Location: Oslo, Norway
Category: Hospital
About
The ICGI perform research in biomedicine and informatics providing new methods for diagnosis and prognosis to improve treatment of cancer [196]. Currently there are around 40 ongoing research projects at the institution [197].

The institute is in lead of a Research Council lighthouse project named Do More! The project is in search for improvements in cancer treatment. By using digital tools within pathology, the project goal is to improve prognosis. Researchers are working with the most common cancers – lung, colorectal and prostate cancer [198]. ICGI has also an ongoing project on clinical decision support where they are aiming for to help clinicians to provide optimal treatment by using available facts including previous experiences [199].

**Methodology used in health specialties**

The DoMore! project goal is to use concepts as image analysis or more specific deep learning, texture analysis, quantification of DNA for transferring the complex thinking and decision-making currently based on visual observation to an digital process with objective and reproducible algorithms [198]. The combination of digital pathology and laboratory automation will reduce human error and remove subjective and time-consuming analysis. Patients will experience these gains by more precise diagnosis and more targeted treatment resulting in fewer cases of overtreatment and thus a better quality of life [200].

**Methodology specialties**

Microscopy based image analysis [196], deep learning and convolutional neural networks [201], texture analysis and of DNA [202].

**Researchers**

Institute Director, Professor Håvard E. Greger Danielsen, Section Manager for Applied Informatics John Arne Nesheim.

**Publications**

Publications since 2006 are listed here: [http://icgi.no/Publications](http://icgi.no/Publications) [203].

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**SINTEF, SINTEF Digital**

**Website:** [https://www.sintef.no/](https://www.sintef.no/)

**Location:** Norway and internationally

**Category:** Enterprise Group

**About**

SINTEF is an independent research organization with 4000 customers and 2000 employees from 75 nations [204]. SINTEF Digital institutions are Human Factor, Big Data, Artificial Intelligence, Autonomy, Cyber Security, Connectivity and Sensors [205].

**Methodology used in health specialties**

SINTEF is a partner in the BIA project Intelligent Cardiovascular Ultrasound Scanner (INCUS) where deep learning methods are used for increasing decision making for ultrasound operators. Echocardiography is an imaging tool for cardiologists assessing cardiac function. Heart echo examination is real time, cost effective and without harmful radiation and therefore it has advantages compared to other medical imaging modalities. The massive computational power of GPUs has made it possible for machines to recognize objects and translate speech in real time [206]. Deep learning utilize GPUs to train neural networks for learning representations from large image databases [207].
Researchers
Research Manager Jon Mikkelsen Hjelmervik and Senior Research Scientist Petter Risholm [207].

University of Agder, Centre for Artificial Intelligence Research (CAIR), Department of Information and Communication Technology

Website: https://cair.uia.no/
Location: Kristiansand, Norway
Category: University

About
Artificial intelligence research is conducted at the CAIR center. The center has an AI circle where invited members from the public and private sector will take part of artificial intelligence educational events [208].

Methodology used in health specialties
Sørlandet Hospital Trust is a partner where they collaborate on projects applying machine-learning techniques on narratives of the electronic health records. The hospital is testing new algorithms on detecting allergy before surgery [209].

Methodology specialties
Machine learning, deep information understanding and reasoning, communicating with natural language processing [210].

Researchers
Ole-Christoffer Granmo Professor at Department of Information and Communication Technology, University of Agder [210], Tor Tveit, consultant at Sørlandet sykehus, researcher Geir Thore Berge at Sørlandet Hospital Trust, CAIR and University of Agder [211].

University of Tromsø – The Arctic University of Norway, UiT Machine Learning Group

Website: http://site.uit.no/ml/
Location: Tromsø, Norway
Category: University

About
The group advances statistical and mathematical machine learning algorithms as deep learning, kernel machines and change detection [212]. The group collaborate with clinicians at the University Hospital of North Norway on research projects performed within health analytics. Publications with clinicians from Department of Gastrointestinal Surgery, on research projects performed within health analytics.

