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Hybridization Methodology for Predicting ORE from Mines to end user using Machine Learning Technique

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HYBRIDIZATION METHODOLOGY FOR PREDICTING ORE FROM MINES TO END USER USING MACHINE LEARNING TECHNIQUE

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Abstract— Iron ore is the most important iron ore in India and it is often lost on the way from the mine to its final destination. Manual sorting of many types of iron ore is difficult and time consuming. We deploy the most advanced RFID technology, along with weighbridges and GPS tracking systems, to solve this problem. Instead of using F-CNN , Iron ore grades were classified using a preliminary object recognition algorithm (YOLO V5). One crucial technical job in mining and excavation is locating mineral reserves. Conventional methods, however, are laborious and time-consuming. The concept makes use of machine learning capabilities to provide proactive, data-driven mine-to-end-user logistics, which minimizes environmental impact, lowers costs, and increases efficiency. Thus, datasets pertaining to mineral reserves were classified more accurately through the application of data augmentation and transfer learning. Comparative trials showed that using transfer learning may effectively counteract the improvement of categorization performance, up to and including 94%. This is a new concept for mining problems that can be solved by the above mentioned method.

Keywords— ore ,iron ,data ,mining ,transfer ,classification

I. INTRODUCTION

Iron ore is abundant in India. a location with various floors where ores can be located. The iron bands of the Precambrian volcanic deposits, however, are what are most significant commercially.[1] The two primary iron ores in India are hematite and magnetite. The domestic iron and steel industry uses hematite, which is the most significant iron ore among them and has the highest levels of quality and strength. [2]Various techniques that differentiate between grade and quality are used to supply them to the steel industry. Trucking is primarily responsible for the loss of iron ore from iron ore mines, and after separation, the iron ore is graded manually in laboratories by conveyor. There are some errors and low accuracy. To solve these problems, we use the most advanced image processing and tracking methods.[3] Our ore tracking system uses RFID technology to track ore shipments from mine to plant and beyond. RFID is a complex technology that tracks minerals using specialized RFID tags, detectors and dashboards combined with mining techniques. There are detection stations in large-scale ore processing plants.[4] The card has a longer lifespan than the period without the need for an internal power supply. Based on the visual texture of the ore grains, which changes depending on the amount of minerals present, iron ores may be categorized into groups. Humans have a great sense of vision, so no matter where an object is located or what color it is, they can readily discover and identify it.[5] However, because object identification requires a lot of computation, computers find it more challenging. Computer vision is the study of how computers deduce complex information from digital images or videos. Computer vision includes tasks like object detection, picture categorization, image annotation, and image recognition..[6] Object detection is the cornerstone of artificial intelligence. Convolutional neural networks (CNNs), the most widely used deep learning technique, combine convolution and convolutional processing over a number of layers to increase the speed and accuracy of detection. [7] Convolutional neural networks are used in all object recognition methods. Deep convolutional neural networks, or CNNs for short, are a kind of artificial neural networks that combine non-linear, composite, and fully connected layers with convolutional layers. For training its convolutional filters, back-propagation is utilized. In this study, the effectiveness and efficiency of R-CNN (Regional Convolutional Neural Network) and YOLO (You Only Look Once), two deep learning algorithms, are compared. There are two types of algorithms used in object detection. [8] One-step detection is achieved with the You Only Look Once (YOLO) algorithm. A convolutional neural network is used in the two-step detection process of the Faster R-CNN method. Object localization, which locates things by erecting a bounding box around the recognized item, and object classification, which groups items according to their

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color properties, are the two phases..[9] Increasing face recognition's recognition rate, recall, accuracy, and F-measure is the main goal of this study. In addition, the suggested Hybrid approaches have a shorter execution time than the current algorithms for the palm and face datasets.

