DOI: 10.38146/BSZ-AJIA.2024.v72.i4.pp701-715

# Artificial Intelligence in Forensic Sciences Revolution or Invasion? Part I

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## Abstract

**Aim:** The first half of the two-part study is on the emerging role of artificial intelligence in the forensic sciences. After clarifying the basic concepts and a brief historical overview, the possibilities of using AI in various forensic fields are discussed: genetics, pattern recognition, chemistry, toxicology, anthropology, forensic medicine, and scene reconstruction.

**Methodology:** The study synthesises several recently published international papers.

**Findings:** The penetration of the application of artificial intelligence into some fields of science is undoubtedly an ongoing process. Most of the varied forensic fields also cannot avoid this development. Analysing large databases unmanageable with traditional methods, pattern recognition, and machine learning can all be important tools for forensic science. However, an important conclusion is that AI is a supporter of human expert work, not a substitute.

**Value:** In the field of forensic sciences, no such detailed summary article has been published in Hungarian so far.

**Keywords:** artificial intelligence, forensic science, genetics, anthropology

English-language republication. The Hungarian version of this article was published in Belügyi Szemle 2024, issue 4. DOI link: https://doi.org/10.38146/BSZ-AJIA.2024.v72.i4.pp577-592.

## Introduction

Nowadays, the term artificial intelligence (AI) has become almost ubiquitous, and a mortal on earth would only guess that a computer and a program are working together to do things that were previously done by a human being. This relative lack of knowledge, which also affects us, prompted us to investigate the issue: to what extent has AI been integrated into everyday life and forensic science? What does it know better than we humans, and when will the time come when its use becomes inevitable in forensic practice. Having looked into the topic of AI, we try to better explain the meaning of the commonly used terms: machine learning, deep learning, weak/strong AI, artificial narrow intelligence, artificial general intelligence, artificial superintelligence, etc.

## What is artificial intelligence?

The development of AI (Artificial Intelligence) is constantly evolving and its popularity is growing by the day. AI is the ability of a system or program to think and learn from experience (URL1).

AI is machine intelligence that simulates human behaviour or thinking and can be taught to solve specific problems. AI is a combination of machine learning and deep learning. AI models are trained using huge amounts of data that can make intelligent decisions.

Both deep learning and machine learning are subfields of AI, and deep learning is actually a subfield of machine learning. Deep learning is also essentially a neural network, where 'deep' refers to a neural network that consists of many more than three layers – between the traditional input and output layers, there may be dozens of hidden processing layers working simultaneously. For example, when interpreting images, lower layers are used to identify edges, and higher layers are used to recognise what is depicted.

Deep learning differs from ordinary machine learning in the way that particular algorithms learn. Deep learning automates the majority of the process feature extraction, eliminating some of the manual/human intervention required, and allows the use of larger data sets. Deep learning can also be considered as 'scalable machine learning'. Classical or 'non-deep' machine learning is more dependent on human intervention, and experts define a hierarchy of functions to understand the differences between data inputs, which usually require more structured data for learning. 'Deep' machine learning can use labelled datasets, also known as supervised learning, to inform its algorithm, but does not necessarily require a labelled dataset. It can ingest unstructured data in raw form (e.g. text, images) and automatically determine a hierarchy of features that distinguish different categories of data from each other. Unlike machine learning, processing data does not require human intervention, so we can scale machine learning in more interesting ways. We also need to familiarise ourselves with other AI concepts: narrow and general AI. Narrow AI or Artificial Narrow Intelligence (ANI) – focuses on performing specific tasks. Weak or narrow AI drives much of the AI around us today. The term 'narrow' more accurately expresses the characteristics of this type of AI, as it is anything but weak; it enables some very robust applications, such as Apple Siri, Amazon Alexa, IBM Wats on (see later), or even self-driving vehicles.

