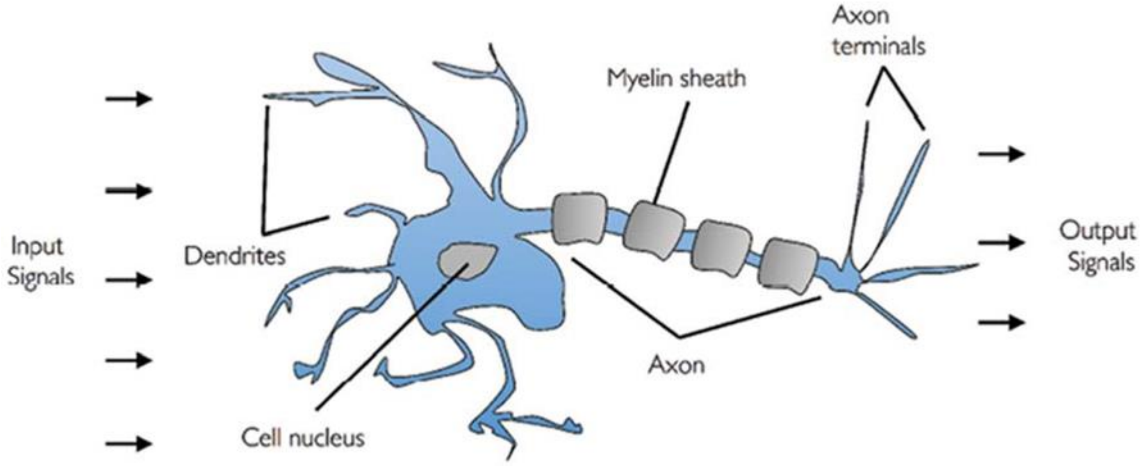
**Chapter 7 AI in Action I**

Artificial neurons and perceptron learning rule

In this chapter, we will discuss the perceptron and other machine learning algorithms. To start with, we need to review the beginnings of machine learning. Trying to understand how the biological brain works in order to design artificial intelligence (AI), Warren McCulloch and Walter Pitts published the first concept of a simplified brain cell, the **McCulloch-Pitts (MCP) neuron**, in 1943. Biological neurons are interconnected nerve cells in the brain that are involved in the processing and transmitting of chemical and electrical signals, which is illustrated in the following figure:




McCulloch and Pitts described such a nerve cell as a simple logic gate with binary outputs; multiple signals arrive at the dendrites, they are then integrated into the cell body, and, if the accumulated signal exceeds a certain threshold, an output signal is generated that will be passed on by the axon.

(McCulloch, W.S. and Pitts, W. (1943) A Logical Calculus of the Ideas Immanent in Nervous Activity. *Bulletin of Mathematical Biophysics* 5(4):115-133)

Only a few years later, Frank Rosenblatt published the first concept of the **perceptron learning rule** based on the MCP neuron model. With his perceptron rule, Rosenblatt proposed an algorithm that would automatically learn the optimal weight coefficients that would then be multiplied with the input features in order to make the decision of whether a neuron fires (transmits a signal) or not. In the context of supervised learning and classification, such an algorithm could then be used to predict whether a new data point belongs to one class or the other.

(Rosenblatt, F. (1957) The Perceptron: A Perceiving and Recognizing Automaton. Cornell Aeronautical Laboratory)

