Journal of Information Systems Engineering and Management
2025, 10(3s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Effective Machine Learning-Based Strategies for Enhancing the Functionality of Hyper Spectral Imaging

Ok-Kyoon Ha
School of Software, Kyungwoon University, 730 Gangdong-ro, Gumi, 39160, Republic of Korea

ARTICLE INFO

Received: 04 Oct 2024
Revised: 09 Dec 2024
Accepted: 18 Dec 2024

ABSTRACT

Hyperspectral Imaging (HSI) is a powerful technology for capturing high-dimensional spectral information across a wide range of applications, including remote sensing, medical diagnostics, and material analysis. However, extracting meaningful insights from HSI data presents unique challenges due to its complex nature and high dimensionality. This study explores innovative machine learning-based strategies aimed at enhancing the functionality of HSI in various applications. One key approach investigated in this research is the implementation of Deep Learning-based frameworks, with a particular focus on Generative Adversarial Networks (GANs). GANs, equipped with Convolutional Neural Networks (CNNs) as generators, which are utilized to create data points that are not only statistically accurate but also semantically meaningful in relation to the underlying distribution. Through an adversarial objective function, the generator is trained to predict the distribution, while the discriminator network distinguishes between real and generated data. This adversarial game between the discriminator and generator has shown promise in improving HSI classification efficiency. Furthermore, the proposed GAN framework incorporates a classifier component capable of categorizing HSI samples based on their spectral characteristics, using a novel algorithm called the Generative Model-based Hybrid Approach (GMHA-HSIC). This approach adds a valuable dimension to HSI data analysis by enabling accurate classification based on spectral features.

Keywords: Generative Adversarial Networks (GANs), Convolutional Neural Networks (CNNs), Hyperspectral Imaging (HSI), Generative Model-based Hybrid Approach (GMHA-HSIC)

INTRODUCTION

Hyperspectral imaging (HSI) analyzes a broad light spectrum instead of just three primary colours (red, green, blue) where each pixel produces different spectral bands, providing more detailed information about the object or material under investigation [1]. Because of their high sensitivity to detail, these images have many applications in various diverse fields like medicine, mining, defence, and environmental protection [2]. For example, hyperspectral imaging can be used in environmental research to enhance our understanding of changes in water quality and pollution levels, which parallels other studies in environmental sciences such as those exploring critical thinking in environmental education [35].

The imaging spectrum was first defined in the early 1980s [3]. Infrared, near-infrared, visible, and ultraviolet electromagnetic radiation can all be captured using this technique. Each pixel in the imaging spectrometer may collect a totally reflected or emitted spectrum at the chosen wavelength. Each individual pixel that makes up a hyperspectral (HS) image can be sorted out with the help of a process known as HSI categorization [4]. The goal is to determine the spectrum of each pixel to identify materials, detect processes, and find objects. Each hyperspectral image (HSI) has its own unique electromagnetic spectrum that sets it apart from others of its kind [5-7]. HSI has found use in agricultural research as well, where it can assist in the identification of sources of resistance in crops, such as groundnut genotypes resistant to leaf spot disease [32, 33].

There are various factors that must be taken into account while classifying HSI:

- Lack of training samples, known as the dimensionality curse or Hughes' Phenomenon.

- Managing a large number of land-cover classifications.
- Classes of data that are distributed in a non-linear fashion.

The right classifier has to be used to overcome these obstacles. For classifiers to perform at a high level of accuracy, it is necessary to cherry-pick the most important aspects of the gathered features and feed them to the system. The term "feature selection" describes this procedure.

Spectral classification and spatial classification are the two main forms of hyperspectral classification [8]. The classification of wavelengths in the spectrum is based on the reflectance values of the pixels. Essential spectral properties including variance, standard deviation, minimum reflectance, maximum reflectance, and mean reflectance may be estimated and used for classification [4, 9]. Textural characteristics, attribute values, and pixel placement and context are all detected by spatial categorization.

Image pre-processing [10], selecting training samples, evaluating classification accuracy, selecting appropriate classification algorithms, and feature extraction are all essential parts of the image classification process. Images can be categorized using a variety of classifiers, including contextual, knowledge-based, per-field, sub-pixel, and per-pixel classifiers. The classification process can be broadly divided into unsupervised, supervised, or semi-supervised approaches, depending on the utilization of training examples [11]. Unsupervised classification involves the discovery of patterns and clusters in data without relying on predefined classes. Supervised classification entails assigning meaningful classes to unclassified pixels using samples with known identities. Semi-supervised algorithms, on the other hand, combine a limited set of labeled data with a substantial amount of unlabeled data during the training phase. Studies in areas like artificial intelligence in the banking sector demonstrate the significant power that machine learning algorithms can bring to these classification systems [33, 36].