Strong AI consists of Artificial General Intelligence (AGI) and Artificial Super Intelligence (ASI). AGI is a theoretical form of AI, where machines would have the same intelligence as humans; they would have self-aware consciousness, able to solve problems, learn and plan for the future. ASI – also known as superintelligence – would surpass the intelligence and capabilities of the human brain. While strong AI is still entirely theoretical and there are no practical examples of it today, developments and research are ongoing. In the meantime, the best examples of ASI can be found in science fiction literature, such as HAL9000, the superhuman computer that turns against the crew in the emblematic 1968 novel and film 2001: A Space Odyssey.

## History of artificial intelligence: key dates and names

The idea of the 'thinking machine' originates in ancient Greece. But since the advent of electronic computing, important events and milestones in the development of AI are (URL2):

**1950: Alan Turing** published an article called *Computing Machinery and Intelligence*, in which Turing – famous for cracking the Nazi Enigma code during World War II – dissected the question 'can machines think?' He introduced the so-called Turing Test to determine whether any computer could exhibit the same intelligence (or at least the same results of intelligence) as a human. The value of the Turing test has been debated ever since.

**1956**: English mathematician **John McCarthy**, one of the founders of modern computer science, introduces the term 'artificial intelligence' at the first AI conference at Dartmouth College. Later that year, computer scientist and cognitive psychologist Allen Newell, political scientist, economist and sociologist Herbert A. Simon, and systems programmer John Clifford Shaw, all of whom worked at the Rand Corporation in Santa Monica, California, developed the Logic Theorist, the first program deliberately designed to mimic the problem-solving abilities of a human being.

**1958**: American psychologist **Frank Rosenblatt**, one of the forefathers of deep learning, builds the Mark 1 Perceptron, the first computer based on a neural network that 'learned' by trial and error. Eleven years later, the American cognitive scientist and computer scientist Marvin Minsky and the American mathematician and computer scientist Seymour Papert published a book entitled *Perceptrons*, which is both a landmark work on neural networks and, at least for a while, an argument against future neural network research projects.

**1980s**: Neural networks that use back propagation to train themselves became widely used in AI applications.

**1997**: IBM Deep Blue computer defeats then world chess champion Garry Kasparov in a chess match (and rematch).

**2011**: IBM Watson defeated champion Ken Jennings and Brad Rutter in the Jeopardy quiz show. IBM Watson (after IBM founder Thomas Watson) uses natural language processing, a technology that analyses human speech for semantics and syntax. Jeopardy! is an American quiz show where players are given one-sentence statements, which they must then formulate the question that the statement would answer.

**2015**: The supercomputer Minwa from Baidu (the 'Chinese Google') uses a special deep neural network, called a convolutional neural network, to identify and categorise images with better than average human accuracy.

**2016**: The deep neural network program AlphaGo from DeepMind (a British AI company) beats Lee Sodol, the world champion Go player, in a five-game match. The victory is significant, given that as the game progresses there are almost 'infinite' possible moves (over 14 500 billion after just four moves). Google later bought DeepMind for $400 million.

**2022**: On 30 November 2022, OpenAI (an artificial intelligence research company) released to the public a free machine learning-trained language model for dialogue called ChatGPT. ChatGPT is a language model that can be used for natural language processing tasks such as text generation and translation. It is based on the GPT-3.5 (Generative Pretrained Transformer 3.5) model, which is one of the largest and most advanced language models currently available. It can be used for a wide range of natural language processing tasks, some of which are listed below.

- Text generation: ChatGPT can be used to generate human-like text responses, making it useful for creating chatbots in customer services, generating responses in the online space (for example, answering questions in forums), or even creating personalised content on social media.

- Language translation: ChatGPT can also be used for translation tasks. By supplying the model with a monolingual text prompt (command line) and specifying the target language, the model can generate accurate and smooth translations from the text.
- Text summary: ChatGPT can be used to create summaries of long documents or articles. This can be useful to quickly review text without having to read the whole document.
- Sentiment analysis: with ChatGPT you can analyse the sentiment of a text. This can be useful to understand the overall tone and sentiment of a piece of writing, or to detect the sentiment of customer feedback to improve customer satisfaction.