More formally, we can put the idea behind **artificial neurons** into the context of a binary classification task where we refer to our two classes as 1 (positive class) and –1 (negative class) for simplicity. We can then define a decision function $\phi(z)$ that takes a linear combination of certain input values $\vec{x}$ and a corresponding weight vector $\vec{w}$:

$$\vec{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_m \end{bmatrix} \qquad \vec{w} = \begin{bmatrix} w_1 \\ \vdots \\ w_m \end{bmatrix}$$

where $z$ is the net input defined by:

$$z = \vec{w} \cdot \vec{x} = w_1 x_1 + \cdots + w_m x_m$$

If the net input of a particular example, $\boldsymbol{x}^{(i)}$ is greater than a defined threshold $\theta$, we predict class 1, and class –1 otherwise. In the perceptron algorithm, the decision function is a variant of a **unit step function**:

$$\phi(z) = \begin{cases} 1, & z \geq \theta \\ -1, & z < \theta \end{cases}$$

For simplicity, we can also bring the $\theta$ to left side, let $w_0 = -\theta, x_0 = 1$, then:

$$z = w_0 x_0 + w_1 x_1 \dots + w_m x_m$$

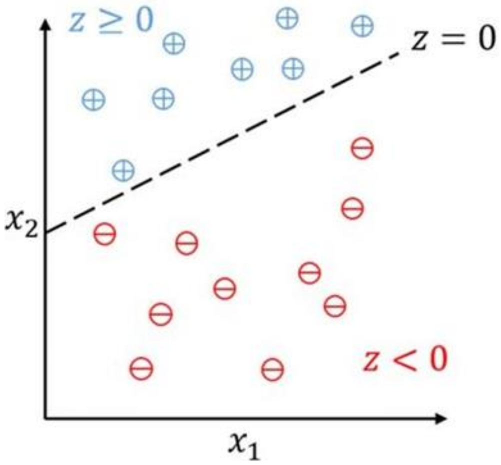
$$\phi(z) = \begin{cases} 1, & z \geq 0 \\ -1, & z < 0 \end{cases}$$

The term $w_0 = -\theta$ is called bias unit.

Let's consider a simple example with only two variables, $x_1$ and $x_2$. Suppose after some computations we have the weights $w_0 = -4$, $w_1 = -1$, $w_2 = 2$, the net input becomes:

$$z = -4 - x_1 + 2x_2$$

This gives the decision boundary $-4 - x_1 + 2x_2 = 0$, discriminating all data points into two **linearly separable classes**.




Now the problem is, how can we obtain suitable values of the weights, so that the decision line can accurately assign the samples into two classes? The idea behind the perceptron model is to use a reductionist approach to mimic how a single neuron in the brain works: it either fires or it does not. Thus, Rosenblatt's perceptron algorithm can be summarized by the following steps:

(1) Initialize the weights to 0 or small random numbers

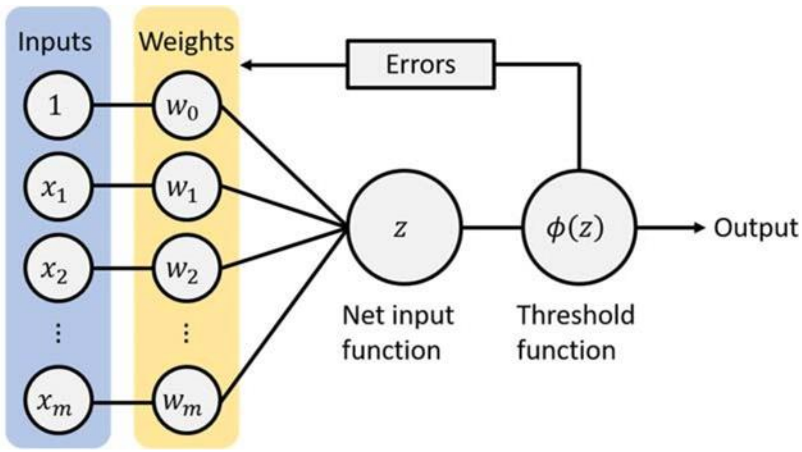
(2) For each training sample $\boldsymbol{x}^{(i)}$, compute the output value $\hat{y}$, then update the weights:

$$w_j := w_j + \Delta w_j$$

where the increment $\Delta w_j$ for updating $w_j$ is calculated by perceptron learning rule:

$$\Delta w_j = \eta \, (y^{(i)} - \hat{y}^{(i)}) x_j^{(i)}$$

where $\eta$ is the learning rate (between 0 to 1), $y^{(i)}$ is the true class label and $\hat{y}^{(i)}$ is the predicted class label $\phi(z)$. This algorithm is illustrated by the diagram below.




