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Artificial intelligence versus natural intelligence in mineral processing

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Abstract: This article aims to introduce the terms NI-Natural Intelligence, AI-Artificial Intelligence, ML-Machine Learning, DL-Deep Learning, ES-Expert Systems and etc. used by modern digital world to mining and mineral processing and to show the main differences between them. As well known, each scientific and technological step in mineral industry creates huge amount of raw data and there is a serious necessity to firstly classify them. Afterwards experts should find alternative solutions in order to get optimal results by using those parameters and relations between them using special simulation software platforms. Development of these simulation models for such complex operations is not only time consuming and lacks real time applicability but also requires integration of multiple software platforms, intensive process knowledge and extensive model validation. An example case study is also demonstrated and the results are discussed within the article covering the main inferences, comments and decision during NI use for the experimental parameters used in a flotation related postgraduate study and compares with possible AI use.

Keywords: NI-Natural Intelligence, AI-Artificial Intelligence, ML-Machine Learning, DL-Deep Learning, ES-Expert Systems, mineral processing

1. Introduction

In the modern world AI, ML and DL are often used interchangeably and at times can be confusing. AI is a very broad term used to describe any system that can perform tasks that usually require the intelligence of a human. ML is a subset of AI whilst DL is a subset of ML algorithms. It is well known that NI of design ability and the nature of design activity can be used together with AI. Fig. 1 shows AI, ML and DL concepts altogether.

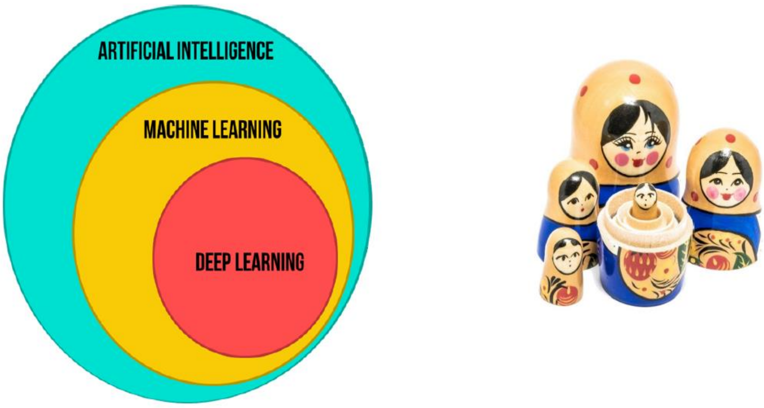

Fig. 1. The concepts of AI, ML and DL (Regunath, 2021)

The ability to design is widespread amongst all people, but some people appear to be better designers than others. Quotations and comments from some acknowledged expert designers are used to reinforce general findings about the nature of design activity that have come from recent design

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research. The role of sketching in design is used to exemplify some of the complexity of designing. The comments are made about the value and relevance of research into AI in design. It is suggested that one aim of research in AI in design should be to help inform understanding of the natural intelligence of design ability. Previous work (Regunath, 2021) also defines as "DL is ML taken to the next level" and it is a subset of ML that is inspired by how human brains work. Typically, when people use the term deep learning, they refer to deep artificial neural networks. DL effectively teaches computers to do what humans naturally do: learning by example. The differences between DL and ML are summarised in the Table 1 as follows:

Table 1. Main differences between DL and ML (Regunath, 2021)

Differences	**Machine Learning**	**Deep Learning**
Data	Performs well on small to medium datasets	Performs well on large datasets
Hardware	Able to function on CPU	Requires significant computing power e.g., GPU
Features	Features need to be manually identified	Learns features automatically
Training time	Quick to train	Computationally intensive

As a simple example of how AI, ML, and DL terminologies relate to a real-world situation, following Fig. 2 can be drawn in order to separate different fruits (such as apples, bananas and oranges) in a basket from each other by using automated sorting system.

In the same example, the all mixed fruits are firstly brought into the sorting plant, then separation is planned for packaging each fruit into cardboard fruit trays and then shipped to local supermarkets. Natural Intelligence uses human labour, with employees sorting fruits based on their knowledge of what each fruit is or inspecting its label. This works well, but the business is expanding, and the throughput of the sorting plant is limited by the speed of the workforce. To overcome this, an automated system using AI is proposed to tackle this problem. An AI-based algorithm is created that segregates the fruits using decision logic within a rule-based engine. For example, if an apple is on the conveyor belt, a scanner would scan the label, informing the AI algorithm that the fruit is indeed an apple. Then the apple would be routed to the apple fruit tray via sorting rollers/arms. The success of the AI-based system hinges upon the fruit being correctly labelled by the fruit pickers and having a scanning system in place that can inform the algorithm of what the fruit is. Here, the plan utilises an AI-based system to automate intellectual tasks generally performed by humans. As this system is based upon a rule-based engine that has been hard coded by humans, it is an example of AI without ML. With the increased throughput, the business has expanded, and the fruit supply is now coming from multiple sources where most of the fruits are not labelled. This has now provoked the need for a system to be more advanced.

