Performance Evaluation of Neural Network Models Applied to the Classification of Mineral Imagery from the Katanga Mining Region

Par Blaise Fyam[1], Ruphin Nyami Nyate[2]

[1]Faculty of Polytechnic / Lubumbashi University **(UNILU)**
[2]Computer Engineering / Higher School of Industrial Engineers/ Lubumbashi University

Abstract

Nowadays, the need for a powerful model in the task of accurate image classification is increasing. This paper focuses on evaluating and comparing the effectiveness of three main neural network models namely the multilayer perceptron model, convolutional neural networks and the transfer learning model for the classification of mineral and rock images in the mining region of Katanga. The main problem addressed is the identification of the most efficient and accurate machine learning techniques in the specific classification of mineral images, with a particular focus on the constitution of the dataset, the analysis of mineral image data and their associated labels. Parameters such as the burial lot, the number of cycles, the size of convolution filters, the precision and the loss have been taken into account. The results show that the transfer learning-based model significantly outperforms the multilayer perceptron models and convolutional neural networks in terms of accuracy and robustness, achieving a classification accuracy of 97.8% compared to 75% for the multilayer perceptron and 96% for the convolutional neural networks designed from scratch. These remarkable results demonstrate the importance of deep learning in processing complex images and open new perspectives for the use of these techniques in the mining sector of the Greater Katanga mining region in the identification of mineral resources. The broader implications of this study include an innovation in mining exploration strategies through faster and more accurate classification of minerals, thus influencing both economic decision-making and environmental policies associated with mining in the region.

Keywords: Performance evaluation, Transfer learning, Deep learning, Convolutional neural networks, Mineral image classification.

Introduction

Every day that passes, huge masses of images are taken, whether they are images of the different minerals extracted or of new strategic minerals discovered, images of boreholes, images of the mapping of mineral reserves, high-risk mining areas, details of machines in exploration sites, information relating to the labeling of minerals, images on compliance and the fight against illegal trafficking of minerals. In addition, the mining area of Katanga is full of varied mineral resources, which poses particular challenges due to the complexity and diversity of textures, mineral compositions for their elucidation and precise classification. Furthermore, the rapid evolution of image processing technologies, especially those based on machine learning, has revolutionized the way geological and mineral information is analyzed and interpreted. At the heart of this transformation, image classification techniques play a crucial role for mineral identification and evaluation, particularly in the context of the Katanga mining region, known for its mineral wealth. However, despite the significant advances in neural networks, there remains a gap in the comparative evaluation of models such as Multilayer Perceptron (MLP), Convolutional Neural Network from scratch (CNN) and the use of transfer learning of the VGG-16 architecture specifically applied to mineral image classification. This finding highlights a key research problem, namely: which neural network model is the most effective for classifying mineral images in this region rich in mineral resources? The objectives of this study are threefold: first, to analyze the respective performances of MLP, CNN and Fine-Tuning with VGG-16 models in the context of mineral image classification; second, to identify the strengths and weaknesses of each model in terms of accuracy and robustness; and finally, to propose recommendations for optimizing classification processes in future applications. Particular emphasis will be placed on the importance of collecting and analyzing mineral image data, which constitute the keystone on which model performance evaluations are based. The importance of this research lies in its ability to fill gaps in the existing literature regarding the application of machine learning techniques in classification, particularly in complex geological contexts. From a practical perspective, a better understanding of the performance of different models can lead to more effective solutions for the management and exploitation of mineral resources, thus contributing to sustainable development practices. Accurate classification of minerals can really make a difference in mining efficiency, production traceability and environmental sustainability. Furthermore, this study aims to strengthen the analytical capacity of deep learning systems by generating useful and applicable knowledge for responsible and efficient mining in the Katanga region, while making a significant contribution to the evolution of mineral image classification methods in the field of machine learning (Carpenter, 2020) (He et al., 2023) (Jayasinghe et al., 2023) (Abadade et al., 2023) (Chae et al., 2023).

To evaluate the Multilayer Perceptron (MLP) model, convolutional neural networks designed from scratch (CNNs) and the VGG16 architecture in mineral imaging, this study is articulated into key sections for clear analysis. First, the introduction shows why mineral imaging is important and how deep learning plays a role here. Next, the state of the art recounts current research on the performance of each model and their details, setting the scene for comparison. Next, the methodology section reviews the experimental setup, covering data collection, pre-processing methods and model training. In the results section, the results are shared with a detailed analysis that highlights the strengths and weaknesses of each model. Finally, the conclusion summarises the knowledge gained and discusses possible directions for future research.

1. Related works

The rapid evolution of machine learning techniques has significantly transformed the mining industry in general, and the field of mineral imaging in particular, by enabling more accurate and efficient analysis of geological data. In this context, the mining region of the Greater Katanga area, renowned for its wealth of mineral resources, is a particularly relevant field of study. Indeed, image classification methods have a direct impact on resource exploration and exploitation, influencing both economic results and sustainable development. In this section, we aim to synthesize existing research on the performance evaluation of MLP, CNN and transfer learning-based models of the VGG-16 architecture in the specific context of mineral imagery in the Katanga region. Drawing on previous studies, this analysis will highlight the strengths and limitations of each approach, while identifying the gaps that currently remain.