The interpretation of the perceptron rule is as follows. If the predicted class label $\hat{y}^{(i)}$ is correct, i.e. it equals to the true class label $y^{(i)}$, then in either case of class label 1 or –1 we have $\Delta w_j = 0$, no need to update the weights.

$$\Delta w_j = \eta(1-1)x_j^{(i)} = 0 \qquad \Delta w_j = \eta(-1-(-1))x_j^{(i)} = 0$$

If the true class label $y^{(i)} = 1$ and the predicted class label $\hat{y}^{(i)} = -1$ is wrong:

$$\Delta w_j = \eta(1-(-1))x_j^{(i)} = 2\eta x_j^{(i)} > 0$$

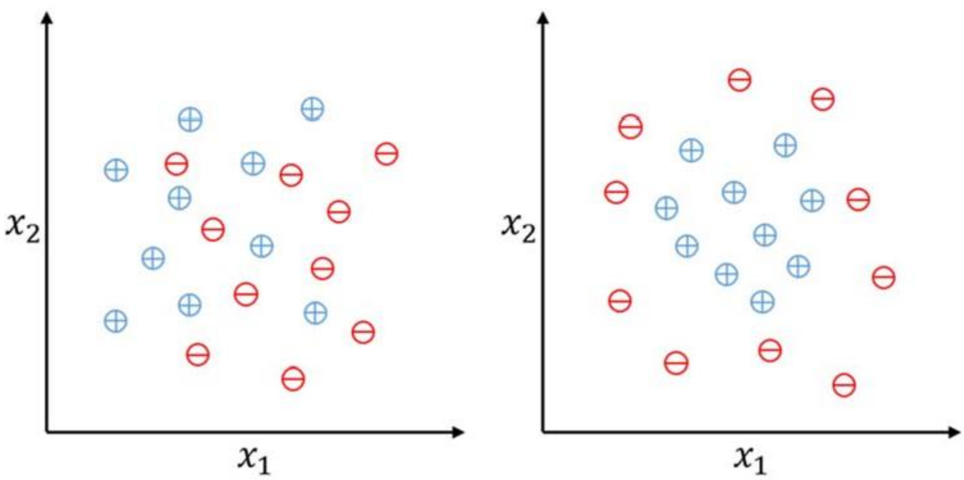
which will push the weight towards the direction of the positive target class.

If the true class label $y^{(i)} = -1$ and the predicted class label $\hat{y}^{(i)} = 1$ is wrong:

$$\Delta w_j = \eta(-1-1))x_j^{(i)} = -2\eta x_j^{(i)} < 0$$

which will push the weight towards the direction of the negative target class.

Notice that the **convergence** of the perceptron model is only guaranteed if the two classes are linearly separable. The following figures show two examples of non-linearly separable points. The one on the left illustrate two classes being highly overlapped and hard to separate. The one on the right is separable but not by a straight line. By observation we might use a circle to separate the space into outer and inner regions for the two classes.




Moreover, if the learning rate $\eta$ is too large it may also cause the model to diverge. Oppositely, if the learning rate is too small it might take a lot more iterations and running time to obtain a satisfactory result.

The healthcare industry has undergone transformative advancements with the integration of Artificial Intelligence (AI), reshaping patient care, diagnostics, and the efficiency of administrative operations. AI's ability to process large amounts of data and automate both front and back-office tasks has revolutionized healthcare management, significantly improving operational efficiency and patient experiences.