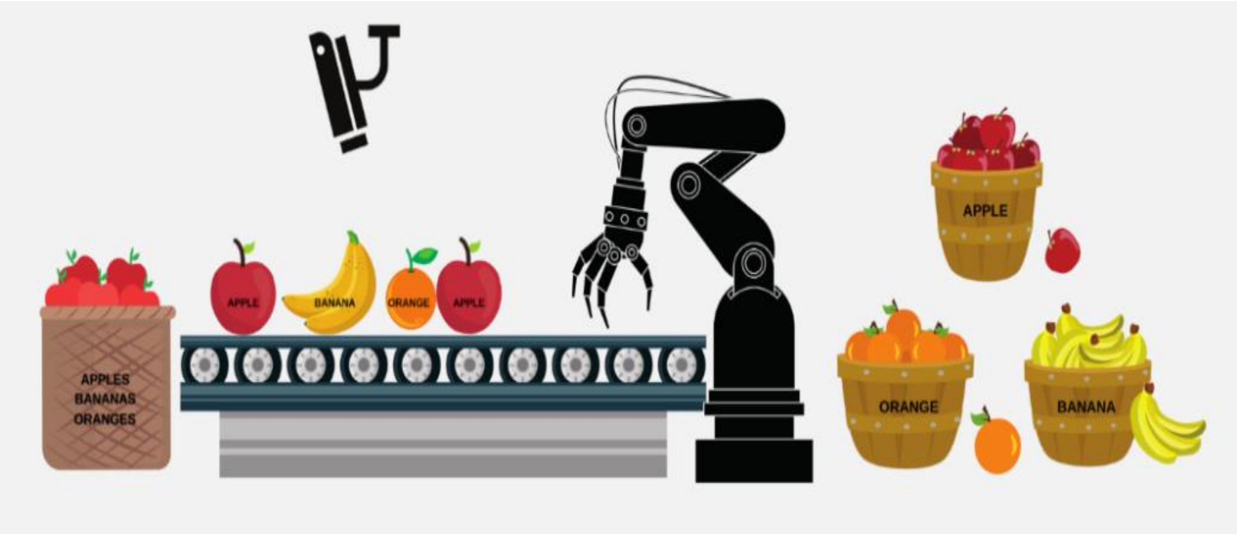

Fig. 2. Artificial Intelligence example (Regunath, 2021)

An ML-based algorithm is now proposed to solve the problem of fruit sorting by enhancing the AI-based approach when labels are not present. To create a ML model shown in Fig. 3, a definition of what each fruit looks like is required: this is termed feature extraction. To do this, features and attributes that characterise each fruit are used to create a blueprint. Features such as sizes, colours, shapes, etc., are extracted and used to train the algorithm to classify the fruits accordingly. For example, once the ML algorithm has seen what a banana looks like many times, i.e., has been trained, when a new fruit is presented, it can then compare the attributes against the learned features to classify the fruit. The algorithm provides a degree of confidence, which can then be used to determine whether the fruit is classified as a banana or not and routed on the conveyor belt accordingly. The system can now automatically classify fruits based on what it has learned. The business has been doing so well at improving the throughput of the sorting plant. It has cut costs and put local competitors out of business, taking over their fruit quota. It now needs to sort even more fruit, but this time fruit it has never seen before and with an added requirement of higher classification accuracy. This has provoked discussions around DL.

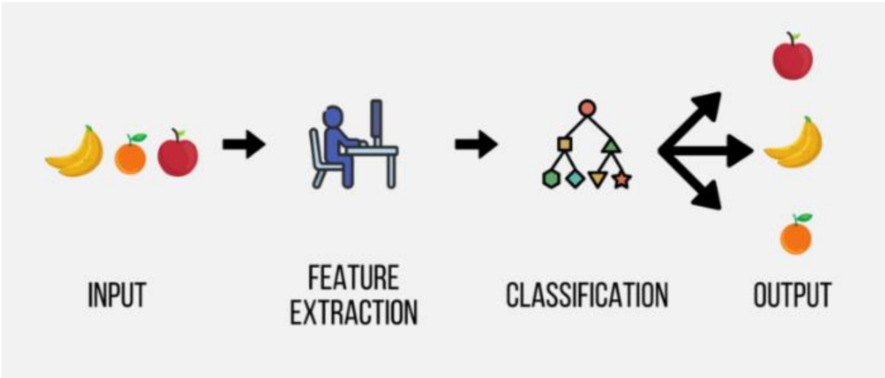

Fig. 3. Machine Learning example (Regunath, 2021)