To this end, it will aim to establish a solid foundation for the future development of image classification tools adapted to mining contexts, thus contributing to the advancement of research and practice in this sector vital to the national economy. For his part, Julien Maitre achieved an impressive performance with around 90% accuracy in the process of extracting super pixel color patterns from 3192 images obtained using an optical microscope (Maitre et al., 2019). The classification of the ore grains was carried out using several machine learning algorithms including classification and regression trees, k-Nearest Neighbors and random forests. For his part, Naseri classified thin-slice mineral images with a class count of 42 minerals in a dataset of 900 microscope images (Naseri & Rezaei Nasab, 2023) ”. He used the Support Vector Machine algorithm to extract color and texture features from an image, then applied classification, and the accuracy obtained was a sharp 99.25% in mineral segmentation. Nevertheless, the manual engineering used by these algorithms remains a major obstacle and challenge for the extraction of more complex patterns or the scaling-up of large datasets. There has been growing interest in evaluating the performance of neural network models for image classification in the Katanga mining region, not least because of the specific characteristics and challenges posed by this type of imagery. In this context, multilayer perceptron neural networks (MLPs), convolutional neural networks (CNNs) and in particular the VGG-16 model are frequently used for classification. Studies have shown that Machine Learning (ML) models based on CNNs, due to their ability to capture spatial features and complex patterns in images, often outperform traditional MLP models in similar applications (Carpenter, 2020) (Gayap & Akhloufi, 2024). For example, the work of (He et al., 2023) demonstrates that CNNs applied to medical imaging data reveal significantly better performance in terms of precision and recall, due to their adaptive architecture. Neural network models, such as multi-layer perceptrons (MLPs), convolutional neural networks (CNNs), and transfer learning with advanced architectures such as VGG-16, have been at the center of concerns relating to image classification. More than two decades ago, early research focused mainly on approaches using regression models and basic statistical techniques, which quickly revealed their limitations in terms of accuracy and generalizability (Carpenter, 2020). However, the rise of machine learning marked a turning point, allowing the introduction of multilayer perceptron (MLP) models which, while effective, remained limited in their ability to capture complex structures in the data (Gayap & Akhloufi, 2024). As a result of technological developments, convolutional neural networks (CNNs) have been adopted, overcoming the limitations of MLPs and offering significant performance improvements thanks to their ability to self-extract features from images with one, two or three dimensions (He et al., 2023). Research in a variety of contexts has demonstrated that CNNs outperform traditional MLPs in imaging and object detection applications, particularly for complex image classification (Jayasinghe et al., 2023). More recently, the VGG-16 model has burst onto the scene and moved the line for its depth and ability to capture fine details in image data (Abadade et al., 2023). Studies have shown that VGG-16, with its 16 layers of depth, offers remarkable performance in classification tasks, achieving almost unrivalled accuracy rates in image classification (Chae et al., 2023). For models using the VGG-16 architecture, several research studies testify that it is an excellent choice for mineral image classification, particularly thanks to its deep layers that enable the extraction of complex, high-dimensional features (Jayasinghe et al., 2023) (Abadade et al., 2023). The performance of VGG-16 has been particularly noted in medical imaging case studies, where it has shown increased robustness to variance in image conditions (Chae et al., 2023) (Orouji et al., 2023). However, some researchers point to the challenges of high clamp costs and training data requirements. However, the VGG-16 model stands out for its use of a deep architecture and dense classification layer, showing promising performance compared to more conventional models such as MLPs (Abadade et al., 2023), (Chae et al., 2023).

Furthermore, recent research has highlighted the relevance of image pre-processing, such as normalization and data augmentation, to further improve model performance (Orouji et al., 2023). As demonstrated by recent research on mineral identification, peak performance of the order of 98% has been achieved by a binary pattern applied to four mineral types (Aligholi et al., 2015), and this with a normalized dataset. However, the constitution of the dataset can become a curse hindering the capture of complex patterns present in various mineral samples. In the context of atypical mineral imagery extracted under diverse light conditions, approaches based on classification combinations appear promising, combining the strengths of different model types to maximize classification accuracy. Thus, the variety of methodologies employed to assess the performance of classification models illustrates the need for an adaptive approach, taking into account the specificities of Katanga's mineral data and specific research objectives. The classification of mineral imagery, particularly in complex environments such as the Katanga mining region, requires in-depth evaluation of machine learning models such as multilayer perceptrons (MLPs), convolutional neural networks (CNNs) and the VGG-16 architecture. Each model offers distinct theoretical perspectives that highlight different learning mechanisms. The performance evaluation carried out by EL BADAOUI between two network models MLP and RBF indicates that the weight vector plays a catalytic role when aiming for the right performance (EL BADAOUI et al., 2014). To this end, CNNs are reputed to be efficient in computer vision, achieving over 99% accuracy on handwritten digits (MNIST) (LeCun et al., 1998). Research results by Golik and his team confirm that MLP can rival CNNs with more layers, for example: 12 fully connected layers versus 6 (1 convolution layer and 5 fully connected) for a CNN (Golik et al., 2015). One study showed that, using filter banks, CNNs are sharp in terms of learning rate (0.007) with a regularization coefficient of 0.9, whereas MLP requires a derivative of filter banks with a shallow architecture every time (Manenti et al., 2016). CNN's strength lies in the first layers, which alone approximately realize the derivative of temporal fields. Moreover, MLP remains sensitive to the number of layers and the number of neurons. Manenti and his team obtained a 1% gain in F-measurement from an MLP with a maximum number of neurons of 300, compared to another model with 50 neurons. However, the CNN was proven to be optimal with a number of neurons between 50 and 400 in the dense layer, all the more so as the number and size of convolution filters has a huge influence on its performance, of the order of 1% to 2%, in absolute terms. With a number of filters between 15 and 120, CNNs can gain up to 1.2%. The bulk of the work therefore lies in optimizing the neural network parameters - number of layers, number of neurons, convolution filters - to obtain the best possible result. Thus, evaluating the performance of MLPs, as well as more complex models such as CNNs, is crucial to finding the best strategies for identifying and managing mineral resources. MLPs, while effective for conventional datasets, may suffer from generalization limitations when faced with complex images (Carpenter, 2020). In contrast, CNNs, which exploit convolutions to extract hierarchical features, demonstrate a superior ability to process image data taking into account the spatial location of pixels, making them particularly suitable for mineral image classification (Gayap & Akhloufi, 2024) (He et al., 2023). On the other hand, the VGG-16 architecture, with its increased depth, further improves performance by enabling finer feature extraction, although it is more computationally intensive (Jayasinghe et al., 2023). In this respect, some researchers emphasize the importance of a hybrid approach that combines these models to take advantage of their respective strengths (Abadade et al., 2023) (Chae et al., 2023). In the context of mineral imaging, the ability of CNNs and VGG-16 to handle complex color