Nevertheless, the considerable complexity and voluminous nature of data generated by HSI instruments introduce numerous challenges. Extracting valuable insights from this data necessitates the application of advanced techniques that surpass the capabilities of conventional analytical methods. In recent years, machine learning has emerged as a powerful toolkit to understand the complexities of HSI data and to overcome key challenges, including high-dimensional data, noise, and the need for automated feature extraction and classification [12]. Machine learning's ability to handle such complexities mirrors its application in fields such as electronic health records to improve decision support systems [34].

HSI was primarily used for laboratory research and remote sensing applications, with limited computational capabilities. In the 1990s, HSI gained prominence in remote sensing and agriculture. Machine learning algorithms were employed to process and analyzed vast amounts of spectral data, allowing more precise monitoring of land use, crop health, and environmental changes [13-16]. For instance, the classification and identification of minerals based on their spectral signatures greatly improved in terms of accuracy and efficiency, benefiting resource discovery [17-18]. In agriculture, HSI aids in the detection of vegetation health and environmental monitoring, much like how remote sensing tools in environmental protection help in pollution control and ecosystem assessments [19-21].

In healthcare, HSI integrated with machine learning has been utilized for tasks such as cancer diagnosis, tissue characterization, and disease detection [22-23]. Due to its great resolving power for environmental, fine spectra, mining, and medical sectors, hyperspectral pictures have several military applications. Imaging spectrometers at different locations capture hyperspectral pictures. Most hyperspectral remote sensing image processing methods include noise reduction, dimensionality reduction, image correction, classification, and transformation [24]. Hyperspectral photographs, unlike conventional photos, include extensive spectral information, which helps categorize objects of interest by showing their chemical composition and physical structure.

The most active field of hyperspectral research is image classification [25]. The digital categorization of RS (Remote Sensing) images detects and extracts feature data by analyzing earth surface and environmental data. RS images are specialized by using automated pattern recognition and remote sensing computer classification. With the increase in features and data volume, advanced hyperspectral remote sensing technologies have increased the threshold for observation technology in various fields such as agriculture and soil salinity [26-28]. Additionally, small spectrum changes in HSI images make them useful for various applications, such as mineral mapping and soil assessment, just as Titanium coagulants have been valuable in water treatment processes.

The present study investigates the integration of advanced machine learning paradigms, such as convolutional neural networks (CNNs), which have demonstrated remarkable potential in addressing the specific intricacies of HSI data. This research endeavors to unveil the transformative synergy between machine learning and HSI, illuminating the path toward novel insights and innovative applications.

GAN Architectures

For the basic GAN structure for games, two competing neural networks are shown in Figure 1. Multi-network management is a high-payoff game. The goal of any neural network is to maximise its reward. Generator and Discriminator are two neural networks used in the architecture. The discriminator and the generator are broken down into more specific sections.

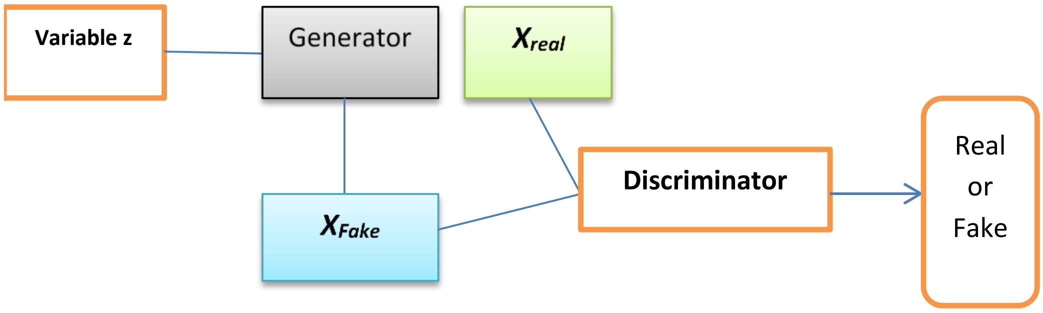

Figure 1. Generative Adversarial Network

Generator

Our key model of interest is the generator G. It's a way to produce test data that closely mimics the training data in terms of statistical significance. Differentiability of the generating function allows for gradient descent to be used to learn its parameters. Even while a deep convolutional neural network is often used to illustrate this concept, any model that has the vibrational characteristic might be used [29]. These are theoretical representations of electrical power generation systems;

$$x = G(z; \theta^{(G)}) \text{ .... } (1)$$

The unknown quantity z in Equation 1 is transformed into the measurable output x. All of x is contingent on z, and likewise. Having x > z is also crucial. These safeguards against the generator being forced into erecting a 2-dimensional or 3-dimensional surface in the x-area.