A DL-based algorithm is now proposed to solve the problem of sorting any fruit by totally removing the need for defining what each fruit looks like. The main advantage of the DL model is that it does not necessarily need to be provided with features to classify the fruits correctly. By providing the DL model with lots of images of the fruits, it will build up a pattern of what each fruit looks like as shown in Fig. 4. The images will be processed through different layers of neural network within the DL model. Then each network layer will define specific features of the images, like the shape of the fruits, size of the fruits, colour of the fruits, etc. A DL based model, however, comes at a considerable upfront cost of requiring significant computational power and vast amounts of data. This is similar to how our brains work to classify objects. Our brains process data through many layers of neurons and then finds the appropriate identifiers to classify objects. In this example, the DL model will group the fruits into their respective fruit trays based on their statistical similarities, (Regunath, 2021).

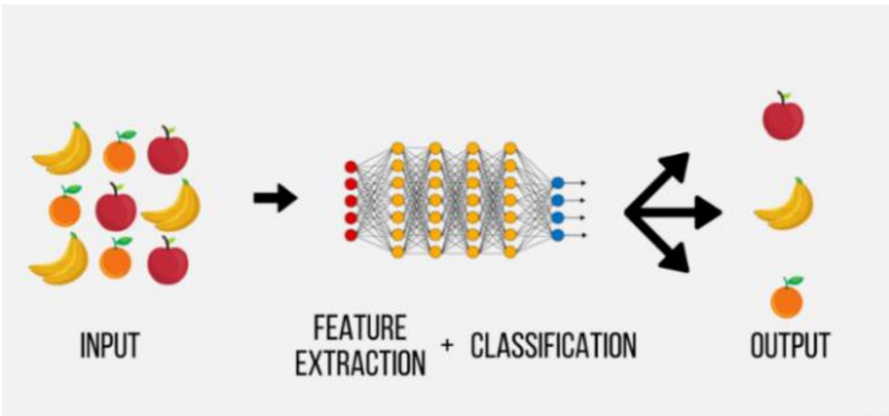

Fig. 4. Deep Learning example (Regunath, 2021)

As a simple example of how AI, ML, and DL terminologies relate to mineral processing or separation, Fig. 5 can be drawn in order to separate different minerals or products (as concentrates, tailings and middlings) from a representative ROM with well-defined geological and mineralogical properties after effective crushing&sizing&comminution for liberation before using an automated sorting system controlled by robots. We may easily simulate these different products to a real-world situation, such as separation of different fruits, such as apples, bananas and oranges in a basket from each other by using automated sorting system as illustrated in Fig. 2.

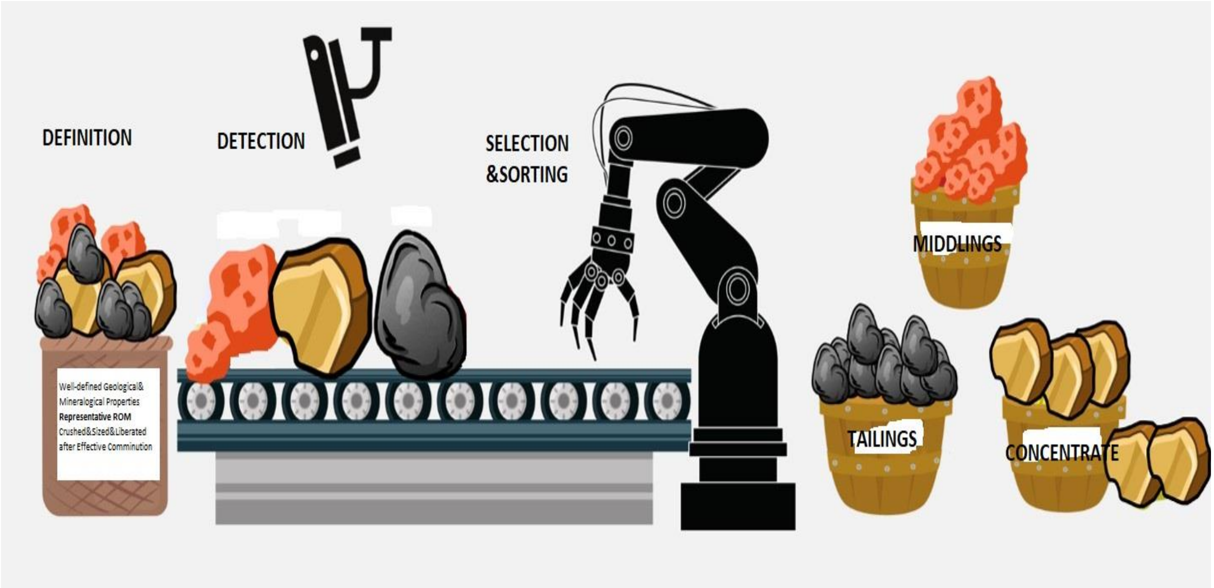

Fig. 5. Possible adaptation of AI for mineral processing (after Regunath, 2021)