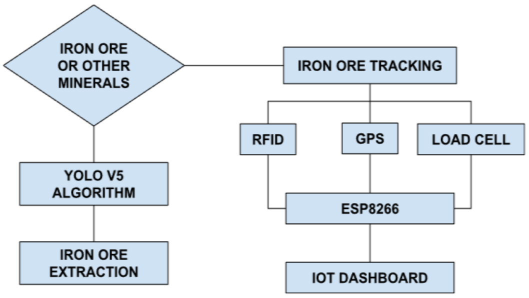

Fig. 1. Block diagram of the idea implemented[2]

II. EXISTING METHODOLOGY

A particular search algorithm based on CPU calculations is used to suggest areas and takes seconds (or seconds) per image. RPN (Region Proposal Network), The quicker R-CNN uses this, which generates region suggestions and reduces the per-frame generation time from seconds to milliseconds.

A. Architecture

Faster R-CNNs use RPNs to enclose an object, a rectangle indicating its location, class (e.g. car or person), and confidence (likelihood of being at that location). generates a box of Usually in this phase we use CNNs to create the properties of these objects. The final feature image that is input to ROI pooling (which sets the image size requirements for object detection) is not the original image, but where the region suggestions are made. The ROI pooling layer's output is (N, 7, 7, 512) in size. where N is the total amount of recommendations that the area proposal algorithm has produced. The outputs of the ROI pool are sent into the regression and sibling classification branches after passing through two fully linked layers. Which class an element belongs to is determined by its categorization level. in Fig 2.The bounding box coordinates are then further adjusted using a regression layer to eliminate any room for error. Anchors are used in RPN to manage objects with different aspect ratios and sizes. The Centre of each spatial window is the anchor for every place on the scrollable convolutional map. A scale and aspect ratio are set to every anchor.

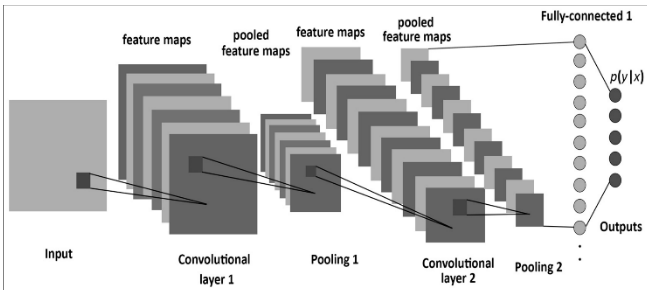

Fig 2: The RPN, a fully convolutional network, predicts if an item is present inside a tiny window (referred to as an "anchor") dragged across the input image's feature map. If so, it refines the anchor to a more precise bounding box.

B. Object Detection using R-CNN

CNNs are feed-forward artificial neural networks in which there is no cycle in the connections between the nodes. The Convolutional layer, Pooling layer, and Output layer (Fully Connected Layer) are the three main parts of CNN. As the classifier in Fig. 3, the fully connected layer applies non-linear changes to the gathered data, while the convolutional and pooling layers function as feature extractors. Convolutional process, This is just the weighted sum of two functions that occurs at the convolutional layer.

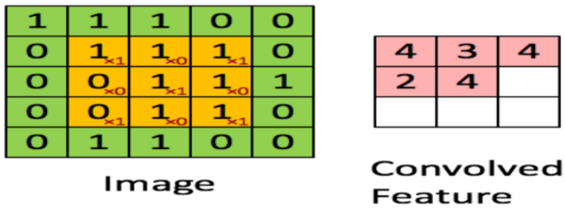

Fig 3: The pooling layer is used to lower the number of trainable parameters after the convolutional layer. The Max-Pooling layer is the most often used type of pooling.

C. Steps in classifying the image

Step 1: Enter a picture.
Step 2: Separate the image into several areas.

Step 3: Treat every region as a distinct image and send it to CNN, which will categorize it into several classifications.

Step 4: To get the original image with the found objects, combine the areas.

D. CNN's limitations in detecting objects

Images can contain objects with varying aspect ratios and spatial configurations; for instance, an object might be big and take up the whole frame or small and only take up a small area. The items' shapes are also subject to change in nature.Fig 4.The aforementioned factors need the use of several areas, which will take a significant amount of calculation time, in order to identify and categorise the items effectively. R-CNN is thus utilised to pick the areas by a proposal technique, hence reducing the total number of regions.