## Artificial intelligence in forensic processes

Forensic science is the use of scientific methods or special expertise to establish facts for the purposes of forensic sciences (detection, investigation, evidence in court). In forensic science, AI applications can contribute to improving the performance of experts. AI can capture new information from vast data sets to enhance knowledge and reduce potential errors due to human subjectivity. This can help to improve the acceptability of expert evidence by providing a broader, more robust scientific basis (Galante et al., 2022). Innovative AI applications have been proposed in various disciplines, which include biological sex and age estimation (Bewles et al., 2019), bite mark analysis (Mahasantipiya et al., 2011), estimation of time elapsed since death (PMI) (Cantürk et al., 2018) and DNA result interpretation (Moretti et al. 2017). For all these reasons, it is essential to consider whether the effects of AI are truly replacing, diversifying or complementing and extending the previously well-known solutions to forensic problems (Spivak et al., 2021). Some of these areas will be described in more detail in the following.

## The 'gold standard' for forensic sciences: DNA testing

Recently, there have been developments in the use of AI – Artificial Neural Networks (ANNs) – to evaluate so-called electrophorograms (EPGs)[1] containing DNA profiles in forensic DNA laboratories. Before the results of these electroforograms can be used in an opinion, experts need to examine them carefully

1 Visualisation of DNA test results in the form of peaks.

to determine which DNA signals (peaks) show true DNA alleles and which are merely artefacts of the DNA profiling process. So ANNs can be used to classify signals on an electrophorogram into categories that have meaning (such as allele, baseline, pull-up or stutter). For this workflow, neural networks were trained on a single type of data, generated in a single laboratory setting and applied to data that matched these factors. Inspired by the way the human brain works, these ANNs are increasingly successful in analysing large data sets, making medical diagnoses, identifying handwriting, playing games or recognising images, and even eliminating cognitive bias (Taylor et al., 2016). In their next work, the authors investigated whether neural networks are able to determine different types (i.e. mixed DNA profiles from one person or from multiple persons) and different laboratory conditions (in particular, the electrophoresis instrument model), whether neural networks are needed for each type of data produced, or whether a single neural network can be used for a wide range of data and still achieve the same level of performance. The results of their study have implications for how a laboratory trains and uses neural networks to classify electrophorogram data in its laboratory (Taylor et al., 2019). Experts tend to favour sophisticated but accurate tools over simpler but less accurate ones. If ANNs trained on individual hardware types (3130xl or 3500xl) or profile types (single source vs. mixed DNA profile) performed better than ANNs trained on combined data sets, the latter would represent a more complex system for laboratories. The authors found that a single set of ANNs can indeed be trained on data that range between hardware types and data types, and still generalise well to profiles with any combination of these factors. It's also worth noting that researchers have trained two kits (GlobalFiler and PowerPlex Fusion 6C) most commonly used by genetic experts in their daily routine with a new version of Probabilistic Assessment for Contributor Estimation (PACE), a method based on a fully continuous probabilistic machine learning (random forest algorithm) to identify artificial products and estimate the number of donors in a mixed profile. This version of PACE can be used in three separate but not mutually exclusive ways: (1) as a system to assist the analyst in identifying artifacts such as stutter, suprathreshold noise, and pull-up; (2) as a tool to determine the complexity of a profile, for example, if a profile is amenable to interpretation; (3) as a tool to assess the probability of the number of participants in a DNA mixture (Marciano & Adelman, 2019). From the above results, it can be concluded that machine learning algorithms in AI could 'soon' take over some of the assessment stages of DNA profile identification from genetic experts, freeing up time for more routine work phases. AI machine learning algorithms are gaining ground not only in forensic genetics, but in all other areas of forensic science.