In general terms, designing and modelling of a robust system is a major component of all engineering disciplines. The details may differ, but the goal is always the same to achieve the optimal results and efficiency by applying optimal conditions with the minimal use of resources. The engineering designer always imagines a solution that requires the minimal set of components to achieve the best results. The ability to design is an important capability for a scientist or an engineer, however some designers might think in a different way from each other and accordingly the outcomes may vary and the final solutions are always affected by their personal inferences from available data, final comments and further decisions. Natural intelligence or design ability of an expert depends on the nature of design activity. Quotations and comments from some acknowledged expert designers are used to reinforce general findings about the nature of design activity that have come from recent design research. The role of sketching in design is used to exemplify some of the complexity of designing, (Cross, 1999).

The current revolution in AI is being driven by machine learning. Machine learning is an approach to prediction which is data driven. It is not the first approach to focus on data, the statistical sciences have combined models with data for a number of years. But machine learning has taken a particular focus on improving the quality of prediction, whereas statistical sciences have traditionally focused more on explanation. Machine learning covering deep learning is giving us information processing engines that are equivalent to the steam engines of the industrial revolution. Machine learning allows us to extract knowledge from data to form a prediction. A machine learning prediction is made by combining a model with data to form the prediction. The manner in which this is done gives us the machine learning algorithm. Machine learning (ML) enables acquisition of knowledge for the main purpose of making decisions and predictions. The different types of learning techniques and algorithms used in ML can be broadly categorized into supervised learning, semi-supervised learning, unsupervised learning, reinforced learning as presented in Fig. 6 detail (Loberfeld, 2019).

In supervised learning, the classifier is trained with known data so that it can predict, or classify, the unknown instances. On the other hand, unsupervised learning is used to learn from the input data without any specific outcome variable/s. Semi-supervised learning uses the labelled data from a smaller subset of the data to identify and label other data in order to subsequently retrain the model.

Reinforcement learning interacts with a dynamic environment to achieve objectives based on rewards and penalties. Unsupervised learning essentially determines hidden patterns based on input data without corresponding output labels. Because unsupervised learning uncovers distinct classes without a teacher, the actual labels must be manually identified. Simply put, the unsupervised learning results generally need manual intervention for confirmation of target classes. Although unsupervised learning is largely suited to more exploratory applications due to it being more subjective and without the straightforward objective of response prediction, its usage is ever increasing. Some common applications of unsupervised learning include inter alia DNA/gene classification in computational biology, physics, wireless communications, building systems and more, (Swana&Doorsamy, 2021).

There are also several types of sub-processes or prediction models used in machine learning, such as Decision Trees, Random Forest, Linear Regression (includes regularization), Gradient Descent / Line of Best Fit, Logistic Regression, Hierarchical Clustering, Agglomerative Clustering, eXtreme Gradient Boosting, AdaBoost, Support Vector Machine (SVM), Naive Bayes, K-Nearest Neighbours (K-NN), K-Means, Density Based Scan (DBS), Convolutional Neural Networks (CNNs)&Recurrent Neural Network (RNNs).