and texture variations is particularly relevant, as indicated by several studies demonstrating their superior performance over traditional MLPs in experimental tests (Orouji et al., 2023).
It is therefore essential to evaluate these approaches through a robust theoretical framework to determine the most suitable model for classifying the specific data from the Katanga region, taking into account the constraints and opportunities offered by each technique. This highlights the interaction between theory and practice in the optimization of machine learning processes for mineral and environmental applications. Analysis of the performance of image classification models, such as multilayer perceptrons (MLPs), convolutional neural networks (CNNs), and the VGG-16 model, has revealed significant prospects for the exploitation of mineral imagery in the Katanga region, raising crucial issues for the mining industry. There is a plethora of studies comparing these different approaches in terms of accuracy, speed and ease of adaptation to the specifics of mineral datasets. However, the application of these models to specific data such as mineral imagery remains little explored, a gap that deserves particular attention. At the same time, the challenges associated with data acquisition in the Greater Katanga mining area, such as difficult access to mining sites, variable image quality and lighting conditions, are crucial factors influencing model performance. Few past studies have focused on the impact of these variables when evaluating the performance of classification algorithms, which raises the question of how to generalize models beyond lighting conditions, laboratories and actual sites. Hence the need for further work to adapt these models to the particularities of mineral data in the Greater Katanga area, and to optimize their effectiveness in real-life scenarios. Furthermore, understanding of the mechanisms underlying the uneven performance between these different models remains incomplete, calling for further exploration of the factors that determine their success in this field. In summary, the work explored in this review highlights the real potential that machine learning models represent for the classification of mineral imagery in Katanga, while opening up promising avenues of research. The future of this discipline will undoubtedly be influenced by the ongoing evolution of available technological tools and their implementation in exploration and mining practices.

2. Methodology

Notwithstanding the multiple important stages of a Machine Learning model, data collection and processing remain the cornerstone of any Data science project. Kilkenny and Robinson point out that the quality of input data directly influences output results (Kilkenny & Robinson, 2018). To this end, we start with a data collection strategy and the creation of a dataset. Thus, the dataset used in this article was obtained by the strategy of taking images of mineral samples from the Museum of Geology / UNILU using a digital camera. The criteria of variability and volume of usable images being imposing, we completed our dataset with mineral images stored in the Minda site. From the sample of images collected, we perform geometric and spatial transformations to increase the size and diversity of the training set. Among the modules integrated into the Keras library, we can use the ImageDataGenerator module, which allows us to perform manipulations and augmentations on images in real time. Among these manipulations, we use resizing by dividing the image values by 255 in order to restrict them to the [0, 1] field, as well as horizontal flipping. Next, the dataset is organized into the classes used in this article, namely Chalcopyrite, Cobalt-calcite, native copper, Katangite and Malachite, as illustrated in Figure 2. Following the organization of the categorized images, we built and trained our three resource classification and identification models "Kumadi: Kumbulibua kua madi" literally the discovery of wealth, namely: "Kumadi_mlp", "kumadi_cnn" and "kumadi_vgg16". Finally, the model was predicted and tested. The following Figure

1 illustrates the methodological approach used in this article, applying deep learning to the classification of mineral rock images in the Greater Katanga area.

Figure 1—Démarche méthodologique

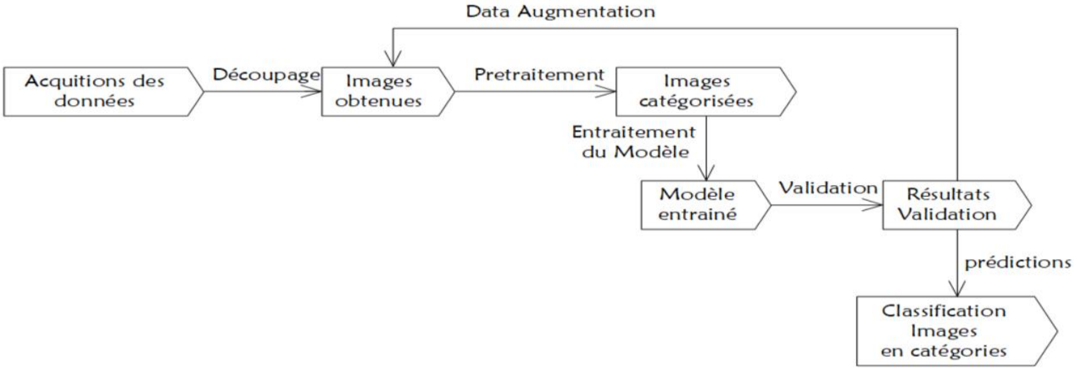
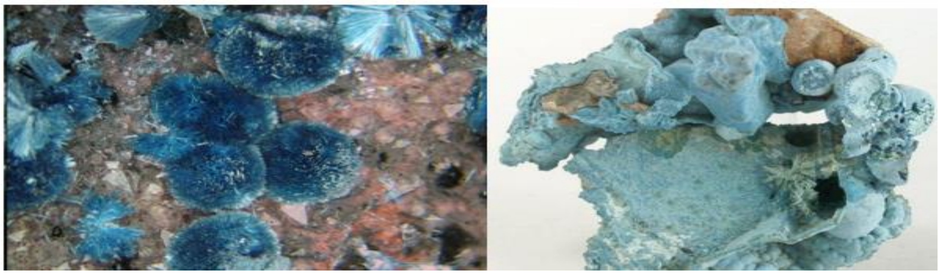
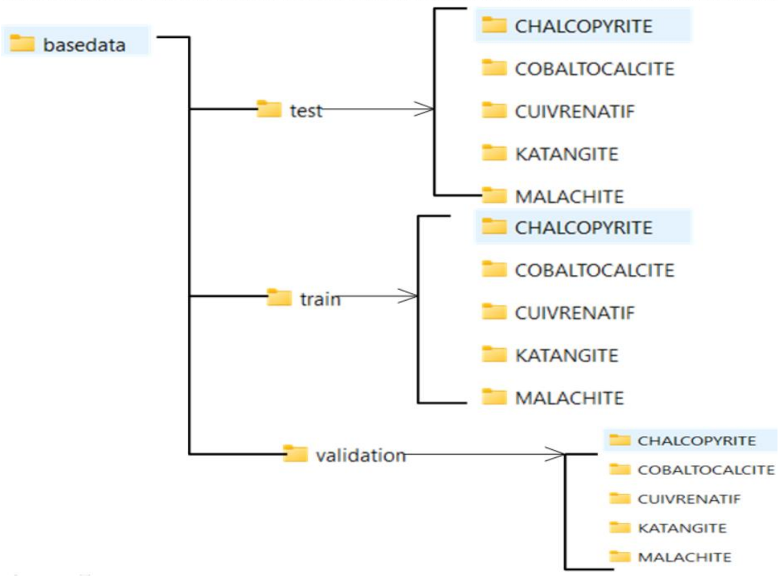