Architecture of Deep Auto-encoder (DAE)

An unsupervised method that trains to recreate the input is a typical auto-encoder (Figure 2) DL methods are suited to knowing different hierarchical nonlinear characteristics, which are recognized as superior presentations for authentic data in a variety of areas, including computer vision and speech recognition [10, 30]. The decoder layer, encoder layer and hidden layer are the general structure of auto-encoder. The encoder layer's output is the hidden layer's input, and the hidden layer's output is the decoder layer's input.

The encoder and decoder with symmetrical architecture form the auto-encoder's function to map information $Rd \rightarrow Rd$. With x input sequence and output sequence, the encode layer parameterized by $\theta = \{W, b\}$ is:

$$y = f_\theta(x) = \sigma(W \times x + b) \text{ .... } (2)$$

While $\sigma(x) = \max(0, x)$ is the activation function, Relu, of the encode layer. When differentiating to Sigmoid, in general, Relu may reduce the requirement for pre-training and speed up the process. Deep learning algorithms are converging toward more discriminative outcomes despite maintaining the network sparse. The decode layers and hidden layer reconstructed function is as follows:

$$z = f_\theta{}'(y) = \sigma(W^J \times y + b^J) \text{ .... } (3)$$

PROPOSED ALGORITHM

Regular synthesis and labeling of spectra are crucial to accurate classification in DALF. Synthetic samples created via an iterative approach and confirmed using a discriminator may provide relevant spectra. It is possible that the framework's classification accuracy may be improved by combining GAN training with deep learning models.

A CNN model is used by the discriminator to decode and produce synthetic spectrum data from noise occurrences based on the input class labels. The discriminator compares a given spectrum sample against a large database of both real and false spectra, none of which are labeled. The discriminator uses a Convolutional Neural Network (CNN) model to do this. Because of this, in an adversarial situation, a Generative Adversarial Network's discriminator provides input to the generator. The feedback increases the discriminator's capacity to generate convincing false samples. Each repetition involves calculating Ls and Lc to enhance G and D's functionality. In order to achieve classification performance with both synthetic examples and labeled actual spectra, classifier such as support vector machines (SVMs) and neural networks (NNs) are utilized.

NN and SVM Parameter Tuning

Training Parameters The Scikit-Learn Python module employs a custom-tailored C and kernel for SVM on real data; they are referred to as svm kernel and svm C. The hyperparameter C provides a second opportunity to mislabeled samples. The decision boundary may be influenced by C, which may have an impact on classification accuracy. In the presence of a high C, the classifier will work to reduce the number of mislabeled examples.

We discovered that C = 1000 produced the most consistent outcomes after testing with C = 0.1, 1, 10,100, and 1000. As a result, we utilise the "linear" kernel approach, which has been demonstrated to be quicker, and set C to 1000. A Pipeline object with many settings is constructed and used for simulated support vector machine (SVM) training.

Data generated with the default parameters are shown to be generally acceptable in Table 1. Multi-Layer Perceptron (MLP) Classifier is used to realise the NN. The values and descriptions of its parameters are shown in Table 2.

Table 1. Pipeline object's stages property SVM parameters

Parameter	Value
Shrinking	True
gamma	auto
Cache size	300
degree	3
probability	False

Table 2. The NN classifier's settings are detailed below.

Parameter	Value
maxiter	200
Learning rate	constant
alpha	0.0001
Early stopping	False
activation	ReLu
Learning rate init	0.001
Hidden layer sizes	100

The suggested DALF architecture generator's output is shown in Table 3 for nine different instances. The table illustrates the F1-score, recall, and precision for various real-world and synthetic spectra data from the HIS classification with SVM. Table 4 displays the recall, F1-score, and accuracy of the HSI categorization on many real-world spectra data instances, and presents the results of HSI classification using NN for various samples of enhanced spectra.