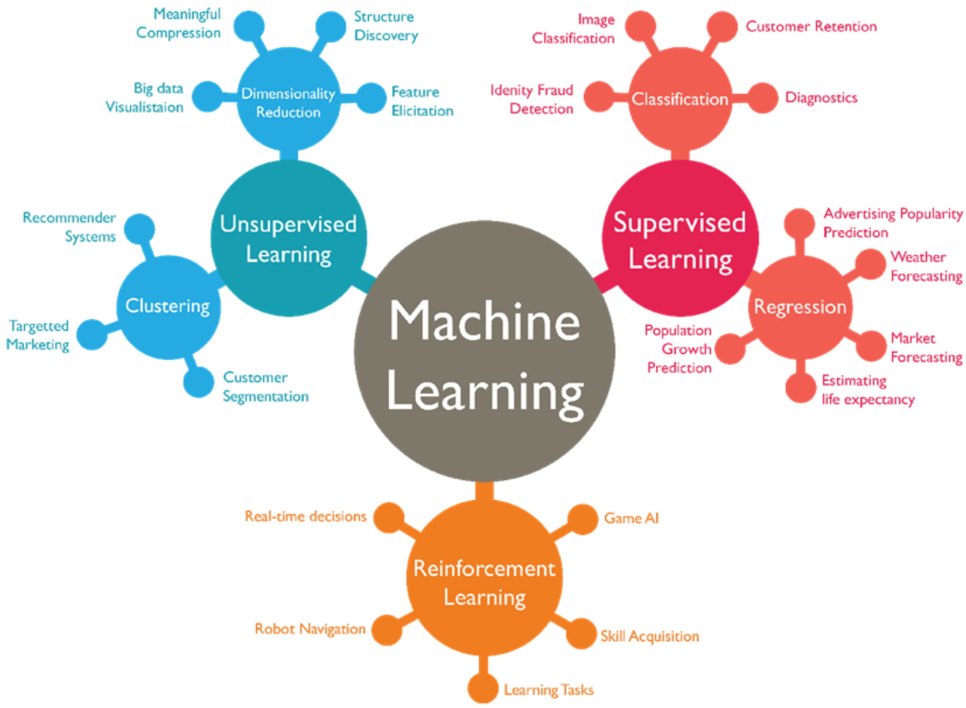

Fig. 6. Machine learning algorithms in general (Loberfeld, 2019)

Machine learning is a technology which strongly overlaps with the methodology of statistics. From a historical/philosophical view point, machine learning differs from statistics in that the focus in the machine learning community has been primarily on accuracy of prediction, whereas the focus in statistics is typically on the interpretability of a model and/or validating a hypothesis through data collection.

The rapid increase in the availability of computers and data has led to the increased prominence of machine learning. This prominence is surfacing in two different but overlapping domains: data science and artificial intelligence. The real challenge, however, is end-to-end decision making. Taking information from the environment and using it to drive decision making to achieve goals, (Lawrence, 2018).

2. Artificial Intelligence examples in mineral processing

There have been a limited number of published reports that process modelling simulations could be widely used to model the mineral processing operations considering various physical, physicochemical and chemical parameters altogether and estimating optimal results without conducting too many experiments. However, development of simulation models for such complex operations is not only time consuming and lacks real time applicability but also requires integration of multiple software platforms, intensive process knowledge and extensive model validation using some modelling simulation methods, such as MODSIM, MESTEM and/or IDEAS. Moreover, modelling a process using AI models can provide valuable information for future applications as well. This will also allow the building of an intelligent system that can be used to predict the outcomes of applied mineral processing methods such as recoveries and grades of the products based on various input parameters including chemical and operational variables. These models sometimes will work provided that the ore characteristics do not change significantly as compared to the ore for which AI models have been developed. If there is any significant change in the characteristics of the ore feed in terms of ore complexity, mineral associations and/or ore variability, re-training of the AI model would be required. In this situation, data obtained through further physical experimentation and/or process model simulations models could serve well in providing the data required for the re-training. It is always important to keep these limitations of AI and ML modeling in mind while adopting these models for automation purposes (Ali&Frimpong, 2020).

In a previous study (Gomez-Flores et al, 2022) prediction of grade and recovery in flotation from physicochemical and operational aspects using machine learning models were investigated in detail. Variables such as collector and frother concentrations, adsorption, size, liberation degree, air and water flow rate, mass flow, and circuit design were known to influence the flotation behaviour. Researchers took the task of modelling and predicting flotation behaviour using mechanistic or empirical models. In "kind learning environments" (e.g., repeated patterns and high–quality measurements), machine learning (ML) was reported to be suitable for empirical modelling of a multivariable unit operation. Operational variables and neural networks (NN) were commonly used to model flotation. Moreover, physicochemical variables were neglected for the modelling and there was a lack of information on database quality based on descriptive statistics. Thus, physicochemical variables and detailed database description were included in their work. The physicochemical variables were selected based on DLVO theory. Multivariable linear regression (MLR), k–nearest neighbours (KNN), decision tree (DT), and random forest (RF) were the ML models to model and predict flotation performance (grade and recovery). Furthermore, variable importance in the modeling and prediction was examined. Using supervised ML, their work made an effort to combine, for the first time, physicochemical aspects and operational aspects to predict grade and recovery. In that study (Gomez-Flores et al, 2022), firstly they obtained a database comprising n = 330 samples (n records under m variables) mined from 19 peer–reviewed flotation studies via an online search of the keywork DLVO from the literature. When physicochemical variables were not available, values with references were used to fill gaps. Only studies that contained most of the required variables were considered to avoid excessive gap filling for physicochemical variables. From each data set, m = 18 variables were recorded to predict two target variables. The variables included nine physicochemical variables (Hamaker constant, Particle mean diameter, Bubble mean diameter, pH, Salt type, Ionic strength, Zeta potential, Bubble potential and Contact angle) and nine operational variables (Mineral type, Number of minerals, Flotation device type, Collector type, Collector concentration, Conditioning time, Frother type, Frother concentration, Flotaion time). The descriptive statistics of all the variables were explored and the Anderson–Darling and Kolmogorov–Smirnov tests were employed to evaluate their distribution at the 1% significance level to apply an appropriate transformation for modelling if required.

