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A Thorough Examination Of Deep Learning And Evolutionary Methods In Hyperspectral Image Processing

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Abstract: *Hyperspectral image processing is like a super tool that combines high-tech photography, smart computing, and nature-inspired problem-solving. It helps us gather, understand, and make sense of information from different kinds of light. This special tool is super important in areas like farming, keeping an eye on the environment, and even in defence. Scientists have recently integrated unique problem-solving methods influenced by nature with self-learning deep learning computer algorithms. The way we perceive and utilize hyperspectral pictures has changed significantly as a result of this potent combination. It's similar to providing us with an extremely clear image of items and materials. The key concepts, techniques, and most current advancements in hyperspectral image processing are clearly illustrated in this study. It focuses particularly on the interplay between these evolutionary and deep learning methods. It also emphasizes how this combination can be quite beneficial in a wide range of professions. This serves as a reminder to continue investigating and learning about this fascinating field, which holds great promise for a wide range of scientific and technological fields.*

Keywords: *Hyperspectral Image Processing, Remote Sensing, Spectral Information, Spatial Information, Classification.*

I. INTRODUCTION:

In digital terms, a hyperspectral image (HSI) is a picture that includes a wide variety of electromagnetic wavelengths or spectral bands. HSIs include thousands of narrow, contiguous bands that cover a large range, in contrast to standard images that only have three RGB bands [1]. An HSI is produced by splitting the electromagnetic spectrum into numerous contiguous, narrow bands, which results in a sizable number of spectral channels. Every channel represents a specific wavelength or a narrow range of wavelengths. The spectral signature of each pixel in a hyperspectral image is made up of intensity values that represent the object's reflectance or radiance at different wavelengths. This spectral information makes it possible to identify and analyze the composition and properties of the items that were photographed. A representation of HSI is shown in Fig. 1.

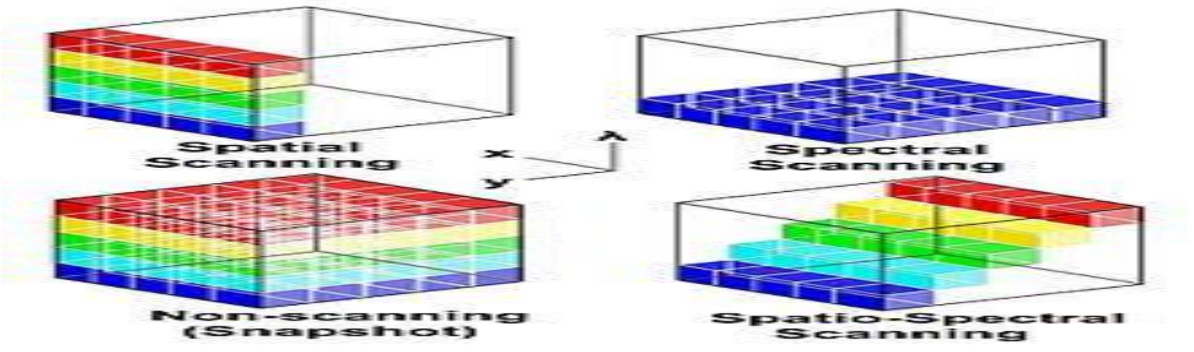


Figure 1: Representation of HSI

The HSI has many application areas which include remote sensing and earth observation [6], agriculture and crop monitoring [7], geology and mineralogy [8], forestry [9], urban planning and infrastructure [10], medical imaging and diagnostics [11], food quality and safety [12].

In the processing of HSIs, various classification methods were employed to classify the pixels or regions into distinct classes by leveraging their spectral characteristics. Some of the widely used classification methods were KNN [13], SVM [14], RF [14], maximum likelihood classifier (MLC) [15]and decision trees (DT) [16]. These approaches' performance was unsatisfactory because they suffer from coupled spectral bands, limited training samples, spectral variability, excessive computing cost, and the curse of dimensionality. Addressing these limitations often requires the development of specialized algorithms.