Table 3. The SVM classifier's performance on actual and synthetic spectra

Samples	SVM Performance (Real Data)			SVM Performance (Synthetic Data)		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score
1	0.82	0.92	0.90	0.91	0.97	0.96
2	0.95	0.93	0.95	0.98	0.96	0.99
3	0.74	0.72	0.78	0.92	0.92	0.98
4	0.98	0.95	0.95	0.99	0.95	0.99
5	0.99	1.00	1.00	0.97	1.00	0.97
6	0.89	0.86	0.89	0.94	0.95	0.96
7	0.92	0.55	0.72	0.91	0.82	0.86
8	0.86	0.89	0.92	0.99	0.96	0.90
9	1.00	1.00	1.00	1.00	0.95	0.98

Table 4. The NN classification performance on real and synthetic spectra

Samples	NN Performance (Real Data)			NN Performance (Synthetic Data)		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score
1	0.9480	0.9396	0.9373	0.9407	0.9483	0.9445
2	0.9677	0.9741	0.9709	0.9679	0.9771	0.9725
3	0.8540	0.7753	0.8127	0.8349	0.7912	0.8125
4	0.9524	0.9429	0.9476	0.9688	0.9433	0.9558
5	0.9976	0.9843	0.9909	0.9953	0.9961	0.9957
6	0.9126	0.9101	0.9114	0.9204	0.9137	0.9170
7	0.8450	0.8437	0.8443	0.8902	0.8594	0.8745
8	0.8567	0.8815	0.8689	0.8625	0.8743	0.8684
9	0.9989	0.9944	0.9966	0.9989	0.9888	0.9938

CONCLUSION

This study introduces a Deep Learning-based framework called DALF, where a Generative Adversarial Network (GAN) is employed. Specifically, a Convolutional Neural Network (CNN) serves as the generator to create data points that are meaningfully connected to the underlying distribution. The generator is trained to predict the distribution by competing with a discriminator network through an adversarial objective function. The discriminator's role is to distinguish between real and generated data. By setting up this competition between the discriminator and generator, the framework aims to improve the efficiency of hyperspectral image (HSI) classification. Additionally, this proposed GAN framework includes a classifier component that can categorize HSI samples based on the spectral information used during training. To classify HSIs, the technique utilizes a sophisticated algorithm called the Generative Model-based Hybrid Approach (GMHA-HSIC).

ACKNOWLEDGEMENT

Funding Details

This research was supported by the Ministry of Trade, Industry and Energy(MOTIE) and the Korea Institute for Advancement of Technology(KIAT) through the “Support for Mid-sized Enterprises and Regional innovation Alliances (R&D, RS-2024-00421022)” program.

Authors' contributions

All authors contributed toward data analysis, drafting and revising the paper and agreed to be responsible for all the aspects of this work.

Declaration of Conflicts of Interests

The author declare that they have no conflict of interest.

Availability of data and materials

Not Applicable

Use of Artificial Intelligence

Not applicable

Declarations

Author declares that all works are original and this manuscript has not been published in any other journal.

REFERENCES

[1] Cao, P., Eckstein, H. H., De Rango, P., Setacci, C., Ricco, J. B., De Donato, G., ... & Apelqvist, J. (2011). Chapter II: diagnostic methods. European Journal of Vascular and Endovascular Surgery, 42, S13-S32.

[2] V. C, G. A, D. K S and S. T. P, "Hyperspectral Information in Urban Areas Using Big Data and Machine Learning," *2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS)*, Coimbatore, India, 2023, pp. 1031-1034, doi: 10.1109/ICACCS57279.2023.10112929.

[3] Rast, M., & Painter, T. H. (2019). Earth observation imaging spectroscopy for terrestrial systems: An overview of its history, techniques, and applications of its missions. Surveys in Geophysics, 40(3), 303-331.

[4] S. Verga *et al.*, "Estimation of The Lower Heating Value of Solid Recovered Fuel Based On Swir Hyper-Spectral Images and Machine Learning," *2022 12th Workshop on Hyperspectral Imaging and Signal Processing: Evolution in Remote Sensing (WHISPERS)*, Rome, Italy, 2022, pp. 1-5, doi: 10.1109/WHISPERS56178.2022.9955135.

[5] S. L. Polk, K. Cui, R. J. Plemmons and J. M. Murphy, "Active Diffusion and VCA-Assisted Image Segmentation of Hyperspectral Images," *IGARSS 2022 - 2022 IEEE International Geoscience and Remote Sensing Symposium*, Kuala Lumpur, Malaysia, 2022, pp. 1364-1367, doi: 10.1109/IGARSS46834.2022.9883894.

