A Systematic Review on Applications of Artificial Neural Networks in the Extraction Metallurgy Industry

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Abstract

Machine learning techniques inspired by the structure and function of the human brain are known as artificial neural networks (ANNs). Their popularity has grown in recent years due to their ability to learn and improve via training, allowing them to be used in a variety of applications. The ANN approach has the appealing advantage of providing an accurate representation of the process input/output data and due to this reason, their application in the extraction metallurgy field have increased over the years. This systematic review aims to investigate the application and efficacy of ANN for facilitating and upgrading mineralogical data processing in the extraction metallurgical field. In this study, 112 research papers, published over years, that discuss ANN application were retrieved and 49 research papers were systematically reviewed. Research trends, ANN algorithms models, and evaluation methods primarily discussed in the 49 papers were discussed. From the review, it was discovered that the main justification to the increase application of ANN in the extraction metallurgy field is due to the ore grade decline which makes extraction processes complex demanding a need for a predicting and optimising tool. The frequently used ANN algorithm was found to Levenberg- Marquardt algorithm (LMA) which was due to its ability to process a lot of data in a short period of time. It was further concluded that the applicability of ANN in metallurgical field diverse from processes optimisation using operational to equipment parameters with least error and high efficiency.

Keywords: Artificial neural networks, extraction metallurgy, optimization, ANN algorithms.

1.Introduction

In recent years, the need for modelling, simulation and optimization of mining and metallurgical processes has increased enormously. The growing requirement of these 3 aspects is attributable to the need of saving power, energy and costs of the mining and metallurgical processing while achieving a desired grade and recovery of the metals processed. Artificial neural network (ANN) or neural network (NN) is a relatively recent branch of artificial intelligence that was developed since 1940s (Kasongo and Mwanat, 2021). ANN is known as a complex coded computational system developed based on the neurological structure of the human brain with the number of simple and highly interconnected processing elements for simulating and processing data. ANN forms a part of machine learning that revolves around the interactions between the artificial neural signals from one end to another to develop optimization algorithms (Gholami and Khoshdast, 2020; Massinaei and Doostmohammadi, 2010; Olga and Shuang, 2021; Tsae et al. 2023).

ANN consists of input and output layers with one or multiple hidden layers within. The chief duty of ANN is to transform the input data into a significant output. In ANN, all the neurons control each other, and hence, they are all connected. The network can concede and detect every aspect of the dataset at hand and how the different parts of data may or may not ally to each other (Kang *et al.*, 2020; Kasongo and Mwanat, 2021). These networks are among the most utilized intelligent algorithms for transmitting data knowledge or rules into network structures by processing experimental data. ANN can be used to perform complex operations in a variety of disciplines, such as pattern recognition, classification, visual systems, and control (Gholami and Khoshdast, 2020). Neural networks are now being trained to solve problems that are challenging for humans or ordinary computers to solve (Gorucu 2004; Gholami and Khoshdast, 2020). Artificial intelligence tools have been used for many years in several metallurgical applications. These networks have been used for different applications such as modeling for particle size analysis (Maxwell, et al., 1995; Otsuki and Jang, 2022), simulation for particle shape quantification (Oja, and Nystöm, 1997), assessment of flotation experiments (Deventer, et al. 1997; Cilek, 2002; Labidi et al. 2007), Bioflotation optimisation (Pereira, et al., 2021; Merma, et al. 2018), the modeling of gold liberation from diagnostic leaching data (Petersen and Lorenzen,1997), and prediction of metal grades (Hosseini and Samanipour, 2015; Jorjarni, et al. 2009; Gholami,et al., 2011; Obiewa, et al. 2020)

In artificial neural networks, the flow of data and information occurs in either feedforward networks or feedback networks. Feedforward networks only permits the signals to travel in one direction, which is towards the output layer (Hosseini and Samanipour, 2015; Kasongo and Mwanat, 2021). These networks have an input layer and a single output layer with zero or multiple hidden layers. Whereas feedback networks are recurrent or interactive networks that uses their memory (trained, validated, and tested algorithms) to process the sequence of inputs (Farghaly et al. 2012). In feedback networks, the signals can travel in both directions through hidden layer/s in the network. They are typically used in time-series and sequential tasks.