## Pattern evidences

AI has also been applied to other areas of forensic science, including footprint identification, facial and clothing recognition, forensic entomology and ballistics. For footprints, they have investigated a method that can estimate human age and gender based on the shoe prints left behind, using an automatic learning approach called ShoeNet. The aim of the study was to limit the large population to a small number of suspects, saving time and resources. A systematic approach to estimating human age and sex from a large shoe print dataset using a machine learning algorithm – 100,000 prints from individuals aged between 7 and 80 years – was achieved in the field of criminal investigation. Using this model, age and sex estimation can be automated with an encouraging level of accuracy, providing cost-effective, better scalability, reliable and unbiased decision support. Furthermore, it successfully addresses computational problems related to noise, patterns, manufacturing designs, wear time and most importantly wear effects (Hassan et al., 2021). Clothes recognition is another useful identification method when facial recognition and biometric evidence are difficult to use. Clothing is a factor that usually reflects gender, age and social status. Researchers have reported on a method using DCNN (Deep Convolutional Neural Network) that has been trained to classify images of clothing based on quality and discriminate more specific features such as logos with good results (Bedeli et al., 2018).

## The application of advanced artificial intelligence in forensic medicine

Forensic science relies on forensic experts who form an opinion based on their training, skills and professional experience. This is usually time-consuming and can often be influenced by a number of subjective factors that are difficult to overcome. The main aim of this chapter is to present a very promising line of research that can be applied to the different disciplines of forensic anthropology and forensic medicine. The use of AI is a new trend in forensic medicine and a potential watershed moment for the entire forensic discipline. Three-dimensional convolutional neural networks (3D Convolutional Neural Network; hereafter: 3D CNN) are effective for image processing and recognition. The advantage of 3D CNN over its predecessors is that it automatically detects important features without human supervision. 3D CNN is used for three-dimensional feature extraction, where the input is a 3D volume or a sequence of 2D images, such as slices from a cone-beam computer tomograph (CBCT) (Szabó, 2019). A recently published article (Thurzo et al., 2021) describes a novel workflow for 3D CNN analysis of full-scale CBCT scans. Its main aim was to form an interdisciplinary bridge between forensic medical experts and MI engineers. To activate clinical forensic experts who may have a basic knowledge of advanced AI techniques and are interested in implementing them in order to further develop forensic research. The authors research and present a 3D CNN method for forensic research design concept in five aspects: (1) determination of biological sex; (2) estimation of biological age; (3) search and assignment of 3D reference points on the skull; (4) prediction of growth vectors; (5) estimation of the facial image from the skull and vice versa. The application of 3D CNN could be a ground-breaking step in forensic medicine, leading to improvements in forensic expert analysis processes based on 3D neural networks. Furthermore, with practical implementations, it will be a watershed moment in the field of forensic medicine dealing with morphological features. In summary, we can assume that 3D CNN as an advanced AI feature will change the paradigm in all the fields described above, and probably in some others as well. Forensic scientists are now being encouraged to move into the era of AI, a useful tool for research and possibly future routine forensic analysis. Forensic 3D reconstructions with AI will be new, exciting and practical methods. The implementation of advanced AI will still require interdisciplinary collaboration, but it can be used to solve unsolved mysteries. This is definitely not a negligible trend (Thurzo et al., 2021).