Figure 2——Image of the KATANGITE rock of TANTARA, NSESA, Shangulowé (Kambove)



As far as the breakdown of the dataset is concerned, we grouped the images into 5 classes based on the minerals in the target rocks, namely chalcopyrite, cobalto-calcite, native copper, katangite and malachite. Once the images had been grouped by class, we had to build a database to carry out the various learning stages. To do this, we set up our files according to the organization shown in Figure 3:

Figure 3—Organisation du jeu de données « Kumadi_5 »



To improve classification accuracy, images of each mineral rock type were randomly distributed within each sub-class as follows: 80% for training and 20% for validation. The exact distribution of data by category and type is described in the following Table 1.

Table 1—Number of images in the dataset

	Train	Validation	Test
CHALCOPYRITE	1920	480	10
COBALTOCALCITE	1920	480	10
CUIVRE NATIF	1920	480	10
KATANGITE	1920	480	10
MALACHITE	1920	480	10

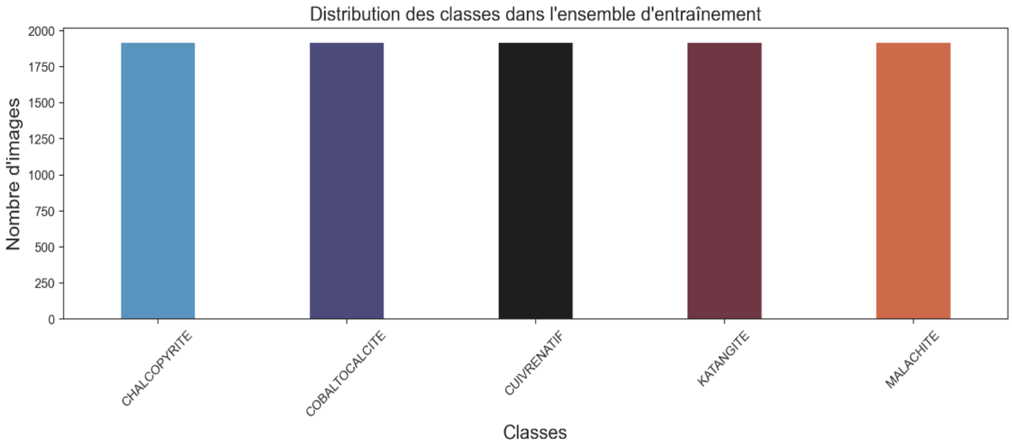
2.1.Training and model validation

Following the structuring of the image dataset into training and test data, a labeling task was carried out to define labels for each of our five mineral types in the Greater Katanga area. In addition, the challenge of RGB (Red Green Blue) image size was resolved by reducing the number of images processed in batches of 64 at a time. On the other hand, the number of times the learning algorithm is reproduced on the dataset (epoch) is fixed at 30. However, iterations can be interrupted (dropout) in the event of overfitting or if no performance improvement is observed. At the end of the epochs, the training model is saved with the best result obtained. We build a first Model "kumadi_mlp" for the classification of rock mineral images from the Greater Katanga area. The MLP model is trained from scratch with the classic architecture consisting of an input or flattening layer whose role is to take each 200 x 200 x 3 image from our Kumadi-5 dataset and apply one-dimensional vectorization; a fully connected hidden layer consisting of 128 neurons with the ReLU activation function; and an output layer consisting of 5 neurons (Kumadi-5 classes) and a softmax activation function. The training of the second model "kumadi_cnn" is carried out from scratch; thus, the architecture of the mineral rock image classification model of the Greater Katanga area is composed of the following layers and components: The input layer consists of a Conv2D with 32 filters and a ReLu activation function. The "Kumadi-cnn" model is divided into 3 convolution blocks with filters of increasing size and a ReLu activation function. In addition, each convolution block has a max-pooling layer of 2 pixels and a dropout (0.2% of neurons). Fully connected layers contain a flatten layer. The output layer is a Dense layer with 5 units and softmax activation. Compiling a CNN model requires 3 parameters: Optimize, Loss function and Metrics. To minimize the cost function, various methods are indicated, in this case gradient descent with a default optimizer which is Adam. With regard to the loss function for model improvement, we have a choice between minimizing loss and maximizing accuracy. In order not to deviate from the rule of minimizing loss with neural networks, we have sacrificed accuracy in favor of loss. To examine this loss, it is necessary to use different formulas such as "categorical_crossentropy" or "binary_crossentropy". In our case, we use categorical_crossentropy for the simple reason that we're doing a multi-class classification. Finally, for the third model, "kumadi_vgg16", we use partial FineTuning to apply certain adjustments to the few parameters of certain layers in order to perform classification on a new data set. In this way, the first layers are spared (frozen) from fine-tuning, in order to retain the old functionalities learned on the initial dataset.

3. Results and discussions

This study focuses on the classification of rock mineral images by building the KUMADI-5 database. The Kumadi-5 database contains 12,000 color images (341 x 380 pixels) divided into 5 classes, with 2,400 images per class. The classes include rock minerals mined in the Greater Katanga area, such as native coppers, Katangites, Malachites, Cobalto-Calcites and Chalcopyrites. The distribution of classes in our training dataset is shown in Figure 4 below:

Figure 4—Distribution of classes in the training dataset



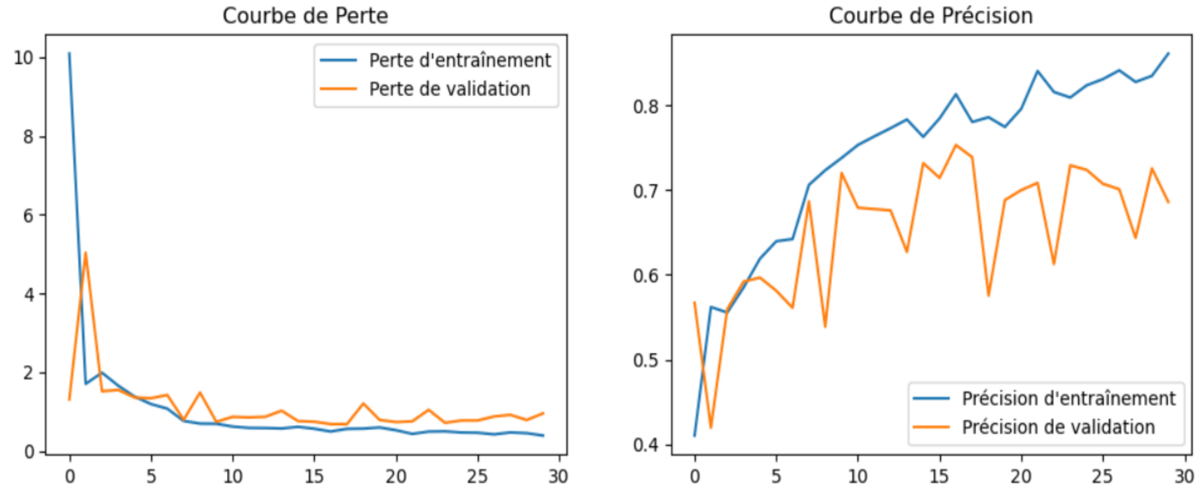
A sample image from the Kumadi-5 dataset is illustrated in Figure 5:

Figure 5—sample images labeled by the model

3.1.Results with the "kumadi_mlp" model

The compilation is subject to the choice of certain parameters capable of defining its performance. For this reason, the "categorical cross-entropy" loss function was chosen for multiclass classification and the "adam" optimizer was used for parameter updating. Finally, the accuracy metric "accuracy" is shown for model accuracies. A summary of the model is shown in the following Figure 6 for information on layers and parameters. Evaluation of the MLP model is carried out on test data, and the performance obtained is summarized as 75% accuracy and 0.8427 loss.

Figure 6—learning curves (loss and precision) with "kumadi_mlp"



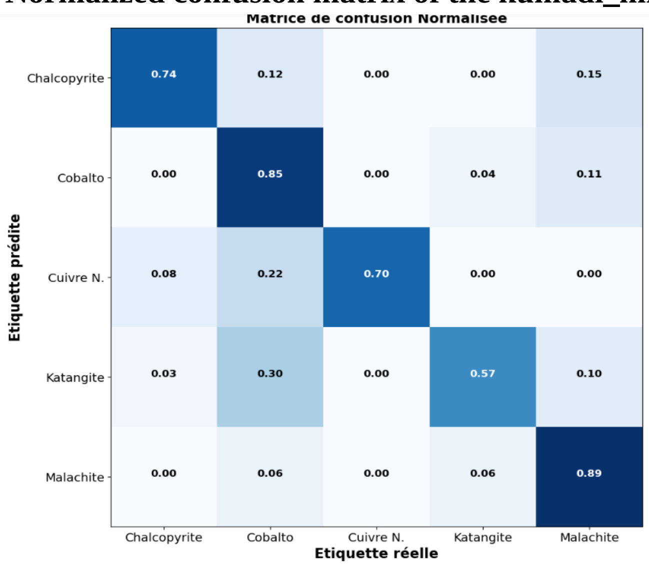

```
Précision sur les données de test : 75.00%
```

Experimental testing of the MLP model with 192 images from the test set, 144 correct classifications and 48 incorrect classifications.

Figure 7—MLP Model Classification Report

	precision	recall	f1-score	support
CHALCOPYRITE	0.82	0.84	0.83	44
COBALTOCALCITE	0.81	0.90	0.85	39
CUIVRENATIF	0.85	0.78	0.82	37
KATANGITE	0.88	0.91	0.90	47
MALACHITE	1.00	0.84	0.91	25
accuracy			0.86	192
macro avg	0.87	0.86	0.86	192
weighted avg	0.86	0.86	0.86	192

Figure 8—Normalized confusion matrix of the kumadi_mlp model

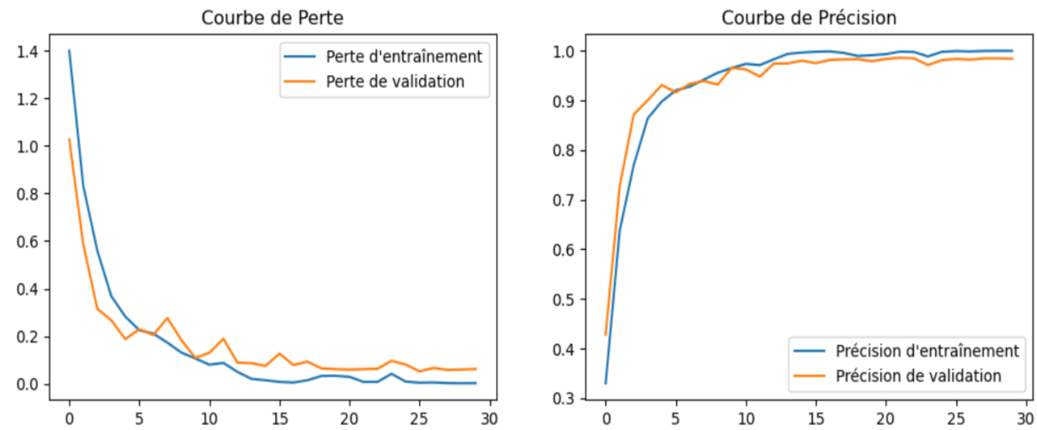


3.2.Result of the model "kumadi_cnn" from scratch

The evaluation revealed model accuracy for training data is: 0.96.88%; model loss for training data is: 0.239%; model accuracy for validation data is: 0.96.88% and model loss for validation data is: 0.239%.