**AI in healthcare industry**

AI in Front Office Automation

AI has proven especially useful in automating front office tasks, where it reduces administrative burdens and enhances patient interactions. AI-powered chatbots and virtual assistants can now manage routine patient inquiries, schedule appointments, and provide basic medical information. These AI systems, driven by natural language processing (NLP) and machine learning algorithms, can understand and respond to patient queries, offering a streamlined communication channel between healthcare facilities and patients. For instance, virtual assistants can guide patients through the intake process by analyzing patient forms, extracting relevant information, and automatically updating electronic health records (EHRs). This automation not only reduces manual data entry errors but also ensures better accuracy of patient data, allowing administrative staff to focus on more complex tasks.

AI in Back Office Automation

In addition to its front-office applications, AI is also transforming back-office operations within healthcare. AI algorithms can process vast amounts of medical data, including clinical notes, lab results, and imaging reports, to extract meaningful insights that aid in clinical decision-making. AI can automate processes like medical coding and billing by analyzing patient records and assigning appropriate codes for diagnoses and treatments. This minimizes coding errors, reduces administrative workload, and speeds up revenue cycles for healthcare providers. Furthermore, AI-powered systems can assist in supply chain management by analyzing historical data and predicting future demand to optimize inventory levels, ensuring essential medical supplies are available when needed.

For example, UK-based company Karantis360 has implemented AI and Internet of Things (IoT) technology in elderly care. Their system monitors patients' daily activities through intelligent sensors and notifies caregivers of any abnormal behaviors, such as falls. This not only enables elderly individuals to live independently at home but also provides peace of mind to caregivers and family members, reducing the burden on healthcare facilities.

Enhancing Healthcare Through Predictive Analytics

One of the most promising applications of AI in healthcare is its predictive analytics capabilities. AI-driven models are being used to forecast patient volumes, optimize resource allocation, and even predict the risk of unplanned hospital admissions. Mount Sinai Health Systems in New York City has developed a predictive model that identifies patients at risk of unplanned admissions. By mining data from their population health program, Mount Sinai's machine learning algorithms can help healthcare providers shift from reactive to proactive care, allowing them to intervene early in high-risk cases. Such models can be particularly useful in reducing avoidable admissions and unnecessary hospital stays, which is crucial for improving healthcare outcomes and lowering costs.

Similarly, AI is used in population health management to detect early risk factors for diseases and enable timely interventions. At Israel's Sheba Medical Center, an AI solution predicts which colorectal cancer patients are likely to suffer from complications post-surgery, such as leakage. Early identification of these at-risk patients allows medical teams to take preventive measures, minimizing risks and improving patient outcomes.

AI in Chronic Disease Management

AI’s role in managing chronic diseases has also shown tremendous potential. Sensely, a US-based company, has developed a virtual nurse assistant that provides personalized care for patients with chronic conditions such as congestive heart failure and diabetes. The AI-powered platform uses speech recognition and text-to-speech technologies to guide patients through their daily monitoring needs, assess symptoms, and notify healthcare practitioners if intervention is required. This system enables continuous, personalized monitoring, which can reduce the need for hospital visits, improve patient adherence to care routines, and prevent avoidable complications.

## Challenges and Future Potential

While AI applications in healthcare offer many benefits, there are still challenges in their implementation. AI models need further development and validation across different populations to ensure their generalizability. As AI systems become more integrated across various healthcare settings, there is potential for even greater innovation in population health management, predictive care, and operational efficiency. However, healthcare professionals need adequate training to use AI tools effectively, especially in understanding how AI models identify risk factors and guide clinical interventions.

In conclusion, AI is revolutionizing both patient care and operational management in the healthcare industry. From automating administrative tasks to providing predictive insights and personalized care, AI holds the potential to improve health outcomes, reduce costs, and enhance the efficiency of healthcare systems worldwide.