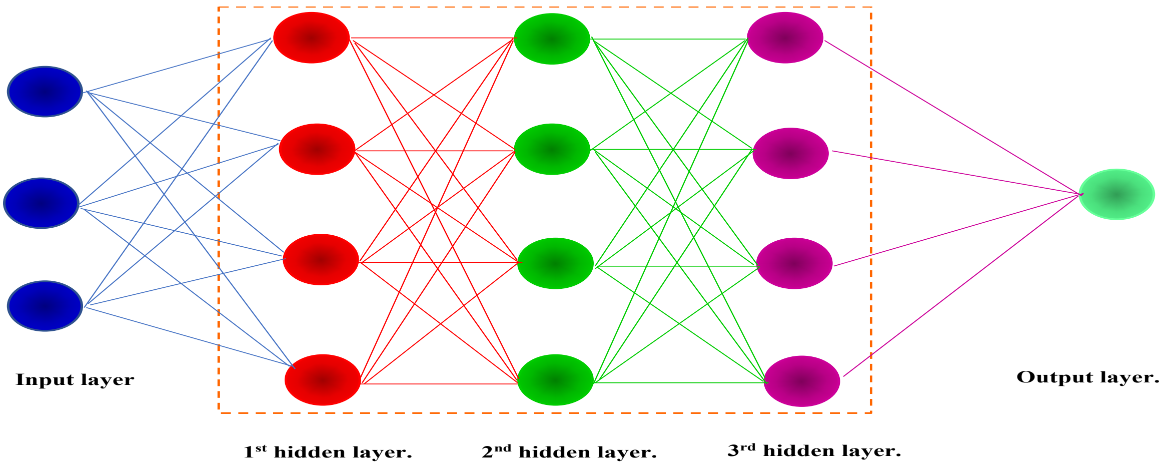

Figure 1: A typical ANN 3-4-4-4-1 structure, based on the arrow's direction one name the ANN architecture feedforward or feedback ANN.

In an artificial neural network, the learning process is initiated by dividing the data into three different sets: training dataset, validation dataset and test dataset (Acharya et al., 2006; Kasongo and Mwanat, 2021; Olga and Shuang, 2021; Simpson 1990). Training dataset allows the ANN to understand the weights between the nodes, validation dataset is used for fine turning the performance of the ANN, lastly, test dataset determines the accuracy and margin factor of the error of the ANN (Kasongo and Mwanat, 2021; Simpson 1990). The model training and testing process should continue until the model is optimized with minimum error and maximum accuracy. Following the segmentation of the data into these three sections, ANN techniques are used to them to train the ANN. There are various sorts of training and activation algorithms, each with its own set of characteristics and attributes such as memory requirements, numerical precision, and processing speed (Allahkarami et al. 2016; al-Thyabat, 2008; Kang et al. 2020; Massinaei and Doostmohammadi, 2010).The ANN model's configuration methods involve the following six steps (Kasongo and Mwanat, 2021; Santosh et al., 2022):

i. Data collection.

ii. Training and testing of the set determination.

iii. Data conversion into the Artificial Neural Network inputs.

iv. Determination, training, and testing of the network topology.

v. Repeating the steps n times until the required optimal model is generated.

vi. Applying the optimal Artificial Neural Network model.

The ANN model's performance criteria are usually the root mean squared error (RMSE) and the mean absolute error (MAE). The variability of the data replicated by the model and the observations is assessed using the coefficient of determination R^2 (Wagh et al. 2018 ; Silva et al. 2019). The average root mean square (RMS) of the difference between the measured or targeted value (T) and the anticipated value (Y) from the model is the Root Mean Squared Error (RMSE). The RMSE number is in the same unit as the variable and should be as low as possible. An error between the predicted and measured values is estimated for each iteration (Wagh et al. 2018 ; Silva et al. 2019). The anticipated value is then corrected by propagating the error backward from the output layer to the input via hidden layers. This procedure is done until the error is reduced to a manageable level (Santosh *et al.*, 2022). RMSE and MAE are both used to calculate residual errors. Equations below are used to calculate all the above-mentioned errors:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(T-Y)^2}{\sum_{i=1}^{n}(Y)^2} \qquad \textit{Equation 1}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}(T-Y)^2 \qquad \textit{Equation 2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(T-Y)^2} \qquad \textit{Equation 3}$$

2. Systematic literature review objectives

This systematic review aims to investigate the application and efficacy of artificial neural networks (ANN) for facilitating and upgrading mineralogical data processing in the extraction metallurgical field. This was done by outlining the challenging problems in metallurgical industries that give rise to the need of using ANN to model, predict and optimise metallurgical processes. To further comprehend the application of ANN, there was a necessity to evaluate different ANN algorithms and parameters used for modeling and optimising different metallurgical processes. Given that ANN techniques are generally used to discover useful associations in data to predict specific outcomes in the context of supervised learning or to identify significant patterns among input features in an unsupervised setting, the last objective is to investigate ANN models performance based on the main findings in the existing literature by evaluating R^2, and MSE/ MAE. The remaining part of the paper is partitioned into three distinct sections. section 2 summarizes the research methods used in this study. Section 3 discusses the analysis's findings briefly. Section 4 concludes with recommendations for future research.

3. Methodology

The fundamental goal of a systematic review is to study the body of knowledge with an aim to answer a set of research questions (Bruce and Mollison, 2004).For the sake of transparency and ease of assessing the objectivity and trustworthiness of the data analysis and outcomes given to possible readers, this must be done using concrete methodologies and procedures. Given the revolutionary advancements and expanding improvements in the discipline of artificial neural networks, it has been used in a variety of fields to handle convoluted problems that could not be properly addressed using traditional techniques. Considering the importance of mineralogical monitoring at every stage of the metallurgy industry, and the complexities associated with extracting valuable information from mineralogical data, there has been a rising application of ANN for data handling and processes optimisation in the metallurgy industry. The research questions that this systematic literature review should address and build the understanding of ANN application in extraction metallurgy are as follows:

a) What is the necessity of applying ANN in processing mineralogical and metallurgical data?
b) What are the ANN algorithms frequently used in modeling and predicting the output of the metallurgical data that is being processed?
c) What are the prevalent trends in the main findings of the process optimization in terms of mean squared error (MSE) / mean absolute error (MAE), root mean squared error (RMSE) and percentage error?