## Artificial intelligence-based identification in forensic anthropology

The importance of identification in today's society is indisputable. The need for accurate and robust devices in this field is constantly growing. The most commonly used methods in identification are DNA testing and automated fingerprint matching systems (AFIS), mainly due to their high accuracy (above 99%). These methods are expensive (AFIS can cost millions of dollars depending on the complexity of the system) and time-consuming (DNA testing from bone can take weeks). However, their main drawback is their limited applicability: both require a prior record, a reliable baseline and preserved test material for DNA extraction or fingerprint comparison. In other words, these methods may fail if insufficient ante-mortem (AM) or post-mortem (PM) information is available due to lack of data (reference DNA sample) or the condition of the corpse. While the skeleton generally survives decomposition processes (fire, salt, water, etc.), soft tissue gradually degrades and disappears, making dactyloscopic identification difficult or impossible. If the circumstances are not favourable (e.g. skeleton, burnt or highly decomposed, fragmented, even commingled remains, mass graves, etc.), methods based on forensic anthropology (FA) may be the main alternative. FA is the study of bone remains in forensic investigations, and includes skeleton-based forensic identification (SFI) techniques such as skull-face super-imaging or comparative radiography. According to the findings of several experts, in certain challenging cases (such as those listed above), SFI techniques have been effective in 70–80% of cases compared to DNA (around 3%) and dactyloscopy-based (15–25%) identification. SFI methods used by forensic anthropologists, dentists and pathologists are often the victim's last chance for identification (Mesejo et al., 2020). AI techniques have been applied with remarkable success to a number of challenging tasks, including healthcare and medical imaging. From this perspective, the modest presence of AI in the daily practice of forensic anthropologists may be surprising. Even with the emergence of some integrated tools, forensic anthropologists still lack AI-based tools to automate SFI tasks. AI techniques are used in various biomedical imaging modalities, mainly X-rays, CTs and MRIs, but also for 3D scanning of PM materials, i.e. bone remains, with the aim of contributing to forensic identification of deceased and living persons. Some of the described solutions use CV (Computer Vision), SC (Soft Computing[2]) and ML (Machine Learning) techniques in the identification process, for example to automate CFS (Craniofacial Superimposition) or CR (Comparative Radiography), by impartial and accurate processing, analysis and comparison of AM data and PM data. In addition, some of the solutions presented allow fast and multiple comparisons, offering powerful screening tools to significantly reduce the number of candidates in minutes instead of days. On the other hand, objective and reproducible results can support expert judgments, which might have a stronger impact on the legal practitioner. The studies cited here show that AI techniques can be trained to estimate an individual's Biological Profile (BP) or to describe traumatic or pathological conditions based on skeletal remains or radiographs. Other techniques can help to automatically perform high-precision visual comparisons of anatomical structures, and can eliminate human bias in doing so. There are, of course, limitations: at present, there are relatively few multidisciplinary working groups and there is a lack of large and open public

2 A set of soft computing algorithms, including neural networks, fuzzy logic and evolutionary algorithms. These algorithms tolerate imprecision, uncertainty, partial truth and approximation.

databases for research purposes. Note that, as in many other medical applications, accuracy of results is not the only goal to be achieved. The results must also be made understandable to human users. The recently introduced concept of explainable AI includes AI systems for opening black-box models, improving the understanding and comprehensibility of what is learned from the models, and explaining individual predictions. FA requires solutions that take into account the explicability of individual tasks while achieving the desired performance and accuracy, ensuring the ability of the designed (human-centric) models or decision support systems to trust the system output.

Future development opportunities for CFS, CR and BP identification methodology:

a) In relation to craniofacial superposition, i.e. CFS, it would be particularly important to carry out systematic and thorough studies to verify the effectiveness of this identification technique. AI techniques would be very useful to handle large data sets and to automate and objectify subtasks of the CFS process. This would help to increase the scientific support for CFS and to consider the skull as a primary identifier similar to dactyloscopy, DNA and dentition (currently a secondary identifier similar to scars, tattoos, other medical data).
b) Comparative radiology, i.e. CR, is now practically a primary identification technique. (Although we note that it is not yet recognised as such by Interpol, see Angyal & Petrétei, 2019.) The objective here is to automate and integrate all stages of the CR process and ultimately to develop a decision support system that can aggregate as much information as possible to assist the forensic expert in the decision-making process.
c) There is also a need for justice system to use tools to facilitate biological profiling, such as estimating the age of living persons, which is particularly relevant in the case of images or videos linked to paedophile cases or unaccompanied migrant minors (Mesejo et al., 2020).