Methodology used in health specialties
The machine-learning group and their team working with electronic health analytics and image analysis are working towards improving deep learning research. The group is working with predicting and preventing postoperative complications with deep learning for better quality of care by leveraging data from electronic health records, analyzing and integrate imaging colonoscopy for polyp detection.
and analyze imagery and time series data to prevent perioperative complications [213]. Other research conducted by the team is reinforcement learning optimal control for type 1 diabetes [214].

In collaboration with researchers and clinicians from Department of Gastrointestinal Surgery, University Hospital of North Norway and The Norwegian Centre for E-health Research a study was done on early detection of anastomosis leakage (AL) by using free text from electronic health records to detect AL before the actual complication occur [215].

**Researchers**

Associate professor Robert Jenssen, professor Fred Godtliebsen, other researchers are listed on the website.

**Publications**

The latest publications are found on their website: [http://site.uit.no/ml/recent-publications/](http://site.uit.no/ml/recent-publications/)

**University of Oslo, Department of Informatics, The Faculty of Mathematics and Natural Science, Language Technology Group (LTG)**

Website: [https://www.mn.uio.no/ifi/english/research/groups/ltg/](https://www.mn.uio.no/ifi/english/research/groups/ltg/)

Location: Oslo, Norway

Category: University

**About**

The LTG is organized under the faculties thematic focus area information and communication technologies (ICT) [216]. The LTG are interested in data-driven modeling for a range of Natural Language Processing (LNP) tasks; dependency and unification-based parsing; natural language generation; dialogue modeling; lexical acquisition; sentiment analysis [217].

**Methodology used in health specialties**

The LTG is a part of the BIGMED project at Oslo University Hospital where they have an intention of integrating patients health record information with genomics data [218].

**Methodology specialties**

Computational semantics, Natural language processing and machine learning [217].

**Researchers**

Associate professor Lilja Øvrelid and the other researchers are listed on their website.

**Publications**

LTG latest publications are found on their website: [http://www.mn.uio.no/ifi/english/research/groups/ltg/publications/](http://www.mn.uio.no/ifi/english/research/groups/ltg/publications/)

**Norwegian Centre for E-health Research**

Website: [https://ehealthresearch.no/en/](https://ehealthresearch.no/en/)

Location: Tromsø, Norway

Category: University Hospital

**About**
The center work with e-health research including writing assessments. The center has four strategic areas, which are future health record, health analytics, personal e-health and patient pathways and coordinated care.

**Methodology within health analytics specialties**

The Health Analytics team is working towards gaining knowledge within Natural Language Processing through the incubator project NorKlinText. Professor Hercules Dalianis at Stockholm University is involved to contribute with knowledge within text mining of the electronic health record.

Currently the Health Analytics team is working on writing an report on health analytics, the report contain short introductions to machine learning, Natural Language Processing, and knowledge discovery databases.

Additionally the Health Analytics team is working on an infrastructure project where data from the general practitioners are extracted from the electronic health records for the use of research.

The researchers have knowledge within practical privacy-preserving distributed statistical computation of health data, secondary use of data for Clinical, Decision Support Systems (CDSS), CDSS semantic model, machine learning and statistical data analysis.

**Researchers**

The center employees are listed on the website: https://ehealthresearch.no/en/employees

6.3. Swedish stakeholders

**Karolinska Institut, Danderyd Hospital, Department of Clinical Sciences collaborate with Department of Robotics, Perception and Learning (RPL), School of Computer Science and Communication, KTH Royal Institute of Technology**


**Location:** Stockholm, Sweden

**Category:** University/hospital

**About**

The department of Clinical Sciences is at the medical university Karolinska Institutet that is Sweden’s largest center of medical academic research. At Danderyd Hospital, the orthopaedic surgeon Max Gordon who also is a researcher at the Karolinska Institute perform research within epidemiology, machine learning, neural networks and deep learning. The aim for the research is to work towards improved patient-safety, health-care efficiency and patient outcomes [30]. At the Danderyd’s Hospital the researchers work on describing the possibilities by using deep learning for skeletal radiographs [31]. There is a collaboration with the Royal Institute of Technology, School of Computer Science and Communications and the Robotics, Perception and Learning lab where they perform research within computer vision, robotics and machine learning. The lab has many EU H2020 projects, which are listed on this website: https://www.kth.se/rpl/projects. At Danderyd Hospital they are working in collaboration with KTH data science department to improve patient-safety, health-care efficiency and patient outcomes [219]

**Methodology used in health specialties**

At Karolinska Institutet, Danderyd hospital researchers tested if deep learning networks could be trained to identify fractures in orthopedic radiographs. The study findings support that deep learning methods are capable of performing at human level [220].
Methodology specialties
Neural networks, deep learning and machine learning [219].