Figure 9—Évaluation de la précision et perte du modèle « kumadi_cnn »

```
6/6 - 3s - 442ms/step - accuracy: 0.9688 - loss: 0.2398
Précision sur les données de test : 96.88%
```

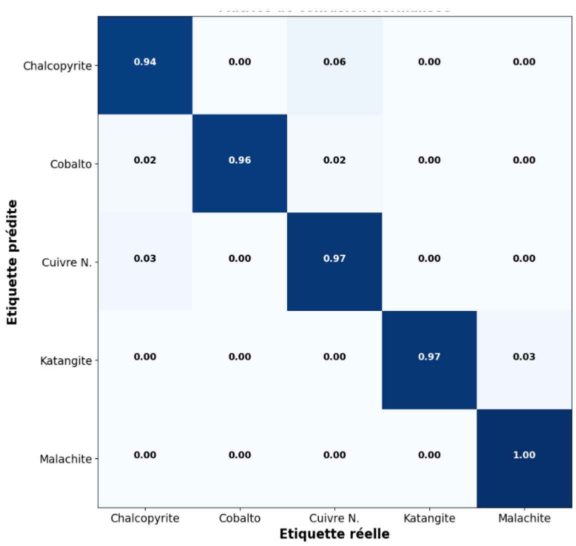


Prediction using the Kumadi_cnn model yielded the following results: Model accuracy for test data: 98.88%; Model loss for test data: 0.018%; Correct predicted classes: 186 and Incorrect predicted classes: 6

Figure 10—Ranking report of model "kumadi_cnn"

	precision	recall	f1-score	support
CHALCOPYRITE	0.94	0.94	0.94	34
COBALTOCALCITE	1.00	0.96	0.98	46
CUIVRENATIF	0.92	0.97	0.95	37
KATANGITE	1.00	0.97	0.99	40
MALACHITE	0.97	1.00	0.99	35
accuracy			0.97	192
macro avg	0.97	0.97	0.97	192
weighted avg	0.97	0.97	0.97	192

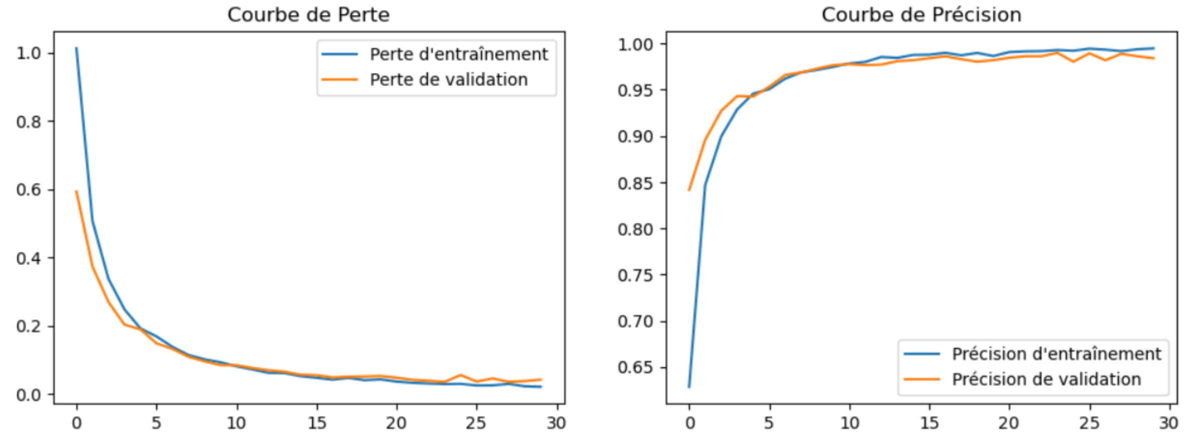
Figure 11—Confusion Matrix of our model "kumadi_cnn"



3.3.Result with Transfer Learning with VGG16

The model was trained for 30 cycles (epochs) with a batch_size of 64 images and revealed 95% accuracy in just 10 epochs. The result is shown in the following figure 13.

Figure 12—Evaluation of the Kumadi Transfer Model



The ranking score gave 188 correct rankings, 4 incorrect. The confusion matrix is shown below:

Figure 13—Classification results with VGG16

	precision	recall	f1-score	support
CHALCOPYRITE	0.97	0.97	0.97	34
COBALTOCALCITE	0.98	0.96	0.97	46
CUIVRENATIF	1.00	1.00	1.00	37
KATANGITE	1.00	0.97	0.99	40
MALACHITE	0.95	1.00	0.97	35
accuracy			0.98	192
macro avg	0.98	0.98	0.98	192
weighted avg	0.98	0.98	0.98	192

Figure 14—Confusion matrix of the kuma_transfer model

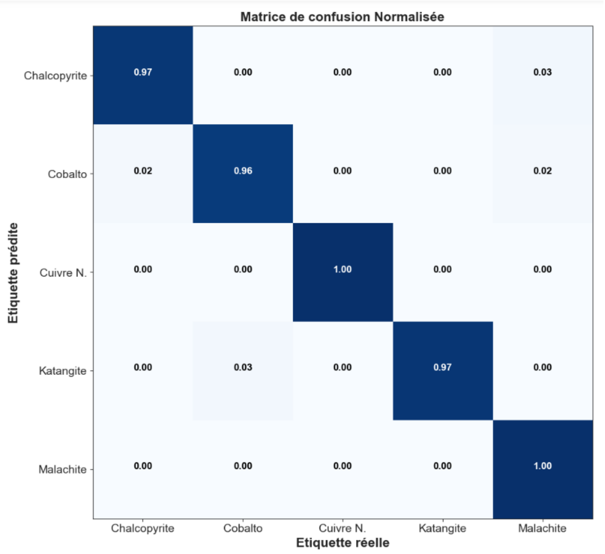


Table 2 summarizes the performance of our three models:

Table 2-Comparative table of model performance

Epoch	10			30		
	Val. Acc	Train acc	loss	Val. Acc	Train acc	Val. loss

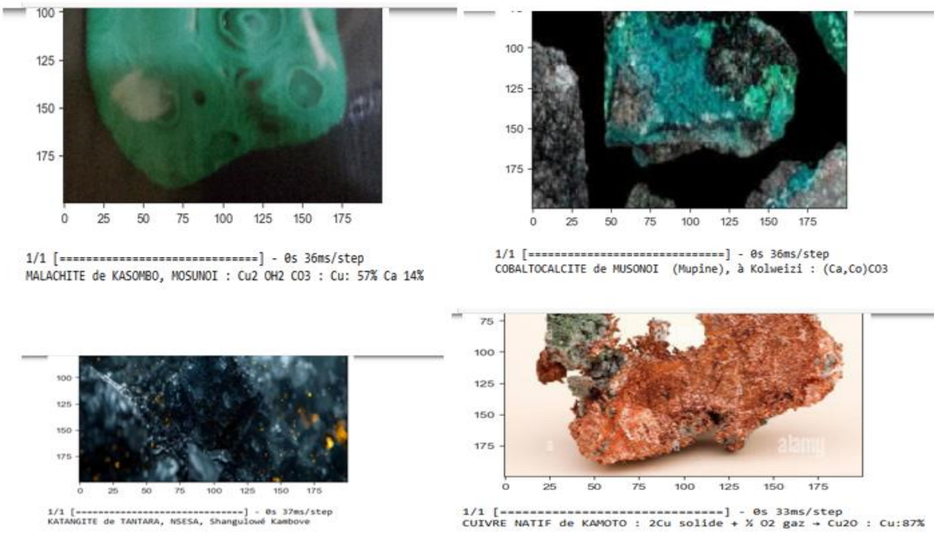
kumadi_mlp model	0.72%	0.72%	0.74%	0.75%	0.85%	0.8429
kumadi_cnn from scratch model	0.93.5%	0.98%	0.23%	0.96.8%	0.99%	0.2398
kumadi_vgg16 model	0.97%	0.98%	0.3856	0.97.89	098	0.055

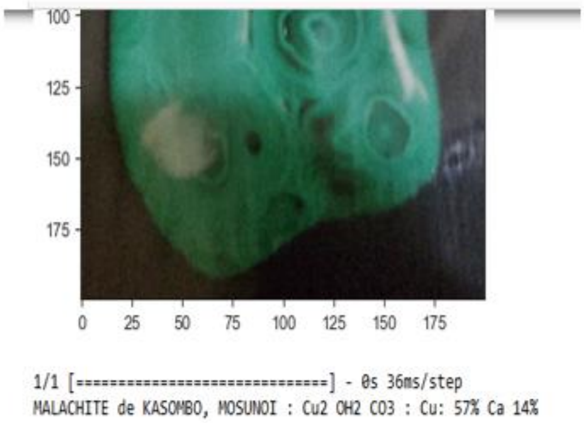
Discussion

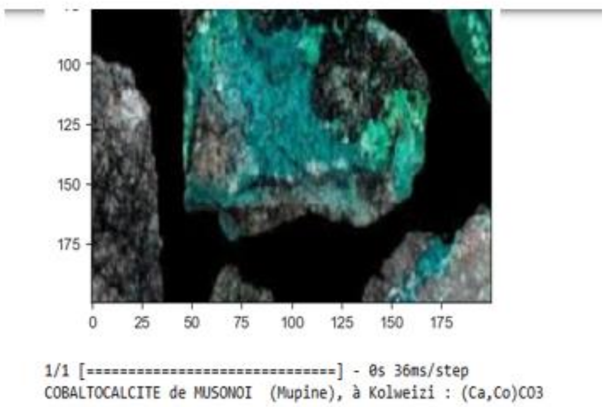
The comparison of multilayer perceptron (MLP), convolutional neural networks (CNN) and transfer learning with VGG-16 revealed important information about their abilities to classify mineral images from Greater Katanga. The "kumadi_mlp" model could handle basic classification, but had difficulty with complex features. This led to an accuracy rate 0.75% lower than that of deeper models in terms of layers. In addition, the "kumadi_cnn" model was effective at spotting detailed patterns in mineral images with an accuracy of 096%, however it requires a large and varied image mass and a lot of resources and training time. Its performance improved greatly thanks to its transfer learning approach with VGG-16 "kumadi_transfer", which features many deep convolutional layers and has been trained on large datasets, achieved the highest accuracy of around 0.98% compared to the other two models tested. This proves just how well it handles subtle visual data. Overall, the results highlight the need for advanced neural network architectures, in particular VGG-16, in tasks that require accurate classification of high-dimensional images, improving mineral identification in geological research. When selecting the best model to classify images, it is essential to consider the architecture, model parameters, performance metrics and unique characteristics of the dataset. Analysis of multi-layer perceptron (MLP) models, convolutional neural networks (CNN) and VGG16 transfer learning shows the importance of considering accuracy, loss minimization and resilience and computational efficiency. Nevertheless, if the dataset is small or computational power is limited, MLPs can be a practical option without losing much accuracy. Ultimately, model selection must involve verification of performance measures such as precision and recall, as well as cross-validation. This will ensure that the selected model achieves the right balance between complexity and predictive capability.

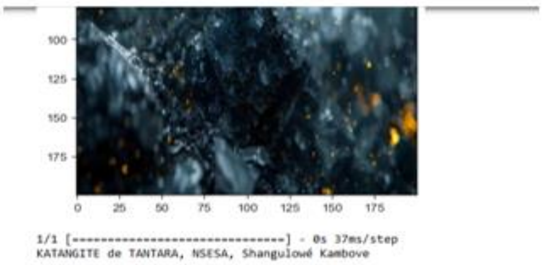
An example of the output generated by the system after image capture is shown in the following figures.

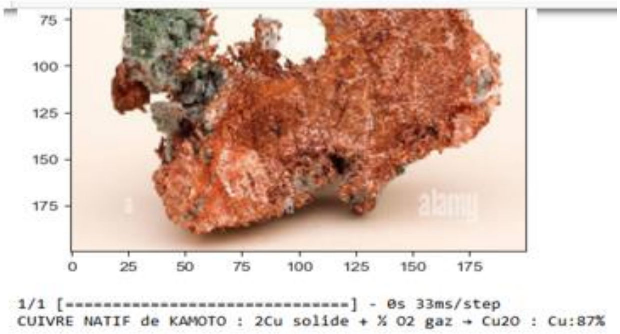
Figure 16—Exemples d'images de sortie : roches minérales