3.1. Search strategy

The search strategy was developed from the 3 different ranks of keywords as illustrated in figure 2 below. The targeted modelling, predicting, simulating, and optimising tool reviewed in this paper is artificial neural networks including its algorithms applied in metallurgical process optimisation. To narrow down the search, three target mineral processing and extraction metallurgy processes known as comminution, concentration, and metal extraction processes were selected as the main processes in the search. The search was set such that at least one of the keywords in each rank should be in the title, abstract, or list of keywords.

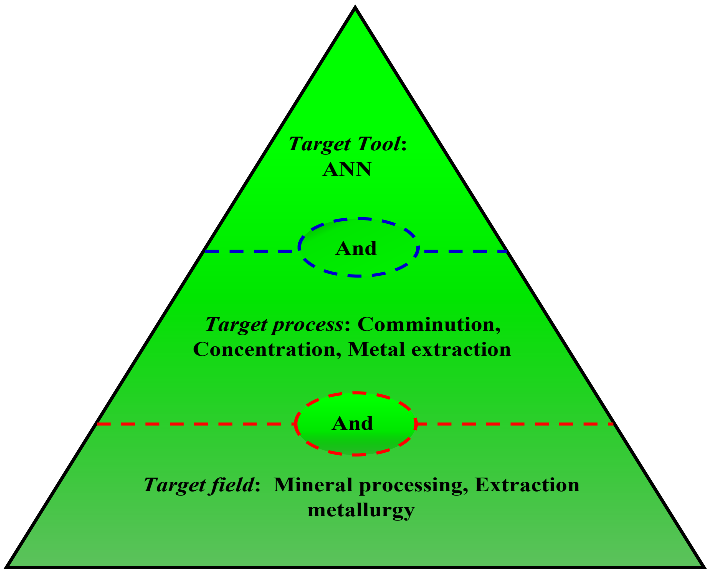

Figure 2: search strategy using keywords ranks as per their search criteria.

3.2. Eligibility Criteria

The use of the selection tool referred to as Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) was implemented in this research. In the form of diagram, the PRISMA provided a clear understanding of the amount of work involved through the selection of information from different databases where they have been retrieved. The PRISMA diagram (figure 3) outlines the research process from the article's identification, screening, eligibility till included articles in compiling this systematic literature review. To ensure a systematic and logical construction of this review of the literature (Bruce and Millison, 2004), a table known as inclusion table was used as a decision-making tool in terms of the years to be covered for the literature findings, the content to be looked at, and its origin. This table is represented in table 1 below.