Researchers
Orthopedic surgeon and researcher Max Gordon at Danderyd Hospital [219], researcher Ali Sharif Razavian and associate professor Atsuto Maki at KTH [221].

Publications
Selected publications are listed here: https://ki.se/en/people/maxgor

Stockholm University; Faculty of Social Science, Department of Computer and Systems Sciences, DSV, Language Technology Group

Website: Stockholm University: https://www.su.se/, Faculty of Social Science, Department of Computer and Systems Sciences, DSV, https://www.dsv.su.se/, Language Technology Group https://dsv.su.se/en/research/research-areas/language

Location: Stockholm, Sweden

Category: University

About
The language technology group have interest in the medical domain, clinical text mining with focus in Swedish language. The group work with developing Natural Language Processing methods. Research on information extraction, text summarization, text generation, semantic modeling, information retrieval and health informatics [222].

Methodology used in health specialties
The clinical text-mining group perform research in language technology and health informatics where they interpret clinical texts using domain experts and machines. The aim is to create tools for clinicians. Research data is obtained from Stockholm EPR Corpus [223] and saved in the Health Bank, Swedish Health Record Research Bank that contain large sets of structured and unstructured electronic patient records. The research groups has developed clinical text mining tools with use of the information [224].

Methodology specialties
Natural Language Processing (NLP) methods [222].

Researchers
Professor Hercules Dalianis, he is also working on the NorKlinText project at Norwegian Centre for E-health Research [225] and the author of the book «Clinical text mining: Secondary use of electronic patient records» [165], professor Uno Fors, and professor Panagiotis Pappetrou [222].

Publications
Search of the group’s publications can be done on their website: https://dsv.su.se/en/research/publications.
7. Summary

The growth of digital health has resulted in large amounts of data continuously generated. There is a great potential in these data, both for providing healthcare services (primary use) and for planning, management, and quality improvement of health system, public health and research (secondary use). New technologies make it possible to collect, store and process data of different types time- and cost-effectively. Health analytics gains insight from health data to support decision making for improving the quality of care and patient safety.

Norwegian government’s vision for future healthcare, One Citizen - One Record, highlights increasing and simplifying the use of health data for quality control, monitoring, management and research.

Structured and unstructured health data is stored in many different systems and formats. In order to retrieve new insights from health data, effective analytical tools and techniques are required in addition to integrated interoperability and seamless processing of health data. The combination of large amounts of various data, high parallel processing power, and improved theoretical knowledge has enabled rapid development of machine-learning algorithms.

Moving to proactive healthcare will be led by prescriptive analytics. Currently, health analytics can, for example, identify patients at high risk of sepsis or readmission to hospital within 30 days of discharge. Machine-learning methods together with genomic data give the opportunity to shift to a personalized medicine.

Machine learning has been tested in many research and pilot projects with promising results; it can lead to disruptions in prognostics, interpretation of medical images, and diagnostics. To use machine learning in clinical practice, the algorithms must be integrated into clinical workflows, which requires immediate access to patient data, in addition to the trained ML model. Integration of ML system with patient data can be done in differently: either by incorporating it into the EHR or radiology system or it can be delivered as a cloud service by a third-party service provider or in a private cloud. There are, however, restrictions on what kind of cloud solutions to use, in particular with regard to where the data is stored physically, as clouds can move across country boarders.

Natural language processing can be used to structure and quality-check registered data for errors and conflicting information in EHR systems.

Knowledge discovery and data mining provides a set of techniques for secondary use of health data. These techniques are applicable to enhance healthcare services, improve individual patient experience and reduce per capita costs of care. Knowing the relevant tools for exploiting the ML algorithms, their maturity and capabilities is important for implementing new services.