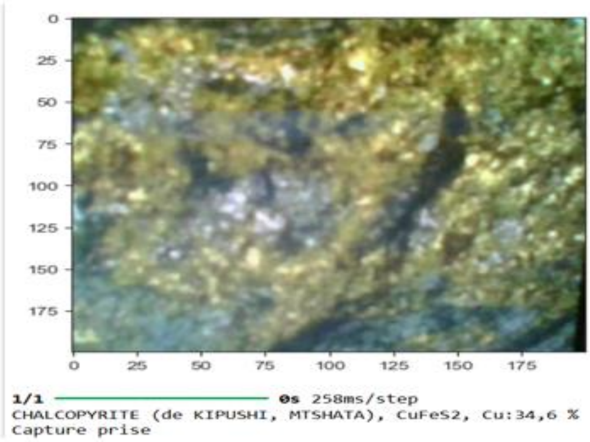












Conclusion

In this article, we have evaluated the performance of three neural network architectures for the classification of mineral images of rocks in the Greater Katanga area. First, we built a model based on the Multilayer Perceptron “kumadi_mlp”; then, a model with a CNN architecture “kumadi_cnn” was built from scratch; and finally, we used transfer learning of the VGG-16 model to compare performance on image classification. The results show that the transfer learning-based model of the VGG-16 architecture outperforms the MLP and CNN models in terms of accuracy and robustness, achieving a classification accuracy of around 98% versus 75% for the MLP and 96% for the CNN from scratch. These results underline the importance of deep learning in the processing of complex images, and open up new prospects for the use of these techniques in the monitoring and analysis of mineral resources. Indeed, the use of multi-layer perceptron models, convolutional from scratch neural networks or transfer learning with VGG-16 has had a considerable impact on mineral classification, particularly in the mining regions of the greater

Katanga area. The successful use of these models could lead to further research. This could encourage the study of combined methods that combine machine learning with traditional geology. Ultimately, progress with these models shows that they play a crucial role in helping to make intelligent choices about mineral exploration and resource management, which is important for both academia and industry. The field of mineral classification is in a state of flux. Future research should aim to improve the accuracy and speed of classification models. This includes multi-layer perceptron (MLP) and convolutional neural networks (CNN), with an emphasis on advanced transfer learning designs such as VGG-16.

References

1. Abadade, Y., Temouden, A., Bamoumen, H., Benamar, N., Chtouki, Y., & Hafid, A. S. (2023). A comprehensive survey on tinyml. IEEE Access. https://ieeexplore.ieee.org/abstract/document/10177729/
2. Aligholi, S., Khajavi, R., & Razmara, M. (2015). Automated mineral identification algorithm using optical properties of crystals. Computers & geosciences, 85, 175-183.
3. Carpenter, C. (2020). Multilevel Strategies Improve History Matching of Complex Reservoir Models. Journal of Petroleum Technology, 72(04), 71-73.
4. Chae, J., Lee, S., Jang, J., Hong, S., & Park, K.-J. (2023). A survey and perspective on Industrial Cyber-Physical Systems (ICPS) : From ICPS to AI-augmented ICPS. IEEE Transactions on Industrial Cyber-Physical Systems. https://ieeexplore.ieee.org/abstract/document/10285426/
5. EL BADAOUI, H., ABDALLAOUI, A., & CHABAA, S. (2014). Perceptron Multicouches et réseau à Fonction de Base Radiale pour la prédiction du taux d'humidité [Multilayer Perceptron and Radial Basis Function network to predict the moisture]. https://www.researchgate.net/profile/El-Badaoui-Hicham/publication/303785709_Corresponding_Author_Hicham_EL_BADAOUI_55_Perceptron_Multicouches_et_reseau_a_Fonction_de_Base_Radiale_pour_la_prediction_du_taux_d'humidite_Multilayer_Perceptron_and_Radial_Basis_Function_network_to_/links/5751f1ae08ae17e65ec36df2/Corresponding-Author-Hicham-EL-BADAOUI-55-Perceptron-Multicouches-et-reseau-a-Fonction-de-Base-Radiale-pour-la-prediction-du-taux-dhumidite-Multilayer-Perceptron-and-Radial-Basis-Function-network-to.pdf
6. Gayap, H. T., & Akhloufi, M. A. (2024). Deep machine learning for medical diagnosis, application to lung cancer detection : A review. BioMedInformatics, 4(1), 236-284.
7. Golik, P., Tüske, Z., Schlüter, R., & Ney, H. (2015). Convolutional neural networks for acoustic modeling of raw time signal in LVCSR. Sixteenth annual conference of the international speech communication association. https://www-i6.informatik.rwth-aachen.de/publications/download/974/GolikPavelT%7Bu%7DskeZolt%7Ba%7DnSchl%7Bu%7DterRalfNeyHermann--ConvolutionalNeuralNetworksforAcousticModelingofRawTimeSignalin%7BLVCSR%7D--2015.pdf
8. He, R., Niu, X.-Y., Wang, Y., Liang, H.-W., Liu, H.-B., Tian, Y., Zhang, H.-L., Zou, C.-J., Liu, Z.-Y., & Zhang, Y.-L. (2023). Advances in nuclear detection and readout techniques. Nuclear Science and Techniques, 34(12), 205.
9. Jayasinghe, S. L., Thomas, D. T., Anderson, J. P., Chen, C., & Macdonald, B. C. (2023). Global Application of Regenerative Agriculture : A Review of Definitions and Assessment Approaches. Sustainability, 15(22), 15941.

10. Kilkenny, M. F., & Robinson, K. M. (2018). Data quality : “Garbage in – garbage out”. Health Information Management Journal, 47(3), 103-105. https://doi.org/10.1177/1833358318774357
11. LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11), 2278-2324.
12. Maitre, J., Bouchard, K., & Bédard, L. P. (2019). Mineral grains recognition using computer vision and machine learning. Computers & Geosciences, 130, 84-93.
13. Manenti, C., Pellegrini, T., & Pinquier, J. (2016). Influence de la quantité de données sur une tâche de segmentation de phones fondée sur les réseaux de neurones. Journees d’Etudes sur la Parole (JEP 2016), pp-392. https://hal.science/hal-01530230/
14. Naseri, A., & Rezaei Nasab, A. (2023). Automatic identification of minerals in thin sections using image processing. Journal of Ambient Intelligence and Humanized Computing, 14(4), 3369-3381. https://doi.org/10.1007/s12652-021-03474-5
15. Orouji, A., Ghasemi, F., & Hormozi-Nezhad, M. R. (2023). Machine Learning-Assisted Colorimetric Assay Based on Au@Ag Nanorods for Chromium Speciation. Analytical Chemistry, 95(26), 10110-10118. https://doi.org/10.1021/acs.analchem.3c01904