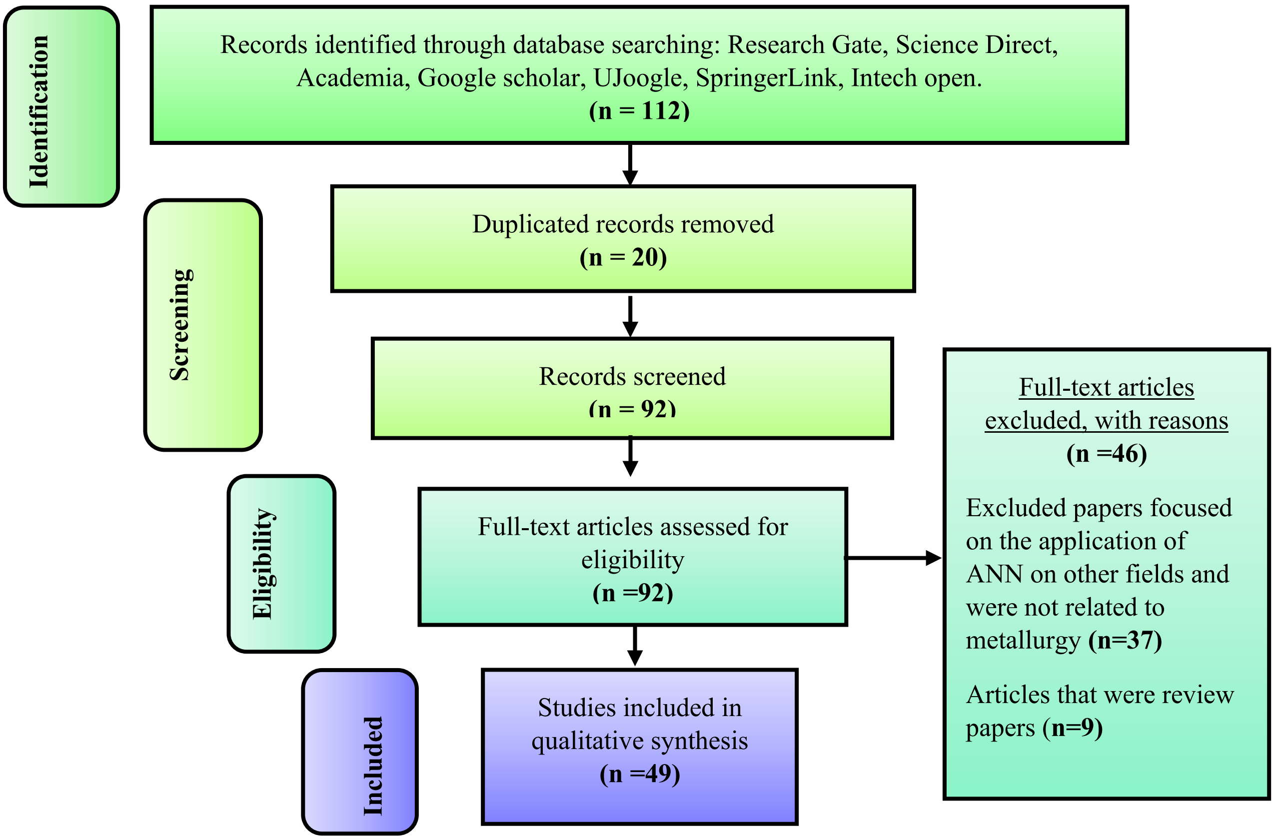

Figure 3: Prisma diagram

Table 1: Inclusion table for building the systematic literature review.

Criteria	**Inclusion**
Years	Longitudinal data (no specified time range)
Language	English only
Field	Mineral processing and extraction metallurgy
Countries	Any country
Authors	Any author
Publication	All published research articles, journals, and conference articles
Content	The focus of articles include: a) Modelling, simulating/ predicting, optimizing using ANN. b) ANN should be used in mineral processing and extraction metallurgy processes.

3.3. Research Design : Customization of the research onion to build the research.

The collection of principles governing the worldview or perspective from which the study is performed is referred to as *research philosophy*. Ontology and epistemology are commonly used to study it. Ontology refers to the authenticity of the information and how one interprets its presence in this context, whereas epistemology refers to the legitimate information needed for the research and how to collect it. To build a coherent and logical research, the development of efficient strategies for such research is a very important step. The praise for engineering such an approach needs to be attributed to Saunders et al. (2007) who developed the concept of the research onion. The research onion below in figure 4 was customized to relate to the concept of the research conducted in this paper.