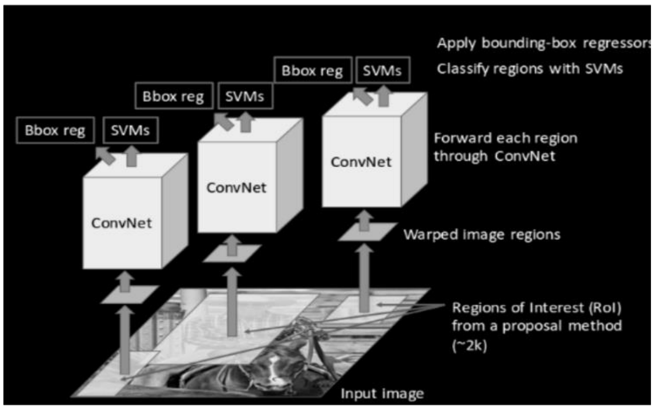

Fig 4: A pre-trained CNN is used, and depending on how many classes must be recognized, it is retrained on the network's final layer.

E. Detecting objects using R-CNN

A technique that uses Selective Search to extract just 2000 areas (also known as region proposals) from the picture. Unlike CNN, where we had to deal with the categorization of many areas, R-CNN only requires us to work with 2000 regions. The selective search technique is employed to create these 2000 region recommendations in Fig 5. One can think of the four zones that make up an item as having different enclosures, colors, textures, and scales. By looking for these kinds of patterns in the image, the selective search suggests several areas. Selective search involves a number of procedures.

Step 1: Take an image input and create the first sub-segments to extract various sections from the picture.

Step 2: Based on the compatibility of color, texture, size, and shape, combine comparable sections to make a bigger zone.

Step 3: The areas now yield the Region of Interest, or the final object placements.

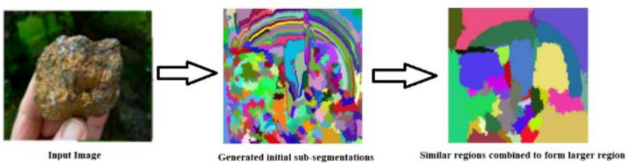

Fig 5: The categorization of many areas, however we now just need to work with 2000 regions in R-CNN.

III. HYBRIDIZATION METHODS

The first step of extracting iron ore from the mines involves a conveyor belt. In the second stage, different forms of iron ore, such as pellets, magnetite, and hematite, are classified using image processing. A method based on the visual texture of the ore particles has been proposed to categorize the ores for iron. The mineral makeup of ore particles affects their visual texture. For instance, the color and shape of magnetite, hematite, and pellets vary. We employed the advanced YOLO V5 objection detection technology to categorize the different forms of iron. These iron ores are sorted and are sent through the mill on a conveyor belt equipped with RFID tags. The microcontroller will get the data from the RFID reader after reading the tag and processing it further. The iron ore is then loaded onto trucks and sealed with an RFID tag. A GPS tracker is then utilized to follow and keep an eye on the vehicle via the thinger.io dashboard. Additionally, the HX711 amplified load cell is used to measure and track the weight of the iron ore, which is shown on the thinger.io dashboard. The ESP8266 microcontroller, commonly known as the Node MCU, is utilized in this instance to transmit data over Wi-Fi to an IOT dashboard. From the control room, the user may log in to the Dashboard and follow and see the mining process. We are employing image processing using the YOLO V5 method to categorize the different forms of iron ore with high accuracy in accordance with our problem. The object detecting technique is precise. The weight of the categorized iron ore is tracked by a load cell and an RFID and GPS tracking device. An image can now forecast items and their locations thanks to a cutting-edge technique called YOLO (You Only Look Once). For instant object identification, neural networks are used. The first version of this method was YOLO v1 (or unified), which had a number of localization issues. With a graphics processing unit (GPU), a regular computer may nearly achieve the real-time capabilities of YOLOv5. With a relatively simple CNN structure, the entire system can quickly finish the target identification regression and forecast the class and bounding box positions. YOLO uses the entire image to forecast the bounding boxes and calculate the class likelihood to label the boxes. It anticipates a finite number of bounding boxes in order to accomplish its objectives. It doubles the overall average accuracy (mAP) of earlier models by classifying objects in real-time at up to 155 frames per second (fps). It's a single convolutional network that generates class probabilities for each element after predicting multiple bounding boxes for multiple objects simultaneously in Fig 6. For YOLO: The picture is divided into M grids, each having PxP portions of the same size. The function of each of these grids is to locate and identify the contents. The bounding box coordinates with respect to the cell coordinates, the element's name, and the likelihood that the object would be discovered in the cell are all predicted by these M-grids.