## Artificial intelligence in forensic toxicology

The expansion of chemical databases and the widening scope of searches is a challenge in the investigation of drug and substance abuse. Automated chemical analysis has enabled the identification of compounds and the availability of previously unimaginable amounts of information. By 2020, the Chemical Abstract Service (CAS) had more than 160 million organic and inorganic compounds in its databases. This vast amount of data is a challenge for research and requires the use of computers and AI to manage it (Gasteiger, 2020). The marriage of expanding chemical databases with information technology has given rise to chemical informatics. This discipline contributes to solving reaction equations, predicting reaction products, developing statistical methods for analysing chemical data, and analysing compounds and spectra. For example, statistical methods can be used to identify compounds by comparison with spectral databases (Dotzert, 2021). Machine learning models add a new dimension to the identification of mixed chemicals by distinguishing compounds based on their composition, knowledge of analytical conditions and other information. For example, chromatographic separation results are interpreted along with mass spectrometry results and separation information such as mobile phase and separation column (Gasteiger, 2020).

## Summary

Forensic expert work is a complex process of investigation, collecting data from many sources and integrating them to draw logical conclusions. Extracting such data is undoubtedly an interesting and usually efficient task, but managing the ever-increasing volume of data can often be challenging and sometimes even chaotic. In the course of an investigation, AI can assist forensic experts to manage the data appropriately and perform multi-level meta-analysis. This can save forensic investigators considerable time, while ensuring they have the time and energy to focus on other vital tasks. From fingerprinting and DNA identification to forensic anthropology and conservation criminology, forensic science covers a wide range of disciplines. Despite their different backgrounds, all forensic scientists face the same problems. Database analysis, natural language processing, speech recognition and machine vision are some of the specific applications of AI. AI systems work by consuming huge amounts of labelled training data, evaluating the data for correlations and patterns, and then using these patterns to predict future states. In this way, a chatbot can learn to generate lifelike conversations with people through text chat examples, or an image recognition program can learn to identify and describe things in photographs by analysing millions of images.

Where a criminal investigation is concerned, AI can be a great tool in many ways:

1) data management and analysis to support investigations,
2) problem management and resolution methodology,
3) pattern recognition,

4) transparently presenting the steps of reasoning,
5) reducing the number of false positives or false negatives in the analysis, which are very common in forensic science,
6) a structured presentation of expertise, which also assists legal practitioners in quick and accurate decision-making,
7) well-organised performance evaluation,
8) data mining,
9) statistical substantiation of evidence,
10) integration with current architecture, tools and applications (Kamdar & Pandey, 2011).

AI technology can help in pattern recognition, for example in identifying the different components of a single image, detecting patterns in emails and messages, and matching new information with different forms of data in system databases. It can also help investigators link suspect information to existing criminal records and inform them of any past crimes in which the suspect in question may have been involved (Chinnikatti, 2018). Forensic statistics provide scientific methods for managing evidence in the justice system. With more sophisticated and comprehensive information databases, AI can help justice system with quick solutions when needed. The forensic operation requires seamless communication between experts and practitioners, the lack of which can lead to misinterpretation of data, which can lead to delayed or incorrect decisions by practitioners. AI helps bridge the communication gap between different actors in the sector, who can use strong statistical evidence to support their narrative and arguments. AI can create a graphical, visual environment for different scenarios of reconstruction and for the appropriate presentation of the different mechanisms of action. It can also be used to model the circumstances of the crime graphically, which can be used to support or refute victim-suspect claims, enabling the court to make informed decisions (Kamdar & Pandey, 2011).

The AI could also help to create an online repository of all digital forensic investigations, data, tools and records. With the exponential growth of storage capacity, it is becoming increasingly difficult to store and evaluate all this data. AI can be a good tool to store, analyse and use data for legal purposes (Kamdar & Pandey, 2011).

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## Reference of the article according to APA regulation

Lontai, M., Pamjav, H. & Petrétei D. (2024). Artificial Intelligence in Forensic Sciences. Revolution or Invasion? Part I. *Belügyi Szemle*, *72*(4), 701–715. https://doi.org/10.38146/BSZ-AJIA.2024.v72.i4.pp701-715

## Statements

**Conflict of interest**

The authors have declared no conflict of interest.

**Funding**

The authors received no financial support for the research, authorship, and/or publication of this article.

**Ethics**

No dataset is associated with this article.



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