For modelling of databases, MLR, KNN, DT, and RF were generated using Python and Sklearn library. The performance of these models was evaluated using the mean absolute error (MAE), which is a dimensional measure of accuracy, because this measure has the same scale as the grade and recovery percent. They firstly draw an algorithm showing all parameters that might affect the results. The database was split into training (90%) and holdout (10%) data sets; shuffling was applied before the split. The models were trained using the training set and evaluated on a testing set using a three–times repeated 10–fold cross–validation. The cross–validation is a resampling method to evaluate the performance of the models applied in small databases. Only DT and RF models were run six times because of their random nature. The best model (lowest MAE) was selected and used for additional evaluation of variable importance. Importance of physicochemical and operational variables was evaluated using variable selection in recursive feature elimination with the repeated cross–validation (RFECV).

In conclusion, Gomez-Flores et al (2022) criticised the mechanistic models, which were unable to consider a wide range of variables (from fundamental to engineering aspects) simultaneously, the applied ML effort (a regression work) in the study enabled prediction of GR and RC from physiochemical and operational features. In detail, their approach enabled quantitative prediction of GR and RC considering both physicochemical and operational variables without mechanistic understanding of flotation behaviour, which is a multivariable, multi correlated, and nonlinear unit operation. They envisioned that this approach could more easily bring together fundamentals of surface chemistry and operational engineering variables, which had previously been disconnected in many flotation studies. Mechanistic models are important because they help to understand the fundamentals of flotation. However, currently they are not suitable to unite the vast number of variables that can be included in flotation modelling.

Ali et al. (2018) reviewed the related following work and stated that there have been some applications of the AI methods to identify the micro processes during mineral processing, especially coal flotation. Different influencing variables including pulp pH, impeller speed, reagent dosage and reagent conditioning time were studied using different AI methods. (Jorjani, et al. 2007) used the multi-layered artificial neural network for predicting sulphur reduction (both organic and inorganic) in coal using mixed culture microorganisms. (Al-Thyabat, 2008) used a multilayer feed forward neural network to predict the effect of feed size, collector dosage and impeller speed on the flotation recovery, and the concentrate grade of siliceous phosphate. (Mohanty, 2009) designed a feed forward artificial neural network for handling the interface level in a flotation column. The model used three values of tailing valve opening and an interface level as input data and made a prediction on future interface levels. (Jorjani, et al. 2009) also used multi layered artificial neural network to predict the combustible recovery of coal after flotation using proximate analysis data (moisture, volatile matter and ash) and group maceral data (liptinite, fusinite, vitrinite and ash) as the inputs and compared the results with that of nonlinear regression. (Cheng, et al. 2010) used a single-layer artificial neural network to predict the solid concentration of coal-water slurry (CWS). Hard grove grindability index (HGI), moisture content and degree of parent coal coalification were used as inputs to predict the maximum CSW solid concentration. (Zhang, et al. 2011) used RBF neural networks to predict the washability curve of the coal washing process. Digital image processing was used to extract a total of 13 image feature parameters to be used as the inputs for the neural network model. (Khoshjavan, et al. 2011) used a multi-layered artificial neural network to study the effects of coal physiochemical properties on its free swelling index (FSI). Chemical properties including nitrogen, oxygen, carbon, hydrogen, volatile matter, BTU, fixed carbon content, moisture, ash and total sulfur content were used as inputs, and FSI was taken as the predicted output. (Bekat, et al. 2012) used a multi-layered artificial neural network for predicting the bottom ash quantity in a coal-fired power plant. Moisture, ash content and coal heating value were used as inputs. (Sadeghiamirshahidi, et al. 2013) used a multi-layered artificial neural network for predicting pyrite oxidation in coal washing tailing piles in northern Iran. The depth of the spoil, annual precipitation, initial pyrite amount present in the spoil and the effective diffusion coefficient were used as the inputs and the pyrite quantity remaining in the pile at various depths was taken as the predicted outcome. (Feng, et al. 2015) evaluated the support vector machine (SVM), the alternating conditional expectation (ACE) and the artificial neural network (ANN) for predicting the gross calorific value of coal by using the proximate analysis data and concluded that SVM performs the best, but ACE can be made to outperform ANN if initialised properly. (Pusat, et al. 2016) used the adaptive-neuro fuzzy inference system (ANFIS) for estimating moisture content at any time during the coal drying process. Dying air temperature, drying air velocity, bed height and sample size were the variables used as inputs to the ANFIS model. (Khodakarami, et al. 2017) successfully employed multi-layered ANN for predicting the ash content and the combustible recovery of clayey coal, processed using froth flotation technology in the presence of hybrid polymer aids.