Gartner, an international consulting company, considers AI as one of the most disruptive technologies for the next five to ten years. Developing intelligent systems able to learn, adapt and potentially act autonomously, instead of performing predefined instructions, becomes very important in the competition between technology providers in the future. Many health-related AI systems are currently at the pilot stage and there remains work making these systems mature for large-scale use.
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A. Publication statistics about machine learning in PubMed

Publication statistics

75 papers were found using “machine learning Norway” as keywords in PubMed. The first paper was published in 1993, and the second in 2005. Below is an annual summary table of published papers.

<table>
<thead>
<tr>
<th></th>
<th>2014</th>
<th>2015</th>
<th>2016</th>
<th>2017</th>
<th>2018</th>
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</thead>
<tbody>
<tr>
<td>Total</td>
<td>7</td>
<td>8</td>
<td>13</td>
<td>25</td>
<td>5</td>
</tr>
</tbody>
</table>

The number of publications in this area is increasing. All major universities and university hospitals in Norway are represented. Read more about the Norwegian stakeholders in the filed in Chapter 6.

Main areas

Main research areas in machine learning in Norway are image analysis, fMRI, Support vector machines, and neural networks. A few papers focus on natural language processing of clinical data (2 papers). A large group of papers uses various machine-learning methods.

The found topics and institutions and listed below.

Image analysis

<table>
<thead>
<tr>
<th>Topics</th>
<th>Institutions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image analysis</td>
<td>Institute for Cancer Genetics and Informatics, Oslo University Hospital</td>
</tr>
<tr>
<td>Image analysis</td>
<td>Norwegian Centre for Mental Disorders Research, KG Jebsen Centre for Psychosis Research, Division of Mental Health and Addiction, Oslo University Hospital</td>
</tr>
<tr>
<td>Image analysis</td>
<td>Section of Rheumatology, Department of Neurology, Rheumatology</td>
</tr>
<tr>
<td>Tumour segmentation based on image</td>
<td>Faculty of Science and Technology, Norwegian University of Life Sciences, Ås</td>
</tr>
<tr>
<td>Multivariate machine learning of MRI image</td>
<td>Department of Physical Medicine and Rehabilitation, Oslo University Hospital</td>
</tr>
<tr>
<td>fMRI image analysis</td>
<td>NORMENT, KG Jebsen Centre for Psychosis Research, Division of Mental Health and Addiction, Oslo University Hospital &amp; Institute of Clinical Medicine, University of Oslo</td>
</tr>
<tr>
<td>Resting-state fMRI images</td>
<td>NORMENT, KG Jebsen Centre for Psychosis Research, Division of Mental Health and Addiction, Oslo University Hospital &amp; Institute of Clinical Medicine, University of Oslo</td>
</tr>
<tr>
<td>Medical imaging, pattern classification, Euclideanized s-reps</td>
<td>Stavanger University Hospital</td>
</tr>
<tr>
<td>fMRI, mind wandering, model-based neuroscience</td>
<td>Department of Psychology, University of Tromsø</td>
</tr>
<tr>
<td>-----------------------------------------------</td>
<td>------------------------------------------------</td>
</tr>
<tr>
<td>fMRI, intrinsic networks</td>
<td>Department of Biological and Medical Psychology, University of Bergen</td>
</tr>
</tbody>
</table>

### Support vector machines

#### Topics
- Support vector machine learning
- SVM
- Support Vector Machines
- Support Vector Machines (SVM) model
- Support Vector Machines (SVM) routine
- Support Vector Machines, new joint Scatter SVM algorithm
- Support Vector Machines

#### Institutions
- Department of Clinical and Molecular Medicine, Norwegian University of Science and Technology
- Department of Physics, NTNU - Norwegian University of Science and Technology
- Department of Tumor Biology, Norwegian Radium Hospital, Oslo University Hospital
- Intervention Centre (K.E.E., A.B.), Department of Radiology
- Intervention Centre, Rikshospitalet
- Department of Physics and Technology, University of Tromsø
- Neuropsychological Service, Helgeland Hospital

### Neural networks

#### Topics
- Neural network machine learning algorithm
- Recurrent neural network (RNN), echo state networks (ESNs)
- Artificial neural network, Decision support system, Decision tree, IgA Nephropathy, Neuro fuzzy system, Support vector machine