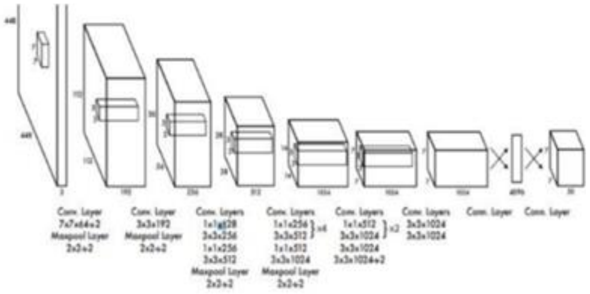

Fig 6: The computational speed is greatly reduced because the image cells manage both detection and recognition. All boxes are filtered using zero-maximum suppression, which also eliminates overlapping boxes and redundant predictions.

3.1 EXPERIMENTAL CONFIGURATION

The PyCharm integrated development environment (IDE) was used to write the program code for this study, which used Python 3.7.. The main foundation for the software implementation was TensorFlow2.1, which Google released in 2020. A GPU, CUDA, CUDNN, and an NVIDIA graphics card combined to provide a platform for parallel computing that increased computation speed.

3.2 DESIGN OF EXPERIMENT

Step 1: Every one of the five trained model types had a dropout layer before to the final fully connected layer.

Step 2: Transfer learning and data augmentation techniques were used gradually based on the initial experimental model to see how they affected the final performance.

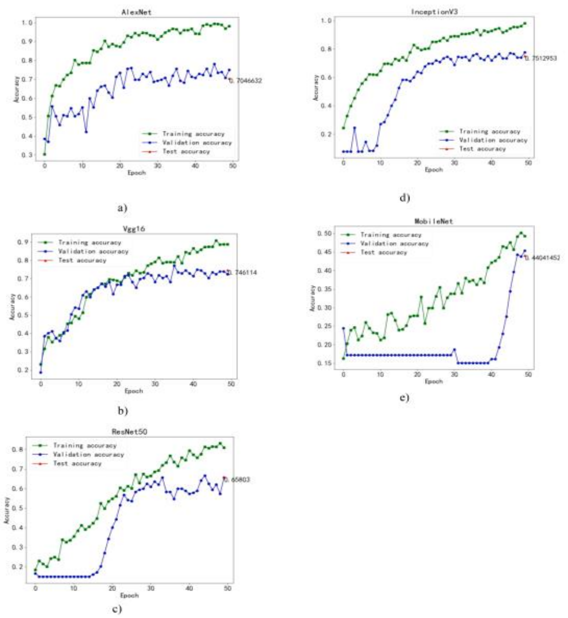

Fig 7: (a) Alex Net results.(b)VGG16 results. (c) ResNet50 results.(d) Inception V3 Results. (e)Mobile Net Results.