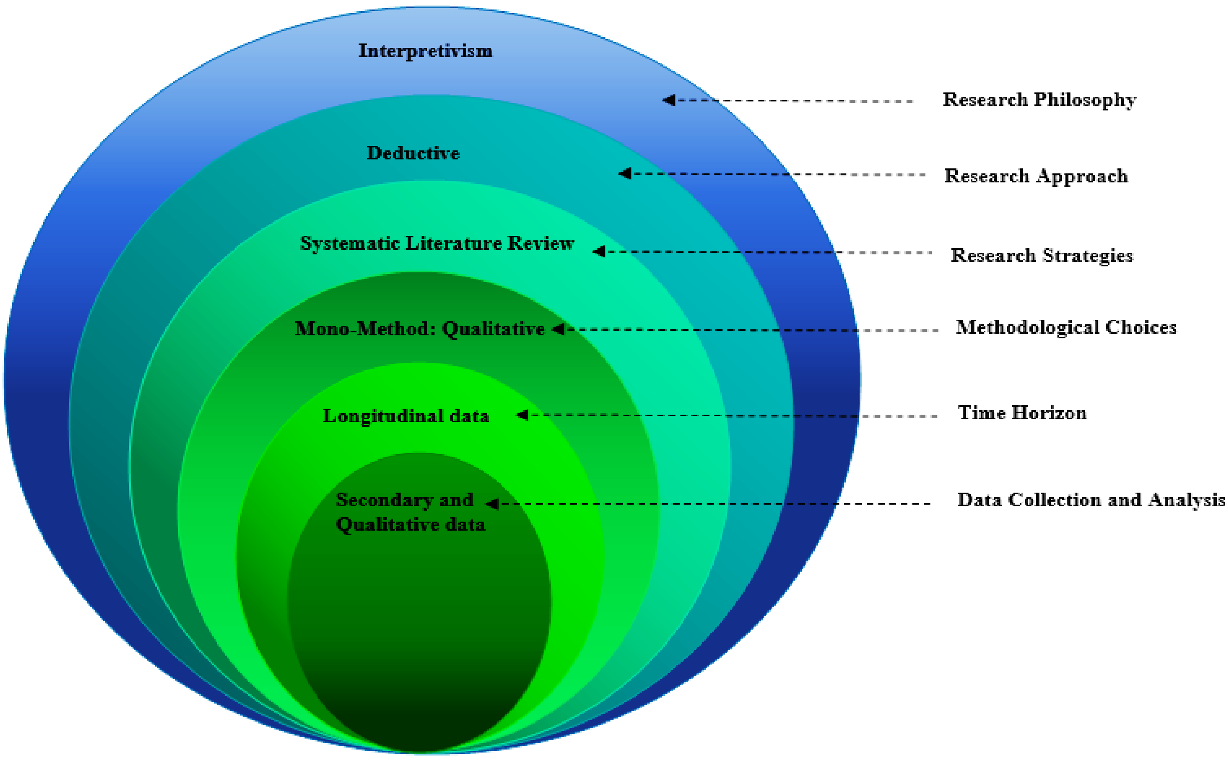

Figure 4: customised research onion

In this study, interpretivism research philosophy was adopted. Interpretivism claims that individual observers have their own perception and understanding of reality and because this research is qualitative in nature, the conclusions drawn are based on the existing literature covered by numerous authors with varying interpretation and application of ANN. The research approach used in this paper is a deductive approach. This research started with specific research objectives and questions developed based on the existing literature review that has been observed by the authors of this paper. As outlined on the tittle of this paper, the research strategy is a systematic literature review.

The methodological choice was chosen based on the research strategy used. A systematic literature review is built mainly from secondary data which resulted in employing a qualitative approach. The time horizon refers to the timeframe of the research and in this research longitudinal data was chosen as the observations discussed, in this case, for ANN, articles are available for several years, quarters, months or even days. Lastly, data collection and analysis as aforementioned is mainly secondary data and qualitative data.

3. Results and Discussion

This section presents the descriptive analysis to provide an overview on the increasing demand/ research of artificial neural networks (ANN) application in the extraction metallurgy field, the processes in which ANN is frequently applied. Furthermore, the ANN algorithms used as well as the trends in the results of the reviewed articles are presented in this section. Brief discussion of the descriptive analysis results is presented in this section. Lastly, statistical analysis of the obtained results based on ANN application in metallurgical processes optimization will be presented.

3.1 Descriptive analysis of the papers reviewed.

Figure 5 below addresses research question (a), it shows the expanding research and application of ANN over the years. This shows that there has been an intensified need to utilize ANN to address complex challenges in the metallurgy field.

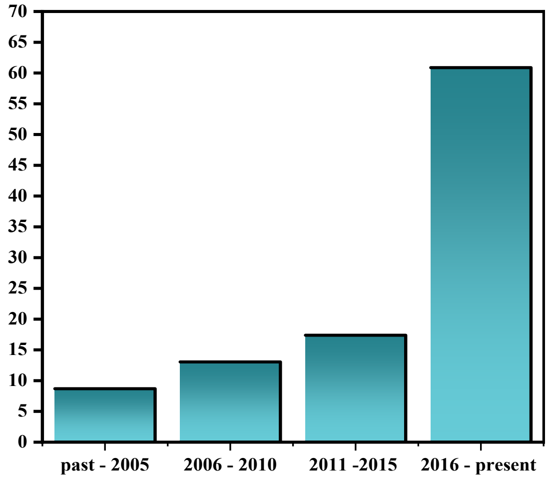

Figure 5: Increasing application of ANN in metallurgical field over the years.

Globally, mineral reserves at the surface have declined, and mining companies are spending more money than ever to access increasingly shallow deposits (Ali, 2022; Samanta et al., 2006; Tsae et al. 2023). Recently discovered mineral resources are typically of low grade, making extraction more difficult. The difficulty of exploiting the mineral resource economically and effectively has increased. Mining sectors are facing a growing data volume dilemma because the data is not linked to the value chain, only 10% of it may be used to manage variability and optimize operations (Ali, 2022). Mineral processing and metal extraction processes contribute significantly to greenhouse gas emissions. A significant emphasis is being placed on ethical mining to lessen the environmental and material footprint of the entire process chain (Ali, 2022). Mining and metallurgical industries are already locating economically viable minerals at tremendous depths. Due to the limits of traditional procedures, excavating from smaller ore resources can be challenging and lengthy. Artificial neural networks can help build more accurate models for predicting the type of minerals and discovering high-concentration resources, saving time and money (Abdulhussein and Alwared, 2019; Bergh, 2016). Mining activities demand extensive data processing, which is still done manually. The capacity of ANN to provide rapid outcomes by gathering and analysing data on-site has the potential to dramatically improve workflow while reducing errors. During the past few decades, the ANN technique has been attracting attention and has been successfully applied to the problems in the fields of pattern recognition, image processing, data compression, forecasting, and process modeling (Charan et al., 2014; Kasongo and Mwanat, 2021; Kumar et al. 2019). According to Ali (2020), using ANN can save companies up to 80% more money than previous methods. Furthermore, the collected data can be used in future rehabilitation efforts to restore the area's natural ecology.

Figure 6 below shows the percentage of ANN application in the mineral processing and metallurgy processes as per the articles processed.

