Trends and applications of artificial intelligence methods in industry

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Abstract: *This article describes the actual trends and applications in industry where artificial intelligence models are deployed. This paper provides a more detailed description of the principles and methods of deploying models in the field of quality evaluation in industry and also in the areas of predictive maintenance and data analytics in the manufacturing process. Computer vision is increasingly coming to the fore due to its wide range of applications - object detection, categorisation of objects, reading QR codes and others. The area of predictive maintenance is important in terms of reducing downtime and saving costs for machine components. Models designed for data analytics, in turn, help to optimize the parameters of the production process so that the desired parameter is maximized or its optimal value is achieved.*
Keywords*: ARTIFICIAL INTELLIGENCE, COMPUTER VISION, PREDICTIVE MAINTENANCE*

1. Introduction

This article describes the actual trends and applications in industry where artificial intelligence models are deployed. In this paper, we mainly focus on artificial neural network models, namely convolutional artificial neural network models, nonlinear autoregressive artificial neural network models, and feedforward artificial neural network models.

Implementing computer vision models in the areas of product quality evaluation leads to savings in personnel costs, increased productivity and better management of the organisation of the production process. Computer vision is increasingly coming to the fore due to its wide range of applications. Due to the increasing scarcity of skilled workers, adherence to predetermined product quality, speed and repeatability, artificial intelligence (computer vision) is increasingly being used for product quality control in various industries. It is because of these benefits that we have described in this paper the issues associated with deploying these methods and algorithms to solve sub-problems associated with a specific manufacturing process. In this research, we worked with MATLAB and Python programming languages, which offer different libraries focused on Machine Learning and thus have a diverse range of desired AI models. Camera systems process and evaluate the captured image (within computer vision) - this includes reading text, QR/barcodes, recognizing objects (Fig 1a), determining the position of products, checking the filling of bottles with liquid, etc. This paper summarizes some specific applications of computer vision and training a convolutional neural network using a concrete example. To achieve the best possible computer vision results, it is necessary to create suitable conditions for the camera system to capture the object - use appropriate lighting, prevent larger debris from getting caught on the lens, etc. It is also possible to find leading manufacturers of industrial cameras who provide their own software for some of the applications of computer vision, e.g. distance measurement and orientation of the sensed object.


Fig. 1 *a) Detection of protective equipment on the worker [1] b) Predictive maintenance [2]*

This paper provides a more detailed description of the principles and methods of deploying models in the field of quality evaluation in industry and also in the areas of predictive maintenance (Fig 1b)and data analytics in the manufacturing process. The area of predictive maintenance is important in terms of reducing downtime and saving costs for machine components. Models designed for data analytics, in turn, help to optimize the parameters of the production process so that the desired parameter is maximized or its optimal value is achieved.

2. Computer vision

Almost all industrially produced goods are more or less intensively visually inspected (inspected by sight). This task is carried out by qualified personnel who have been trained in visual inspection. Nowadays there is a great deal of automation in production, and it is camera systems that reliably replace human operators in the inspection of products. [3]

The tasks of visual inspection are: recognizing familiar objects/patterns, distinguishing surface condition/texture, optical properties (e.g. color), material identification, defect detection, etc.

Significant disadvantages of visual inspection include: monotony, tediousness, tiring work, image evaluation is subjective, lack of good reproducibility, visual inspection is often very slow compared to machine vision, and it is also expensive.

Table 1: *Comparison of human visual system and technical visual inspection system [3]*

	Human visual system (eyes and brain)	Technical visual inspection system (camera + computer)
Sensors	- low optical resolution - intensity values and dimensions cannot be captured - limited to visible light - spectral perception with three channels	- high optical resolution - ability to capture intensity and dimension values - possibility to use illumination outside the visible part of the spectrum - possibility to use multichannel spectral resolution
Image processing and analysis	- huge number of parallel, highly interconnected and slow neurons - programmed by learning from examples	- one or more powerful processors - algorithm must usually be explicitly designed
Special abilities:	- experience and basic knowledge - adaptability and ability to learn - tremendous cognitive abilities - intuition	- precise calculations - high processing speed - lossless storage of large amounts of data

Computer vision applications

Computer vision as the automatic analysis of images and video by computers, has a wide range of applications - use in the engineering industry, food industry, medical industry, etc. Specific applications of machine vision are e.g. checking the position of parts in automotive production, checking the use of correct parts or fasteners, categorizing objects, checking printed circuit boards, checking defects on products, finding fingerprints on apples, detecting chocolates on a conveyor and placing them in a box via a delta robot, automatically reading license plates on vehicles, the ability to record multiple players on the ice (during hockey) and then give a penalty to that team, airport security checks, inserting virtual objects into movies, helping drivers by warning them (vibrating the steering wheel) when they are swerving out of their lane, creating 3D models from old photographs, classifying species of plants, etc.