As AI technology continues to evolve, its applications in healthcare will likely expand, touching more aspects of both clinical and non-clinical operations. One of the areas where AI is poised to make a profound impact is in the realm of population health management. AI can be leveraged to analyze large datasets, identifying patterns and correlations that can guide public health initiatives and interventions. For instance, AI-powered systems are already being used to predict health outcomes for large patient populations by analyzing clinical data and identifying risk factors early. This approach allows healthcare systems to focus more on prevention and early detection, which can lead to better overall population health outcomes and more sustainable healthcare systems.

AI's ability to process vast amounts of data also plays a significant role in epidemiological studies. By analyzing health data collected from wearables or electronic health records (EHRs), AI can uncover previously unnoticed correlations between lifestyle factors and health outcomes. This not only enhances our understanding of disease risk factors but also helps in designing more effective public health policies. The growing use of AI in epidemiology could lead to significant breakthroughs in preventative medicine by identifying potential health crises before they occur and allowing healthcare providers to take preemptive measures.

## AI in Predictive Care

Predictive care is another area where AI is making strides. By using AI algorithms, healthcare providers can predict the progression of chronic diseases, such as diabetes or heart disease, and intervene early to prevent complications. In the European Union (EU), chronic diseases are a leading cause of death and disability, and AI-powered tools are being developed to help slow disease progression and improve patient outcomes. For example, AI-based models in use at some healthcare facilities can predict unplanned hospital admissions for patients with chronic conditions, enabling providers to take proactive steps to prevent these admissions.

In addition, AI's ability to predict patient outcomes is being explored in surgical care. At Sheba Medical Center in Israel, an AI solution is being used to predict which colorectal cancer patients are at risk of suffering complications such as surgical leakage. By identifying these at-risk patients before surgery, healthcare providers can take steps to mitigate risks, potentially saving lives and reducing the need for further hospitalizations.

## AI's Role in Reducing Healthcare Costs

The financial implications of AI in healthcare cannot be overlooked. AI's ability to streamline operations and optimize resource allocation helps reduce operational costs. For example, AI-powered predictive models can help healthcare institutions manage staffing levels more effectively by forecasting patient volumes and resource needs. This ensures that hospitals and clinics are neither over- nor under-staffed, resulting in cost savings and more efficient use of resources.

Moreover, AI has the potential to reduce costs by improving the accuracy of medical coding and billing. With AI automating the coding process, healthcare providers can minimize coding errors that often lead to billing issues or delays in reimbursement. By accelerating the revenue cycle, healthcare organizations can maintain better financial health while ensuring that patient care remains the top priority.

AI in Pharmaceutical Adherence and Clinical Trials

AI is also finding applications beyond healthcare facilities, particularly in the pharmaceutical industry. Virtual assistants and AI-powered tools are being used to support pharmaceutical adherence by reminding patients to take their medications as prescribed. This is especially useful for patients with chronic conditions who need to follow strict medication regimens. Pharmaceutical companies are also using AI to monitor patient engagement during clinical trials, ensuring that participants follow protocols and take medications correctly. By improving adherence, AI contributes to better health outcomes and enhances the reliability of clinical trial data.

Future Directions and Ethical Considerations

While the integration of AI in healthcare presents numerous advantages, it also raises important ethical questions. Concerns about patient privacy, data security, and the generalizability of AI models are at the forefront of discussions. AI models are often trained on specific populations, and their accuracy and reliability may diminish when applied to different demographic groups. Ensuring that AI systems are properly validated and tested across diverse populations is critical to avoiding biases in healthcare delivery.

Furthermore, the use of AI in healthcare must comply with strict regulatory standards, particularly when it comes to patient data. Healthcare providers and organizations adopting AI tools must prioritize data security and ensure that AI systems adhere to privacy laws such as HIPAA (Health Insurance Portability and Accountability Act) in the United States or the GDPR (General Data Protection Regulation) in the European Union.

Looking ahead, AI-driven innovations in healthcare will likely continue to evolve, driving improvements in personalized care, operational efficiency, and population health management. AI has the potential to revolutionize not only how we deliver healthcare but also how we think about healthcare as a whole. As AI tools become more advanced and widely adopted, healthcare providers, policymakers, and researchers will need to work together to ensure that these technologies are used ethically and effectively to benefit all patients.