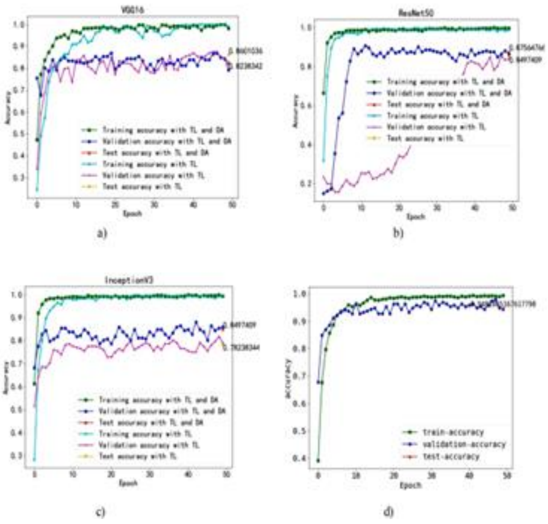

Figure 8: VGG16 findings (a).(b) The ResNet50 outcomes.(c) Results of Inception V3.(d) The results of MobileNet.

Step 3: After selecting the model that outperformed the others in the first two phases, SENet was included.

IV. RESULTS AND DISCUSSIONS

The monitored data will be displayed in the Thinger.io dashboard and the data will be saved in events of the thinger.io platform. The RFID tag data will be displayed in the RFID tracker box of the dashboard and the led will blink in the appropriate color based on the location standard. The load cell data will be displayed in the gauge meter and tachometer, approximate value is also displayed in the Thinger.io dashboard with graph plots. The wi-fi must be always connected with the microcontroller for transferring the data of the sensors for every 5 seconds. The implemented idea of the iron ore tracking, and monitoring made by using the RFID and GPS tracker system with calculating the weight measured by the load cell. The iron ore classification is done by the YOLO V5 algorithm by uploading the images in the YOLO platform. The YOLO will classify the images by pre-defined data and the output shown by the dashboard and the text is displayed as hematite and magnetite or pellets. Both YOLO and Faster R-CNN start with CNN as a foundation and have the same main goal of using CNN to improve the breakdown of regional offers, while having quite distinct conceptual backgrounds. Both YOLO and Faster R-CNN start with CNN as a foundation and have the same main goal of using CNN to improve the breakdown of regional offers, while having quite distinct conceptual backgrounds. On the other hand, the YOLO architecture is more similar to a fully connected convolutional neural network because it only runs the picture through the FCNN once before generating predictions. YOLO generates less than half the background errors as compared to Faster R-CNN. The YOLO architecture's exceptional average accuracy enables end-to-end training as well as real-time speed. Faster R-CNN likewise offers end-to-end training, but it includes more levels than YOLO. If sophisticated GPUs are accessible on deployed devices, then faster R-CNNs ought to be utilized. R-CNN acceleration aims to accelerate R-CNN designs by pooling computational resources and substituting neural networks for selective search in area proposals. In real time, both faster and R-CNN perform badly, despite faster being more accurate and faster. Fig 9.The YOLO V5 algorithm is a very accurate and good object detection algorithm. In real time implementation, the image processing can be done by using a high-quality camera with Raspberry Pi for advanced image classification. If any other minerals are found in the conveyor belt, an alarm will indicate and the robotic arm will pull down the other minerals to a bin. Here the RFID frequency is 125Kz for reading the tag which travels in the conveyor belt. In future the lora module and Lora WAN can be used for transferring the data from the sensors, mines to the control room for long range without any data loss or any lag in transfer speed.

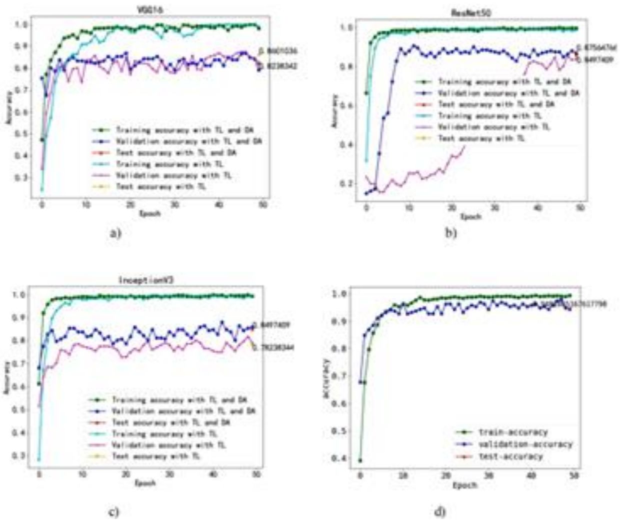

Fig 9 : (a) Analysis of VGG16 errors. (b)ResNet50 error analysis. (c) InceptionV3 error analysis. (d)Mobile Net error analysis.