Popular computer vision applications:

a) Object classification
b) Object identification
c) Object verification
d) Object detection
e) Object landmark detection
f) Object segmentation
g) Object recognition

Checking the date of manufacture and reading barcodes

When bottles/jars are filled with food, the date of manufacture/consumption (Fig. 2a) and the barcode (Fig. 2b), as shown in Fig. 32b, shall be indicated on the packaging of the bottles/jars. These labels and codes are printed by automated production, which can cause the data on the product packaging to be misprinted or not printed at all. In order for the consumer to have all the necessary information on the product as a result, some kind of control must already be included in automated production. The inspection can be either visual (a human operator would inspect individual product packages), which would greatly reduce the number of packages produced, or camera inspection, which in this case is the most appropriate in terms of efficiency and reliability.

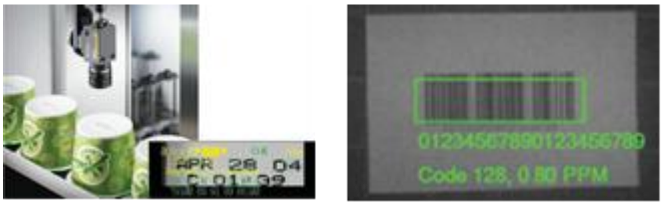

Fig. 2 *a) Checking the date of manufacture [4] b) Reading the barcode [5]*

Gravure cylinder inspection

Gravure printing consists of the continuous movement of the printed material, which presses the pressure roller against the gravure roller (Fig. 3) on which the gravure ink is applied. This type of printing, which makes it possible to achieve high quality printing of full-colour illustrations, is the reason why it is mainly used for printing full-colour high-cost products, e.g. magazines and catalogues.

Computer vision was used for detecting the defects on the printing cylinder, where the accuracy of the automated classification is 98.4%.

Fig. 3 *Gravure roller [6]*

Searching for animals with thermal cameras

Thermal imaging is the most effective method for finding problems or potential problems in a variety of applications in many fields. For this purpose, thermal imaging cameras are used, which are currently of great use in - search for wanted persons (police helicopters are often equipped with thermal imaging cameras), firefighting (thermal imaging cameras allow you to quickly find out where the fire is located), maritime navigation, road safety, military and defense applications, etc. Fig. 4 shows an image produced by a thermal imaging camera, from which the presence of animals at the imaged site can be easily detected (by the different colour of the individual objects - yellow/red).

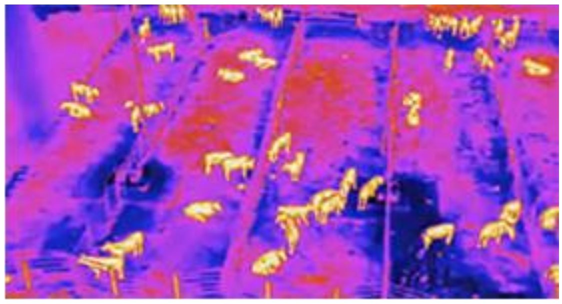

Fig. 4 *Drones could apply thermal imaging to identify sick livestock in feedlots [7]*

Mobile robots

Humanoid robots, in their design and functions, are similar in appearance to ordinary humans. They should also behave like humans and have similar means of communication to humans. The pace of robotics development is rapid, and individual countries often encourage this development because of its potential to bring economic benefits to the country. For example, the workforce in Japan is declining significantly, seriously threatening Japan's economy, and it is robots that are seen as the current solution. In addition to using robots to produce goods, the aim is to use robots as cleaners, sales assistants, museum guides, carers for the young and old, presenters of TV programmes, and they could also work as teachers. (Newton a Newton, 2019). Hanson Robotics has created one of the most human-like humanoid robots in existence today. This humanoid robot is named "Sofia" (shown in Fig. 5a).

Fig. 5 *a) Sofia - humanoid robot [8] b) Spot - the agile mobile robot [9]*

Sofia is the world's first robot citizen, and the first Robot Innovation Ambassador for the United Nations Development Programme. Sofia currently speaks at hundreds of conferences (as well as on various TV shows). Its artificial intelligence combines work from the fields of neural networks, expert systems, machine perception, natural language processing, motor control, and cognitive architecture. Sofia is able to recognise human faces, see emotional expressions and also recognise different hand gestures. It can also estimate the feelings of the people with whom it communicates (directly during the conversation) and tries to find a way to achieve certain goals of communication with the communicating people. It has its own emotions that roughly simulate human evolutionary psychology. [8]

Spot is a mobile robot that can handle terrain with great agility, allowing to automate regular inspection chores and data collection in a safe, accurate, and timely manner. The spot has an implemented thermal camera, through which it senses the image in its surroundings. The sensed image is processed by computer vision models. [9]