#### Institutions
- Centre for Elite Sports Research, Department of Neuromedicine and Movement Science, Faculty of Medicine and Health Science, Norwegian University of Science and Technology
- Machine Learning Group, Department of Physics and Technology, University of Tromsø
- Kavli Institute & Centre for Neural Computation, NTNU
- Department of Clinical Medicine, Renal Research Group, University of Bergen

### NLP

#### Topics
- NLP
- Cluster labeling, Multi focus, Text mining

#### Institutions
- Department of Mathematics and Statistics, UiT The Arctic University of Norway
- Norwegian Computing Center, Blindern
### Machine learning classifiers

<table>
<thead>
<tr>
<th>Topics</th>
<th>Institutions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Well-known Machine Learning classifiers (Random Forest, k-statistic)</td>
<td>Department of Informatics, University of Oslo</td>
</tr>
<tr>
<td>Regularized linear discriminant analysis (rLDA)</td>
<td>Sunnaas Rehabilitation Hospital HT</td>
</tr>
<tr>
<td>Machine-learning classifiers</td>
<td>K.G. Jebsen Centre for Research on Neuropsychiatric Disorders, University of Bergen</td>
</tr>
</tbody>
</table>

### Various methods

<table>
<thead>
<tr>
<th>Topics</th>
<th>Institutions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random forest machine-learning algorithm</td>
<td>Norwegian College of Fishery Science, UiT The Arctic University of Norway and Physical Medicine, Helse Farde, Department of Endodontics, Institute of Clinical Dentistry, Faculty of Dentistry, University of Oslo</td>
</tr>
<tr>
<td>MaxEnt software, a machine learning modeling approach</td>
<td>Department of Food Safety and Infection Biology, Norwegian University of Life Sciences</td>
</tr>
<tr>
<td>De novo machine learning algorithm</td>
<td>Computational Biology Unit, Department of Informatics, University of Bergen</td>
</tr>
<tr>
<td>Linked independent component analysis</td>
<td>NORMENT, KG Jebsen Centre for Psychosis Research, Division of Mental Health and Addiction, Oslo University Hospital &amp; Institute of Clinical Medicine, University of Oslo</td>
</tr>
<tr>
<td>Supervised machine learning</td>
<td>Marine Harvest ASA</td>
</tr>
<tr>
<td>Hidden Markov model</td>
<td>Department of Information Science and Media Studies, University of Bergen</td>
</tr>
<tr>
<td>Logistic regression</td>
<td>Department of Registry Informatics, The Cancer Registry of Norway, Oslo</td>
</tr>
<tr>
<td>Machine learning-based Bayesian network</td>
<td>Department of Clinical Science, University of Bergen and Laboratory of Clinical Biochemistry, Haukeland University Hospital</td>
</tr>
<tr>
<td>Computational biology, sparse Bayesian learning and relevance vector machine</td>
<td>Pathology Department, Oslo University Hospital</td>
</tr>
<tr>
<td>Pattern classification algorithm</td>
<td>University of Agder</td>
</tr>
<tr>
<td>Logarithmic regression, neural networks, support vector machines</td>
<td>Department of Computer Science, University of Tromsø</td>
</tr>
<tr>
<td>Signal processing and machine learning algorithms, Linear and quadratic discriminant analyses</td>
<td>Department of Electrical Engineering and Computer Science, University of Stavanger</td>
</tr>
<tr>
<td>Clinical decision support, Kernel methods, Gaussian process regression, time warping, imputation methods</td>
<td>Dept. Mathematics and Statistics, University of Tromsø</td>
</tr>
<tr>
<td>-------------------------------------------------</td>
<td>---------------------------------------------------</td>
</tr>
<tr>
<td>AED algorithms</td>
<td>Norwegian National Advisory Unit on Prehospital Emergency Medicine (NAKOS), Oslo University Hospital and University of Oslo</td>
</tr>
<tr>
<td>Diffusion tensor imaging, probabilistic tractography reconstruction algorithm, clustering algorithm, multivariate pattern classification technique</td>
<td>Department of Psychology, UiT the Arctic University of Norway</td>
</tr>
</tbody>
</table>