Table I The Outcome of five convolutional neural network (CNN) models.

MODEL	INPUT	TRAINING ACCURACY	VALIDATION ACCURACY	TEST ACCURACY
AlexNet	(227,227,3)	0.9809	0.75	0.7047
VGG16	(224,224,3)	0.8881	0.7340	0.7461
ResNet50	(224,224,3)	0.8094	0.6525	0.6580
Inception V3	(299,299,3)	0.4930	0.7760	0.7513
MobileNet	(224,224,3)	0.9825	0.4531	0.4404

Table II The Outcome of fusing data augmentation (DA) with transfer learning (TL).

Model	Experiment	Training accuracy	Validation accuracy	Test accuracy	Recall	F-measure	Improvement
VGG16	TL Combined TL and DA	0.9913 0.9815	0.8281 0.7917	0.8601 0.8238	0.7409	0.7254	0.1140 0.0777
ResNet50	TL Combined TL and DA	0.9878 0.9972	0.8385 0.8646	0.8497 0.8756	0.7150	0.7200	0.1917 0.2176
InceptionV3	TL Combined TL and DA	0.9913 0.9941	0.7917 0.8594	0.7824 0.8497	0.9430	0.9427	0.0311 0.0984
Mobile Net	TL Combined TL and DA	0.9860 0.9906	0.8020 0.8542	0.8238 0.9482	0.9482	0.9472	0.3834 0.4508

Table III Survey for overallManagement on ore tracking report

Management ore tracking report									
Reader	Read date	Read time	Tag ID	Surveyor	Working place	Panel no.	Issue date	Issue time	Time, days
2R Belt	14-Jun	04H08	A5638	John	Stope 01	BH	13-Jun	9H00	1
2R Belt	15-Jun	17H24	A5637	John	Stope 01	FACE	13-Jun	9H10	2
2R Belt	14-Jun	14H25	A5641	John	Stope 02	BH	11-Jun	9H00	3
2R Belt	26-Jun	09H14	A5631	John	Stope 02	FACE	11-Jun	10H00	15
2R Belt	12-Jul	06H44	A5632	John	Stope 03	FACE	12-Jun	9H00	30
2R Belt	21-Jun	01H30	A5633	John	Stope 03	ASG	12-Jun	9H00	9
3R Belt	4-Jul	16H30	A5711	John	Stope 04	FACE	19-Jun	9H00	15
3R Belt	4-Jul	16H12	A5712	John	Stope 05	FACE	19-Jun	9H10	15
3R Belt	5-Jul	03H15	A5715	John	Stope 06	FACE	19-Jun	9H30	16
4R Belt	21 Jun	15H51	A5751	John	Stope 07	SSG	21-Jun	9H35	0
4R Belt	2-Jul	16H46	A5752	John	Stope 07	FACE	21-Jun	9H00	11
5R Belt	30-Jun	22H56	A5756	John	Stope 08	BH	21-Jun	9H50	9
4R Belt	7-Jul	19H29	A5757	John	Stope 08	FACE	21-Jun	9H45	17
4R Belt	28-Jun	01H45	A5758	John	Stope 09	FACE	21-Jun	9H40	7
4# Reef	30-Jun	18H14	A5759	John	Stope 09	ASG	21-Jun	9H45	9