Ali et al. (2018) also reported that different process variables were used as inputs in their AI and ML studies. These included (1) the dosage of the Al-PAM polymer which was used as a depressant, (2) the dosage of sodium silicate dispersant, which is commonly used at industrial scale to disperse ash particles, (3) the pH of the slurry, (4) the polymers' conditioning time, and (5) the impeller speed of the cell, which is indicative of the energy input. The combustible recovery and ash content of coal in the froth layer were used as response variables (outputs). The present work is the first comprehensive attempt to develop and evaluate principal artificial intelligence (AI) and machine learning (ML) models to predict and model the effect of various parameters on the fine coal flotation process outcomes when hybrid polymeric nanoparticles are used as slime depressants. Five machine learning and AI models namely random forest (RF), artificial neural networks (ANN), the adaptive neuro-fuzzy inference system (ANFIS), Mamdani fuzzy logic (MFL) and a hybrid neural fuzzy inference system (HyFIS), were used. The dataset acquired through experimentation was divided into training and testing datasets. The models were developed using the training dataset and validation was done using the testing dataset.

Ali et al. (2018) finally concluded their results might pave the path for enforcing data based process monitoring in the mineral processing industry. Modern processing industries including the mineral industry requires monitoring of the process to ensure both quality and safety. They stated that although process monitoring could be done through model, knowledge or data based methods, data-based intelligent process monitoring methods had the ability to work with incomplete information of the fundamentals of the process and the associated expert knowledge. As a lot of data has been collected during the past decades due to modern electronic systems and sensors, data-driven process modelling, monitoring, prediction and control has a huge scope in the future of the processing industry.

3. Case studies using natural intelligence in mineral and coal processing

As an example, the data from the present author's Ph.D. thesis (Özkan, 1994) were deeply investigated in order to understand the results according to the natural intelligence (NI) approach and the comments were compared with the ones using the artificial intelligence (AI) methods.

The data below shown in Table 2 were obtained from the previous reports at the references' list of the thesis and they were the inspiration of the selection of the experimental parameters during flotation studies and considered for comparison during the experimental plan.

Table 3 also shows similar data analysis from coal flotation experimental study in a previous article by Özkan (2012).

Table 2. Experimental conditions of colemanite flotation studies (Modified from Özkan, 1994)

Conditions/Previous Researchers	Yarar, 1971	Ayok, 1976	Kose, 1988	Inferences from previous work	Comment and Decision
Feed Particle Size	0.200 mm	0.200 mm	0.150 mm	Optimal particle size for flotation feed was needed due to liberation degree.	Necessity for crushing-grinding-sieving to obtain minus 200 microns.
Slime Particle Size	0.053 mm	0.071 mm	0.053 mm	Slimes were main obstacles before flotation.	Necessity for desliming by sieving and decantation to remove the materials at particle size of 53-71 microns before flotation.
Slime/Feed Ratio	25 %	30 %	50 %	Solid materials losses (25-50 %) were unavoidable due to friability of the ore samples.	Controlled crushing and grinding are always necessary for sample preparation.
Solid/Liquid Ratio	30 %	25 %	20 %	Efficient solid/liquid ratio (20-30 %) was recorded.	These should be experimentally checked.
Deslimed Feed Grade	40 % B2O3	40 % B2O3	36 % B2O3	Flotation was effective for the deslimed feed with 36-40 %B2O3) grade.	Total B2O3 % recovery should be questioned.

pH Regulation	Natural	Natural	Natural	No data.	pH change should be measured for each tests.
Collectors	-Naphthenic Acid +Kerosene (1.0+1.2 kg/t) -Naphthenic Acid +Kerosene+AP825 (0.5+0.9+0.3 kg/t) -AP825+ Naphthenic Acid (0.5+0.085 kg/t) (5 % emulsion)	AP825+Kerosene (2.0+0.25 kg/t) (5 % emulsion)	AP825+Kerosene (1.6+0.4 kg/t) (5 % emulsion)	Anionic collectors and fatty acids plus kerosene were tested around 1-2.5 kg/t dosage (as 5% emulsion).	Some alternative anionic collectors can be tried and the optimal dosage should be recorded.
Frothers	MIBC, Flotanol G	Flotanol G	Pine Oil (50 g/t)	Some frother addition was necessary.	Froth structure should be observed.
Cond. Time	5 min	5-10 min	No	5-10 minutes conditioning is necessary before flotation.	Conditioning is necessary for 10 minutes.
Flot. Time	10 min	10 min	10 min	It may continue till froth structure is finished.	If kinetic flotation data are needed, this should be recorded with some intervals.
OUTCOMES	**Yarar, 1971**	**Ayok, 1976**	**Kose, 1988**	**Inferences**	**Comment and Decision**
Conc. Grade	48 % B2O3	48 % B2O3	46 % B2O3	Concentrate quality is 46-48 B2O3%. It may change due to recovery data.	Grade vs Recovery graphs should be carefully investigated.
Recovery	90 %	95 %	88 %	Recovery is acceptable with 88-95 %. It may change according to grade values of concentrate and tailings.	Tailings should be carefully observed.