[6] B. Sucharitha and K. AnithaSheela, "Hyper Spectral Image compression using Higher Order Orthogonal Iteration Tucker decomposition," *2022 IEEE 19th India Council International Conference (INDICON)*, Kochi, India, 2022, pp. 1-7, doi: 10.1109/INDICON56171.2022.10040093.

[7] R. Sharma, D. Pantola, S. D. Kalony and R. Agarwal, "Analysis Machine Learning Approach and Model on Hyper Spectral (Sentinel-2) Images for Land Cover Classification: Using SVM," *2021 10th International Conference on System Modeling & Advancement in Research Trends (SMART)*, MORADABAD, India, 2021, pp. 680-684, doi: 10.1109/SMART52563.2021.9676331.

[8] S. S. Chava, S. L. T. Gunnapaneni and S. Chakravarty, "Hyper-Parameters Tuning for Hyperspectral Image Classification," *2021 6th International Conference on Signal Processing, Computing and Control (ISPCC)*, Solan, India, 2021, pp. 444-449, doi: 10.1109/ISPCC53510.2021.9609398.

[9] Q. Lv *et al.*, "Ensemble CNN with Enhanced Feature Subspaces for Imbalanced Hyperspectral Image Classification," *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS*, Brussels, Belgium, 2021, pp. 3669-3672, doi: 10.1109/IGARSS47720.2021.9554677.

[10] M. S. Kumar, V. Keerthi, R. N. Anjnai, M. M. Sarma and V. Bothale, "Evalution of Machine Learning Methods for Hyperspectral Image Classification," *2020 IEEE India Geoscience and Remote Sensing Symposium (InGARSS)*, Ahmedabad, India, 2020, pp. 225-228, doi: 10.1109/InGARSS48198.2020.9358916.

[11] S. Ullah and D. -H. Kim, "Benchmarking Jetson Platform for 3D Point-Cloud and Hyper-Spectral Image Classification," *2020 IEEE International Conference on Big Data and Smart Computing (BigComp)*, Busan, Korea (South), 2020, pp. 477-482, doi: 10.1109/BigComp48618.2020.00-21.

[12] Wambugu, N., Chen, Y., Xiao, Z., Tan, K., Wei, M., Liu, X., & Li, J. (2021). Hyperspectral image classification on insufficient-sample and feature learning using deep neural networks: A review. International Journal of Applied Earth Observation and Geoinformation, 105, 102603.

[13] Lelong, C. C., Pinet, P. C., & Poilvé, H. (1998). Hyperspectral imaging and stress mapping in agriculture: A case study on wheat in Beauce (France). Remote sensing of environment, 66(2), 179-191.

[14] Skidmore, A. K., Bijker, W., Schmidt, K., & Kumar, L. (1997). Use of remote sensing and GIS for sustainable land management. ITC journal, 3(4), 302-315.

[15] Lamb, D. W. (2000). The use of qualitative airborne multispectral imaging for managing agricultural crops-a case study in south-eastern Australia. Australian Journal of Experimental Agriculture, 40(5), 725-738.

[16] Nilsson, H. (1995). Remote sensing and image analysis in plant pathology. Annual review of phytopathology, 33(1), 489-528.

[17] Bishop, C. A., Liu, J. G., & Mason, P. J. (2011). Hyperspectral remote sensing for mineral exploration in Pulang, Yunnan Province, China. International Journal of Remote Sensing, 32(9), 2409-2426.

[18] Gao, L., Yao, D., Li, Q., Zhuang, L., Zhang, B., & Bioucas-Dias, J. M. (2017). A new low-rank representation based hyperspectral image denoising method for mineral mapping. Remote Sensing, 9(11), 1145

[19] Chang, N. B., Bai, K., & Chen, C. F. (2017). Integrating multisensor satellite data merging and image reconstruction in support of machine learning for better water quality management. Journal of environmental management, 201, 227-240.

[20] Ha, N., Xu, K., Ren, G., Mitchell, A., & Ou, J. Z. (2020). Machine learning-enabled smart sensor systems. Advanced Intelligent Systems, 2(9), 2000063.

[21] Uzhinskiy, A. (2019). Intelligent environmental monitoring platform. In CEUR Workshop Proc (Vol. 2267, pp. 351-358).