V. CONCLUSION

India has technological prowess in mining iron ore and producing different types of steel. Tracking, monitoring and transporting iron ore from source to destination in industry is a difficult task for both government and commercial miners. The above concepts are useful for tracking and classification using object identification methods to address these issues. In the tracking process, an RFID and GPS tracker system with an integrated weighing bridge using load cells can be used to determine the weight of the iron ore. More demanding applications are handled by faster R-CNN than YOLO. YOLO offers comprehensive training and has been proven to perform object identification more effectively and efficiently. While YOLO can perform quicker, more correctly, and more effectively than quicker R-CNN, both algorithms have the same level of accuracy. Since YOLO is a one-shot solution, it is recommended to use it for real-time object detection in both photos and videos. It is simple to set up and includes comprehensive instructions. YOLO provides a more comprehensive object representation than Faster R-CNN, making it more reliable, faster, and more efficient. Comparative tests demonstrated that transfer learning can successfully offset the rise in classification performance (up to and including 94%), presenting a fresh solution for mining problems that can be handled by the aforementioned strategy.

REFERENCES

[1] A. M. ghani Abdulghani and . . enek e Dalveren, oving Object Detection in Video with Algorithms YOLO and Faster R-CNN in Different Conditions," European Journal of Science and Technology, Jan. 2022, doi: 10.31590/ejosat.1013049.Shankar M G, Babu C G, "An exploration of ECG signal feature selection and classification using machine learning techniques", Int. J. Innovative Technol. Exploring Eng. Regul, Issue 2020, 9, 797–804. doi: 10.35940/ijitee.C8728.019320.

[2] J. Redmon and . Farhadi, YOLOv3: n Incremental Improvement." arXiv, pr. 08, 2018. ccessed: Sep. 25, 2022.[Online].Available: http://arxiv.org/abs/1804.02767.

[3] L. Tan, T. Huangfu, L. Wu, and W. Chen, Comparison of YOLO v3, Faster R-CNN, and SSD for Real-Time Pill Identification," In Review, preprint, Jul. 2021. doi: 10.21203/rs.3.rs-668895/v1.

[4] J. Redmon, S. Divvala, R. irshick, and . Farhadi, You Only Look Once: Unified, Real-Time Object Detection," in 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, Jun. 2016, pp. 779–788. doi: 10.1109/CVPR.2016.91.

[5] S. Ren, K. He, R. Girshick, and J. Sun, Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," IEEE Trans. Pattern Anal. Mach. Intell., vol. 39, no. 6, pp. 1137–1149, Jun. 2017, doi: 10.1109/TPAMI.2016.2577031.

[6] H. Jiang and E. Learned-Miller, Face Detection with the Faster R-CNN." arXiv, Jun. 10, 2016. ccessed: Sep. 25, 2022. [Online]. Available: http://arxiv.org/abs/1606.03473.

[7] J. Du, Understanding of Object Detection Based on CNN Family and YOLO," J. Phys.: Conf. Ser., vol. 1004, p. 012029, Apr. 2018, doi: 10.1088/1742-6596/1004/1/012029.

[8] Jie H, Li S, Gang S, Albanie S. Squeeze-and-excitation networks. IEEE Trans Pattern Anal Mach Intell 2017:99.

[9] Pan SJ, Yang Q. A survey on transfer learning. IEEE Trans Knowl Data Eng 2010;22:1345–59.

[10] Lecun Y, Bottou L. Gradient-based learning applied to document recognition. In: Proceedings of the IEEE. 86; 1998. p. 2278–324.

[11] Hinton GE, Salakhutdinov RR. Reducing the dimensionality of data with neural networks. Science 2022;313.

[12] Xu S, Zhou Y. Artificial intelligence identification of ore minerals under microscope based on deep learning algorithm. Acta Petrologica Sinica 2018;34:3244–52.

[13] Krizhevsky A, Sutskever I, Hinton GE. ImageNet classification with deep convolutional neural networks. Commun. ACM. 2017;60:84–90. https://doi.org/ 10.1145/3065386.

[14] Hou Y, Quan J, Wang H. Review of deep learning development. Ship Electr. Eng 2017;37(5–9):111.

[15] Hamed H, Anthony N, Sarvnaz K, Kevin C. Transferability of artificial neural networks for clinical document classification across hospitals: a case study on abnormality detection from radiology reports. J Biomed Inform 2018;85.