Table 3. Experimental conditions of coal flotation studies (Modified from Özkan, 2012)

Conditions/Previous Researchers	Buttermore, Slomka, 1991	Harrison et al. 2002	Feng, Aldrich, 2005	Inferences from previous work	Comment and Decision
Feed Particle Size	0.212-0.150 mm	As received (roughly minus 0.300 mm)	0.250-0.106 mm	Optimal particle size for flotation feed was needed due to high friability of coal samples.	Necessity for controlled dry and wet sieving to obtain minus 200 microns.
Slime Particle Size	0.075 mm	-	0.068 mm	Slimes might be main obstacles before flotation as they contain ash forming clays.	If desliming before flotation is considered, large amount of coal losses might be unavoidable. Ash values should be always observed.
Slime/Feed Ratio	5 %	Unknown	Unknown	Solid materials losses (25-50 %) were unavoidable due to friability of the ore samples.	Controlled comminution and sieving are always necessary for sample preparation.
Solid/Liquid Ratio	10 %	10 %	15-50 %	Efficient solid/liquid ratio (20-30 %) was recorded.	These should be experimentally checked.
Feed Ash Value	21.3%	11.24 %	16.5 %	It should always be measured after each step.	It should always be controlled after each step.

Deslimed Feed Ash	10 %	10.6 %	10 %	When the feed is deslimed by float&sink, flotation with addition of reagents might not be needed.	Total ash and yield data should be always measured and controlled during desliming and flotation.
Reagents and Conditioning	None (Float&Sink in water) (No pH regulation)	None (Float&Sink in water) (No pH regulation)	Pine Oil (200 g/t) Diesel Oil (1.25-2.5 kg/t)	High reagent consumption might be need for high ash coal.	Some alternative non-ionic reagents (frother and collector combination can be tried and the optimal dosage should be recorded.
Cond. Time	-	-	8 min	5-10 minutes conditioning is necessary before flotation.	Conditioning is necessary for 5-10 minutes.
Flot. Time	-	-	4 min	It may continue till froth structure is finished.	If kinetic flotation data are needed, this should be recorded with some intervals.
OUTCOMES	**Buttermore, Slomka, 1991**	**Harrison et al. 2002**	**Feng, Aldrich, 2005**	**Inferences**	**Comment and Decision**
Clean Coal Ash	5%	10 %	5 %	5-10 % ash content might be expected due to changing yield a and combustible recovery data.	Ash vs Yield vs Combustible Recovery graphs should be carefully investigated.
Yield and Combustible Recovery	90 %	85 %	88 %	10 % Yield increase after ultrasonication is expected.	Tailings part of flotation before and after ultrasonication should be carefully observed.

As can be seen from Table 2 and 3, use of Natural Intelligence or rather manual selection of parameters for a research studies especially at laboratory stages throughout a postgraduate thesis about colemanite flotation and an article preparation for coal recovery require and consume too much effort and time in order to get achieavable results. Especially, inferences at different time intervals from previous literature and experimental work at limited numbers seriously affect current researcher in order to decide which important parameters should be taken into account when comment and decision are constructed. While conventional laboratory work deals with too many data and manual calculations to interprete for designing a scale up from less amount of actual experimental results, use of modern digital methods discards unnecessary parameters and derivates from actual data, therefore less amount of time, courage and energy are consumed in use of Artifical Intelligence.

4. Conclusions

As the world is deeply inside a digital era in recent years, it is inevitable that mineral processing is surely affected by these sudden changes in modern technology. Mining and mineral processing technologies definitely create huge amount of raw data and the experts (NI-Natural Intelligence, AI-Artificial Intelligence, ML-Machine Learning, DL-Deep Learning, ES-Expert Systems and etc.) are in charge of commenting these in order to benefit from valuable minerals in the ore bodies. Digitalization, modelling and simulation start from mine exploration, reserve estimation, selection of an effective mining method, effective transportation, calculation of proper liberation degree for optimal comminution, selection of suitable particle size reduction and concentration technology, dewatering, tailings management, suitable storage, etc. Each step for plant design purposes contains large numerical data which always relate from previous to next technological equipment. There have been recently published reports that process modelling simulations have been widely used in an attempt to model the mineral processing operations, such as flotation without requiring actual experiments. Development of simulation models for such complex operation is not only time consuming and lacks real time applicability but also requires integration of multiple software platforms, intensive process knowledge and extensive model validation. In conclusion, the mineral processing industry will sooner or later adopt AI, ML, DL, ES, etc. and we will heavily confront the terms of the digital world during plant design, such as with a large amount of parameters and various data.

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