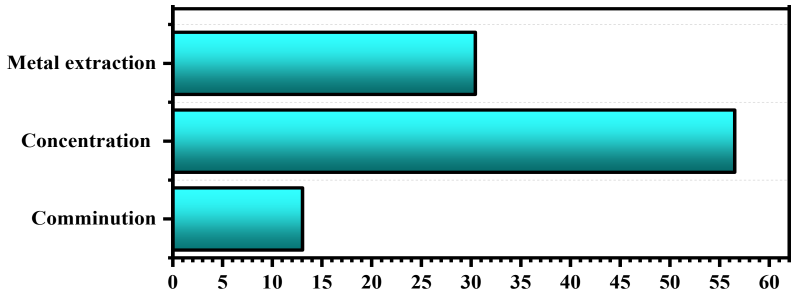

Figure 6: ANN application in the mineral processing and metallurgy processes as per the articles processed.

From the articles, it was found that approximately 13%, 56%, 30% of the existing research on ANN application in extraction metallurgy are addressing the use of ANN on comminution (Grinding and classification), concentration processes (flotation, magnetic separation, gravity concentration), and metal extraction (hydrometallurgy and pyrometallurgy). For concentration and metal extraction processes, the application of ANN was solely to predict and optimize the grade of the metals by evaluating the process and its parameters interaction after the weights and biases have been settled by the ANN (Abdulhussein and Alwared, 2019; Allahkarami et al. 2016; Farghaly et al. 2012; Kasongo and Mwanat, 2021). Whereas for comminution process, ANN was used to evaluate the performance of the equipment (Chaurasia and Nikkam, 2017; Otsuki and Jang, 2022; Panda and Tripathy, 2014). The difference between the between these two evaluations is the input parameters, for the comminution processes the input parameters are mainly equipment parameters and in concentration and metal extraction processes the input parameters are operational parameters. This outlines the wide applicability of ANN in the metallurgical industry.

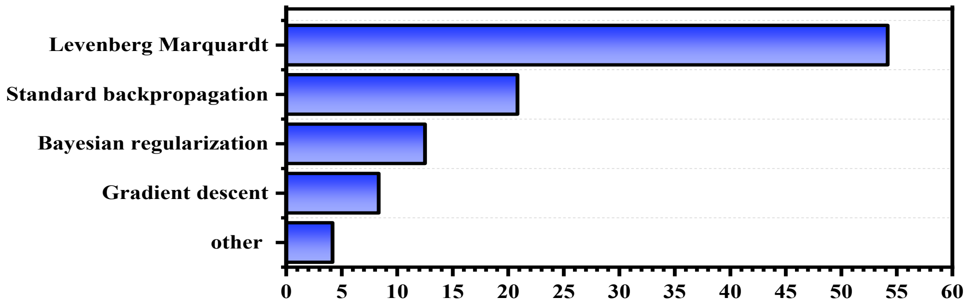

Figure 7: Frequency of different ANN algorithms applied in mineral processing and metallurgy processes as per article reviews

To further comprehend the application of ANN in metallurgical fields, training and testing algorithms used were assessed (figure 7). The most widely used neural-network topology is the multilayer ‘‘perceptron’’ (MLP) comprising of an input layer, output layer, and one or more hidden layers of neurons . It has been found by many authors that the three-layer feed-forward ANN approach has many advantages over traditional methods of predicting responses of different processes (Allahkarami *et al.*, 2016; Charan *et al.*, 2014; Kasongo and Mwanat, 2021; Kumar *et al.*, 2019). This MLP is then trained and tested using different algorithms. The most used algorithm was found to be Levenberg-Marquardt algorithm (LMA) as it was used in 56% of the articles reviewed. This is because the LMA was derived from different algorithms. It blends the steepest descent method and the Gauss–Newton algorithm. Further, it inherits the speed advantage of the Gauss–Newton algorithm and the stability of the steepest descent method (Yu and Wilamowski, 2010). It is more robust than the Gauss-Newton approach because it can converge quicker than the steepest descent method in numerous cases, even when the error surface is much more complex than in the quadratic situation. It achieves a considerably faster convergence than the steepest descent method (Yu and Wilamowski, 2010) . The Levenberg-Marquardt algorithm performs a combined training process: around the area with complex curvature, the Levenberg-Marquardt algorithm switches to the steepest descent algorithm, until the local curvature is appropriate to make a quadratic approximation; then it approximates the Gauss-Newton algorithm, which can significantly speed up the convergence (Yu and Wilamowski, 2010). 21% of the articles used standard backpropagation which is known as a gradient descent algorithm in which the network weights are moved along the negative of the gradient of the performance function. Bayesian regularization algorithm and Gradient descent were used on their own on 13% and 8% of the articles, respectively. This was done in a case of training the network and converting a non-linear regression into a statistical method in a manner of the normal regression method(Kasongo and Mwanat, 2021; Merma *et al.*, 2018, 2019). In essence, the high utilization of LMA is mainly because it often uses more memory but takes less time due to its derivation which blends all the different algorithms which brings in the advantages of these algorithms together in LMA.