Object detection on the shoes

Object detection has received a lot of research attention in recent years because of its tight association with video analysis and picture interpretation. Handcrafted features and shallow trainable structures are the foundations of traditional object identification systems. By generating sophisticated ensembles that incorporate various low-level picture features with high-level information from object detectors and scene classifiers, their performance can quickly plateau. With the rapid advancement of deep learning, more powerful tools that can learn semantic, high-level, deeper features are being offered to address the issues that older systems have. [10]

Fig. 6 shows the training of the convolutional neural network where we wanted to detect different parts of the shoe - shoe uppers ("Zvrsok"), quilting shoes ("Presivanie") and the sole of the shoe ("Podrazka").

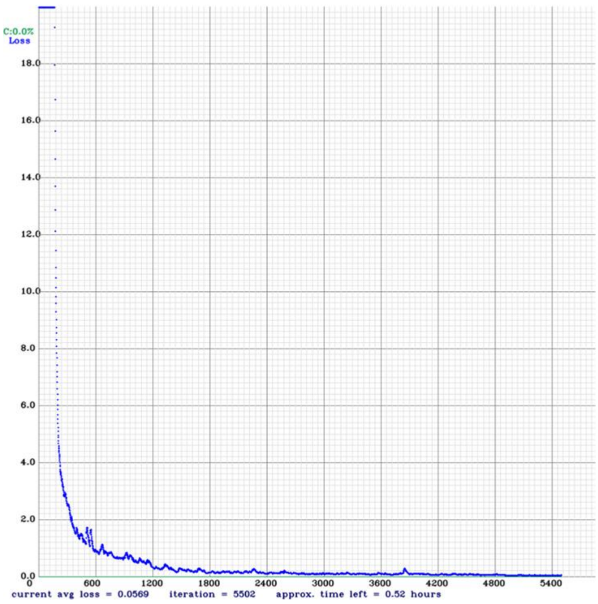

Fig. 6 *Training of the convolutional neural network*

Training was terminated at 5502 iterations, where the current avg loss reached 0.0569. The trained model was applied to a particular photo where we obtained good results - the neural network model detected all three objects on the shoe (Fig. 7).

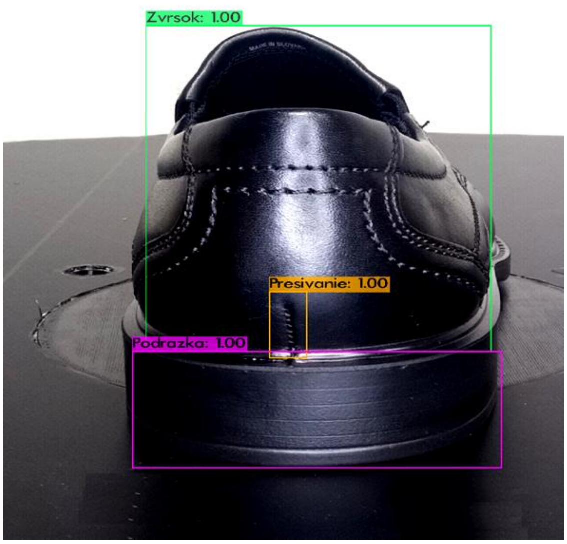

Fig. 7 *Object detection on the shoe*

3. Descriptive, predictive, and prescriptive analytics

Data analysis is a very important process in the terms of Industry 4.0. Availability of collected data allows the experts to have a better understanding and deeper look at the technological processes and the inner dependencies of multiple parameters.

Descriptive analytics is a preliminary stage of signal processing. This kind of analytics gives a better understanding of what has happened in the past. Descriptive analytics is using data aggregation and data mining [11]. This can be very helpful in the areas of signal detection [12] and cluster analysis [13].

Predictive analytics is an area of forecasting the trends of certain parameters. The main goal of this sphere is to get a better knowledge of what will happen in the future. This knowledge can be very helpful in the area of predictive maintenance and cost-saving in shortening the downtimes of industrial machines. Predictive analytics has an invaluable role in informing the decisions of the maintenance department of the company [14].

Prescriptive analytics is mainly dedicated to finding the best course of action for a given situation and it should be able to suggest decision options for how to take advantage of a future opportunity. This kind of analytics improves the accuracy of all predictions and provides better decision options [14].

4. Evaluation of quality based on the technological processes parameters

If we assume that the error or fault can occur during the production processes of the individual parts of the shoes (for example the shoe sole), it is possible to create a model in which the quantities that may have the greatest impact on the defect could enter the input of the model and thus the model can learn the individual dependencies of the technological processes. Such a model can work alone or together with a model that evaluates the resulting quality of the shoes based on the images. To increase the accuracy of the model it is possible to include in the model input not only the data captured by the camera but also the aggregated technological quantities from specific operations.