In conclusion, the application of AI in healthcare is a promising frontier that enhances patient care, automates administrative processes, and optimizes resource management. From virtual nurse assistants like Sensely, which offer personalized monitoring for chronic disease patients, to predictive models that identify high-risk patients before complications arise, AI is already reshaping the healthcare landscape. As AI continues to advance, it holds the potential to drive further innovation in the field, ultimately leading to a more efficient, cost-effective, and patient-centered healthcare system.

**Introduction to Computer Vision**

Computer vision is a subfield of artificial intelligence (AI) that enables computers and systems to extract meaningful information from digital images, videos, and other visual inputs. By mimicking the visual comprehension abilities of humans, computer vision allows machines to observe, interpret, and make decisions based on visual data. The core idea is to train computers to analyze visual inputs using machine learning and deep learning algorithms, creating a system that can perform tasks such as image recognition, object detection, and video analysis with remarkable precision.

In essence, computer vision functions in a manner similar to human vision, though humans naturally benefit from contextual learning and experience over their lifetime. While humans rely on their retinas, optic nerves, and visual cortex to process images, computer vision utilizes cameras, sensors, and complex algorithms to interpret visual data. Machines trained to perform these tasks can eventually exceed human capabilities, especially in industrial or high-speed applications where analyzing thousands of images or videos per minute is necessary.

A key factor in developing computer vision models is the vast amount of data needed for training. The system requires extensive visual datasets to discern patterns, identify objects, and recognize nuances. For example, training a machine to identify automobile tires requires feeding it a diverse set of images of tires, along with variations that include different angles, sizes, and defects, so that the system can accurately distinguish between normal and defective tires.

Two critical technologies behind computer vision are deep learning and convolutional neural networks (CNNs). Deep learning refers to a subset of machine learning that employs layers of artificial neural networks to mimic the human brain's learning process. CNNs, specifically, are instrumental in image processing. A CNN breaks down an image into pixels, assigns labels to those pixels, and uses mathematical operations known as convolutions to analyze the image. Through repeated iterations, the CNN learns to improve its predictions and accurately recognize the content of the image.

CNNs are primarily used for single-image recognition, whereas recurrent neural networks (RNNs) are often employed for video analysis, enabling computers to detect patterns across sequential frames of a video. RNNs excel in identifying relationships between images over time, making them suitable for tasks such as object tracking in videos.

As computer vision evolves, its applications are becoming integral to a wide range of industries. For example, in the automotive industry, computer vision is crucial for the development of autonomous vehicles. Self-driving cars rely on computer vision to process data from cameras and sensors to identify other vehicles, road signs, and pedestrians, making real-time decisions to navigate roads safely. Similarly, in healthcare, computer vision aids in the analysis of medical images, improving diagnostic accuracy through tools that can detect tumors, analyze X-rays, and process MRI scans.

Computer vision is also making strides in sectors such as agriculture, security, and entertainment. In agriculture, it helps monitor crops, assess soil conditions, and predict harvest yields. Security systems use it to analyze live footage for unauthorized access or safety breaches, while content-based image retrieval systems in digital asset management allow users to search vast databases of images based on visual content rather than metadata tags.

One of the key advantages of modern computer vision systems is their accessibility. Previously, the development of vision applications required extensive computational resources and manual data annotation. Today, cloud computing and pre-built models have democratized access to this technology. Companies like IBM offer services that allow businesses to integrate pre-trained computer vision models into their systems without the need for extensive technical expertise or infrastructure.

Common tasks in computer vision include image classification, object detection, and segmentation. Image classification enables the system to identify and categorize images, while object detection goes further by pinpointing the location of objects within an image. Segmentation divides an image into regions, allowing the system to differentiate between multiple objects within a single frame.