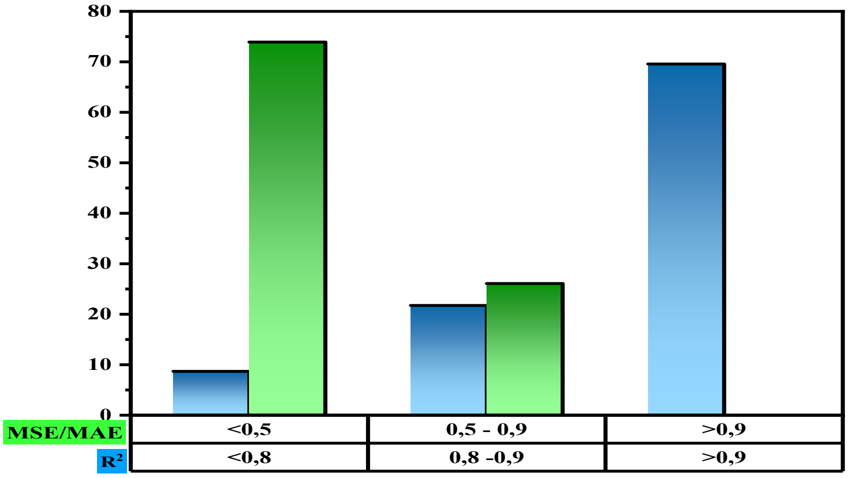

Figure 8: Trend of the results obtained in the articles reviewed.

As aforementioned, the ANN model's performance criteria are the mean absolute error (MAE) / mean squared error (MSE.) The variability of the data replicated by the model and the observations is assessed using the determinant's coefficient R^2 (Acharya et al. 2006; Kasongo and Mwanat, 2021; Olga and Shuang, 2021; Wagh et al. 2018). To identify the trends of the main findings, in terms of accessing the training and testing of ANN when applied to solving metallurgy complex challenging cases, R^2, MEA/ MSE were assessed on the articles reviewed. The results are shown in figure 8 above. It was concluded based on the trend identified that the ANN could predict and be validated through actual/ observed data as 70% of the articles presented the R^2 of greater than 0,9 proving that the network produced has less errors in terms of predicting the outcomes of the process. 74% of the articles further confirmed that ANN could be used for process prediction and optimization as the MSE/MAE was found to be less than 0,5 and none of the articles found an error of greater than 0,9. However, 26% of the article had MSE/MEA ranging from 0,5-0,9 showing the imperfections of either the networks or the actual process.

Table 2 below provides a summary of the articles used and the main objectives of the research presented in the articles. It further shows how the article were grouped.

Table 2: Evidence table: summary of the articles used.

Authors, Year	Purpose of Study	approach	Metallurgical process covered
(Chaurasia and Nikkam, Eren, et al. ,1997; Otsuki and Jang, 2022; Tripathy et al., 2020; Santosh et al., 2022)	The main aim was to use ANN to predict the performance of the grinding and classification processes	Quantitative	Comminution
(Abdulhussein and Alwared, 2019; Allahkarami et al., 2016; Charan et al., 2014; Chaurasia and Nikkam, 2017; Farghaly et al., 2012; Gholami and Khoshdast, 2020; Jorjani et al., 2008, 2009; Khoshdast et al., 2021; Merma et al., 2018, 2019; Mohanty, 2009; Paledi et al., 2021; Panda and Tripathy, 2014; Pereira et al., 2021; Tripathy et al., 2020; Kothari et al., 2022)	The aim was to study the efficiency (by predicting) of either flotation, bioflotation, magnetic separation, and gravity concentration using ANN	Quantitative	Concentration
(Samanta, et al. 2006; Hossein, et al. 2019; Kang et al. 2020; Kabuba and Maliehe 2021; Kasongo et al. 2021; Moatasem 2019; Hosseini	In these studies, the aim was to predict/optimise hydrometallurgy or	Quantitative	Metal extraction

and Samanipour, 2015; Ebrahimzade et al., 2020; Amirjan et al., 2013; Vyas et al., 2020; Gholami et al., 2011 Bhatti et al., 2011; Ilaboya and Izinyon, 2020; Kabuba and Maliehe, 2021; Khalefa, 2019)	pyrometallurgical processes.		

3.2. Statistical Analysis

The estimated effect sizes are the relational values derived from various studies describing the link between two or more continuous variables. Calculating the Pearson correlation coefficient, or r, yields the impact size of research in most cases. The analysis includes studies that give this coefficient or the ability to compute this coefficient. Calculations are done by converting the correlation coefficient's r value into its equivalent z table value, which ranges from +1 to -1. In addition to being represented by the letter r, the correlation coefficient is also known as the coefficient of effect size (Borenstein et al., 2009; Littel et al., 2008).One of the most used methods for calculating effect size is Cohen's d, often known as the standardized mean difference. A measure of an effect's size is its magnitude. For instance, an experimental group set A has a stronger impact than group B. Statistical p-values can indicate the potential impact existence; however, they cannot quantify its size. The impact magnitude of the difference between two means is explicitly measured by the Cohen's d statistic.