As shown in the fig. below, these can be variables such as speed, viscosity, temperature, pressure, or other variables. Each of these mentioned parameters should have some influence on the final quality of the product, so the AI model will be able to abstract the hidden dependencies during the process of training.

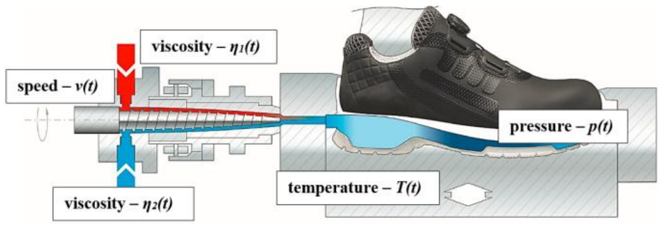

Fig. 8 *Technological parameters which may affect the quality of the shoes. [source: findsourcing.com, edited]*

5. Aggregation of the incoming data from the technological processes

The goal of the aggregation is to reduce time-series data and prepare the historical data for working with the models of artificial neural networks. Data can be aggregated in several ways. From the time series data of a given quantity (for example the speed), it is possible to calculate the standard deviation, minimum, maximum, or other statistical metrics [15]. The principle of aggregation is given and explained in the figure below.

The resampling periods in this case are belonging to the times when the individual shoes were produced. There needs to be an ID parameter for each individual shoe that will be used as a parameter on which the aggregation will be done.

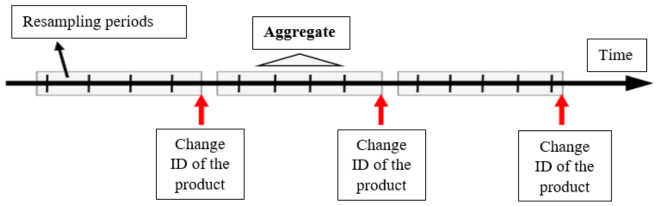

Fig. 9 *Aggregation principle of time series data.*

The proposed models of artificial neural networks will work with the aggregated data at the input and at the output of the model will be calculated or predicted whether the given input data belong to erroneous or defect-less shoes. If the error probability will be labeled as *qualityError*, we can say that the proposed model would estimate the defects that occurred based on the aggregated technological variables. The mathematical formulation of such a problem would look like in the equation given below:

$$qualityError=f(std(speed),min(speed),max(speed),avg(speed), std(viscosity)....avg(pressure))$$

This disadvantage is that a numeric identifier is required, on the basis of which the data are aggregated - shoe ID. It is also necessary to have access to the database, in which all necessary time-series data are stored. In order to be able to create a training data set, it is necessary that information is stored during data collection as to whether a given shoe with a specific ID was faulty or error-free.

6. Used mathematical models of simple feed-forward and recurrent neural networks

When working with aggregated data, it is possible to use deep forward neural networks [16] of different sizes. Models may be over-trained on the current data due to insufficient accuracy, or their structure and size may change arbitrarily. In addition to feed-forward neural networks, we can also work with recurrent models. The difference between them is shown in the figure below.

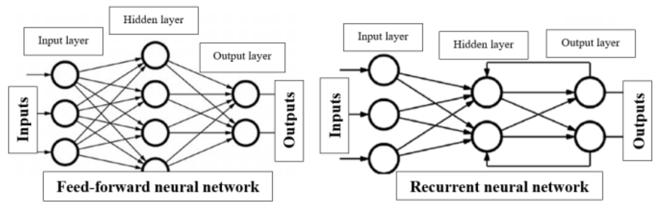

Fig. 10 *Simple feed-forward neural networks and simple recurrent neural network. [source: deepai.org, edited]*

In addition to predicting whether the shoe will be in the wrong or flawless group, we can also predict the development of individual quantities. We use recurrent Nonlinear Autoregressive Neural networks (NAR) or Nonlinear Autoregressive Neural Networks with Exogenous Input (NARX) [16] for such prediction. Results of such time-series prediction by using a MATLAB model is given in the figure below.

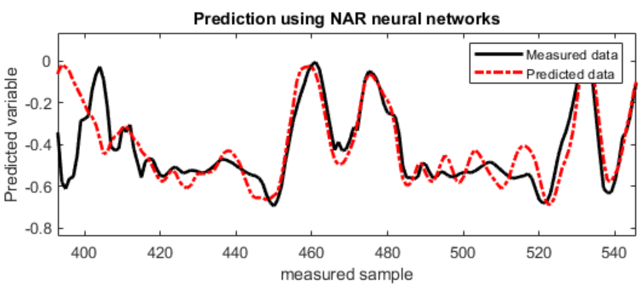

Fig. 11 *Time-series prediction by using the NAR neural networks.*

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