[22] Panigrahi, S., & Swarnkar, T. (2020). Machine learning techniques used for the histopathological image analysis of oral cancer-a review. The Open Bioinformatics Journal, 13(1).

[23] ul Rehman, A., & Qureshi, S. A. (2021). A review of the medical hyperspectral imaging systems and unmixing algorithms' in biological tissues. Photodiagnosis and Photodynamic Therapy, 33, 102165.

[24] S. Mallapragada and C. -C. Hung, "Statistical Perspective of SOM and CSOM for Hyper-Spectral Image Classification," *IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium*, Waikoloa, HI, USA, 2020, pp. 48-51, doi: 10.1109/IGARSS39084.2020.9324200.

[25] S. Kumar, C. Torres, O. Ulutan, A. Ayasse, D. Roberts and B. S. Manjunath, "Deep Remote Sensing Methods for Methane Detection in Overhead Hyperspectral Imagery," *2020 IEEE Winter Conference on Applications of Computer Vision (WACV)*, Snowmass, CO, USA, 2020, pp. 1765-1774, doi: 10.1109/WACV45572.2020.9093600.

[26] R. H. Md. Rafi, B. Tang, Q. Du and N. H. Younan, "Attention-based Domain Adaptation for Hyperspectral Image Classification," *IGARSS 2019 - 2019 IEEE International Geoscience and Remote Sensing Symposium*, Yokohama, Japan, 2019, pp. 67-70, doi: 10.1109/IGARSS.2019.8898850.

[27] A. Mughees and L. Tao, "Multiple deep-belief-network-based spectral-spatial classification of hyperspectral images," in *Tsinghua Science and Technology*, vol. 24, no. 2, pp. 183-194, April 2019, doi: 10.26599/TST.2018.9010043.

[28] L. Qi, J. Li, Y. Wang and X. Gao, "Region-Based Multiview Sparse HyperspectralUnmixing Incorporating Spectral Library," in *IEEE Geoscience and Remote Sensing Letters*, vol. 16, no. 7, pp. 1140-1144, July 2019, doi: 10.1109/LGRS.2019.2891559.

[29] S. L. Borana, S. K. Yadav and S. K. Parihar, "Hyperspectral Data Analysis for Arid Vegetation Species : Smart & Sustainable Growth," *2019 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS)*, Greater Noida, India, 2019, pp. 495-500, doi: 10.1109/ICCCIS48478.2019.8974502.

[30] A. Tehrani and H. Karbasi, "A novel integration of hyper-spectral imaging and neural networks to process waste electrical and electronic plastics," *2017 IEEE Conference on Technologies for Sustainability (SusTech)*, Phoenix, AZ, USA, 2017, pp. 1-5, doi: 10.1109/SusTech.2017.8333533.

[31] Drożdżyk, M. (2012). The offer of services for exhibitors in terms of leisure and other factors increasing the attractiveness of the fairs in Łódź. Acta Innovations, 4, 159–205. https://www.actainnovations.com/index.php/pub/article/view/4_4,

[32] Zanjare S.R., Suryawanshi A.V., Zanjare S. Snehal, Shelar V.R., Balgude Y.S. (2023). Screening of Groundnut (Arachis hypogaea L.) Genotypes for Identification of Sources of Resistance against Leaf Spot Disease. Legume Research. 46(3): 288-294. https://doi.org/10.18805/LR-4370

[33] Hamadani, A., Ganai, N.A., Alam, S., Mudasir, S., Raja, T.A.,Hussain, I. and Ahmad, H.A. (2022). Artificial Intelligence Techniques for the Prediction of Body Weights in Sheep. Indian Journal of Animal Research. https://doi.org/10.18805/IJAR.B-4831

[34] Rolla K.J. (2023). Trends and Futuristic Applications of Big Data and Electronic Health Record Data in Empowering Constructive Clinical Decision Support Systems. Bio-Science Research Bulletin, 39(2), 78-91.

[35] Wihardjo, R. S. D., Muktiono, A. & Suwanda (2024). Exploring Critical Thinking in Environmental Education: A PBL Approach to Reaction Rate Material at Public Senior High Schools in Indonesia. International Journal of Environmental Sciences, 10(1), 14-25.

https://www.theaspd.com/resources/2.%20Exploring%20Critical%20Thinking%20in%20Environmental%20Education.pdf
[36] Vainshnav, S. P., & Dave, K. K. (2022). A study on Artificial Intelligence and Machine Learning in Banking Sector with special reference to term loan. Pacific Business Review (International), 15(3), 34-53.