These Cohen's d statistic results are graphically represented below:

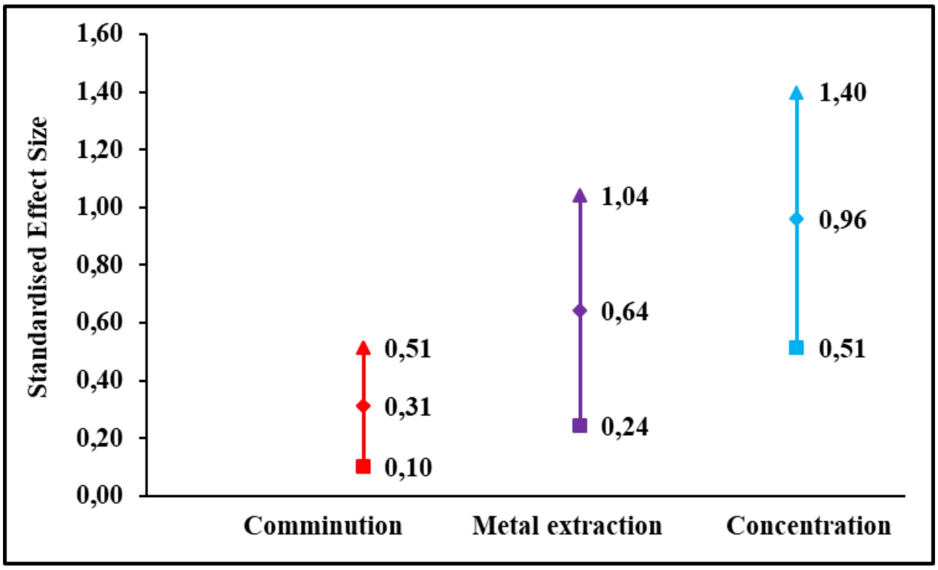

Figure 9: Cohen's d statistical results showing the standardised effect size of comminution, metal extraction and concentration.

The rule of thumb related to Cohen's d results is mainly associated with the following size effect interpretations:

- Small effect, d = 0.2
- Medium Effect, d = 0.5
- Large Effect, d = 0.8

From the graphical results, it is observed that there is a medium statistical size effect between the comminution and metal extraction applications of ANN in the metallurgical field. This is because of the mean proportions observed in the processed articles. It is further observed that a small effect (raise questions about managerial relevance) is observed when comparing the concentration and metal extraction applications of ANN. Finally, the large effect is observed during comparison of concentration and comminution applications of ANN. The fluctuation in terms of effect size measures is as a result of the proportions of data available as depicted in figure 6, wherein it is observed that majority of the data has revealed applications of ANN in concentration processes, followed by metal extraction, and finally comminution. As such, there is a great need for more empirical studies on the statistical effects that each application carries on its own before bringing together their combined effects. This extends on the level of parametrisation required under comminution studies, which is considered relatively low in comparison to metal extraction and concentration in the metallurgical field.

4. Conclusion

This paper systematically reviewed the continuous arising research on applications of artificial neural networks (ANN) in the extraction metallurgy field. This was done to outline the challenges that demand the use of optimisation tools, evaluate the implementation in metallurgical processes optimisation and further access the algorithms used, the ANN efficacy in optimising metallurgical processes. The main findings that addressed the developed research questions were:

- It was discovered that the main justification to the increase application of ANN in the extraction metallurgy field is due to the ore grade decline which makes extraction processes complex demanding a need for a predicting and optimising tool.
- It was found that approximately 13%, 56%, 30% of the existing research on ANN application in extraction metallurgy are addressing the use of ANN on comminution (Grinding and classification), Concentration processes (flotation, magnetic separation, gravity concentration), and metal extraction (hydrometallurgy and pyrometallurgy). It was further outlined that the application of ANN in metallurgy could be to optimise the processes using operational parameters and using equipment parameters.
- The most used algorithm was found to be Levenberg-Marquardt algorithm (LMA) as it was used in 56% of the articles reviewed. The high utilization of LMA is mainly because it often uses more memory but takes less time due to its derivation which blends all the different algorithms which brings in the advantages of these algorithms together in LMA.
- It was concluded based on the trend identified that the ANN could predict and be validated through actual/ observed data as 70% of the articles presented the R^2 of greater than 0,9 proving that the network produced has less errors in terms of predicting the outcomes of the process. 74% of the articles further confirmed that ANN could be used for process prediction and optimization as the MSE/MAE was found to be less than 0,5 and none of the articles found an error of greater than 0,9. However, 26% of the article had MSE/MEA ranging from 0,5-0,9 showing the imperfections of either the networks or the actual process.

From these, it was concluded that the application of ANN in the extraction metallurgy field generate simple ways to understand the processes and as well optimise them. Furthermore, it could contribute to saving power, energy, and costs. The future research on ANN could be on application of ANN on optimising comminution circuits by studying both equipment parameters as well as the ore parameters to produce a network that is more accurate.

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