II. LITERATURE REVIEW

Last few years, deep learning (DL) methods demonstrated huge success across a wide array of applications, particularly in hyperspectral image processing [17]. Amid various DL approaches, CNN is very popular due to its powerful feature extraction technique. In [24], introduces a CNN architecture that transforms 1D spectral vectors into 2D matrices to entirely leverage the spectral information. Likewise, [28] introduces a new CNN model for HSI classification that reduces overfitting by using smaller spatial patches. In [30], authors tackle the overfitting problem by using a combination of 2D-CNN and Gabor filtering. Moreover, spectral-spatial information integration is explored in HSI classification. In [32], proposes an efficient 3D-CNN framework that exploits both spectral-spatial information simultaneously. In [33], a II-stage hybrid deep context jointly extracts spectral-spatial features using CNN and stacked AE. Similarly, [34] introduces a 3D-CNN model that effectively incorporates spectral and spatial features. [35] proposes a double-channel CNN built outline where one Dimension CNN and two Dimension CNN are utilized to extract spectral and spatial structures, respectively. In [37], a combined metric learning based framework with CNN is employed to fuse spectral and spatial features. [38] employs multiscale filtering in the CNN framework to enhance the HSI representational ability. [39] extracts spatial information from a three-channel virtual RGB image and sends them to CNN for multi-scale feature extraction. A semi-supervised 3D-CNN with an adaptive band selection technique is presented in [40] in order to simultaneously exploit spectral-spatial characteristics. Similarly, in [41], a hybrid unsupervised 3D convolutional-autoencoder is used to jointly extract spectral-spatial information. Uses a hybrid strategy in [42] that combines a 2D-CNN model for getting abstract spatial characteristics with a 3D-CNN for utilizing spectral-spatial information. It is clear from the explanation above that enhancing the HSI classification requires both spectral and spatial information. Other than spectral and spatial information, removing noisy bands is important criteria for improving the classification performance. Evolutionary algorithms (EAs) have a substantial impact on processing hyperspectral images for remote sensing, as they effectively tackle intricate issues linked with tasks like feature selection and classification. Paper [71] states that Particle Swarm Optimization's cooperative particle interactions drive iterative fitness improvement, while its application to hyper-parameter selection has shown promise in achieving optimal solutions for tasks such as classification accuracy enhancement in hyperspectral imaging. In [70][52] the proposed Improved Ant Colony Algorithm (IMACA-BS) demonstrated superiority in selecting informative bands for classification of complex land cover classes. [68] introduced methods to enhance classification accuracy in hyperspectral images by removing correlated bands. EAs form a group of optimization and search procedures that draw inspiration from the mechanisms of biological evolution and natural selection [47]. Their primary application lies in answering difficult optimization glitches, particularly in scenarios where conventional gradient-based approaches may not be suitable or efficient. EAs replicate the mechanism of natural selection, favouring individuals possessing advantageous traits to survive and reproduce, thereby passing these traits to the succeeding generation [48]. Likewise, in EAs, potential solutions to a problem are considered individuals in a population, and their fitness is assessed based on their performance in the given task. Unlike traditional optimization techniques that work with a single solution, EAs maintain a population of candidate solutions. Through successive generations, these solutions evolve to achieve better fitness values. In recent times, evolutionary algorithms (EAs) have gained widespread use in feature selection due to their effective search capability in vast feature spaces [66]. The Genetic, Differential Evolution, Cuckoo Search and Artificial Bee Colony algorithms are known for their potential to effectively handle feature selection tasks and offer superior performance [67]. Application of EAs on hyperspectral image (HSI) analysis has emerged as a highly engaging area in the realm of remote sensing, offering significant potential in comprehensively sensing vast environmental landscapes [68]. [69] uses support vector machines as a classifier and genetic algorithms as an optimizer to find the most effective waveband combination of a hyperspectral image for the early detection of disease symptoms in soybean stems. Ant Colony Optimization algorithm has been used in the area of image processing, pattern recognition, and feature selection [70].FCN, a variant of CNN, is precisely crafted for semantic separation duties. It substitutes the fully connected layers found in conventional CNN's to retain spatial details. FCN is highly suitable for tasks involving per-pixel classification and segmentation, such as recognizing objects or notable areas in images. Its adaptation to hyperspectral image processing involves accommodating the numerous spectral bands in hyperspectral data and segmenting objects or land cover categories within these images. This design involves an encoder path (contracting) and a decoder path (expansive), forming a "U" shape. The encoder captures context, and the decoder reinstates spatial details, creating segmentation masks. U-Net proves valuable for tasks requiring meticulous segmentation with well-defined boundaries, like discerning land cover categories in hyperspectral images. The versatility of ResUNET's design allows it to be easily tailored to hyperspectral image processing tasks. It is capable of addressing the complexities introduced by the extensive spectral bands present in hyperspectral data and generating precise segmentation results for various categories of importance.

III. Standard CNN Architecture:

CNN are a specific kind of neural network with multiple layers, designed to identify visual patterns in pixel-based images [43]. In CNN, the word "convolution" refers to a scientific operation that involves multiplying two functions to produce a 3rd function, which describes how one function's shape can be modified by the other. In simpler terms, CNN uses matrix multiplication of two image representations to generate an output that extracts information from the image. CNN shares similarities with other neural networks, but its distinguishing feature is the inclusion of convolutional layers, which add a layer of complexity to the overall structure [44]. A convolutional neural network consists of several levels, including convolution layer, pooling layer, and fully connected layer. The details of each layer are given below:

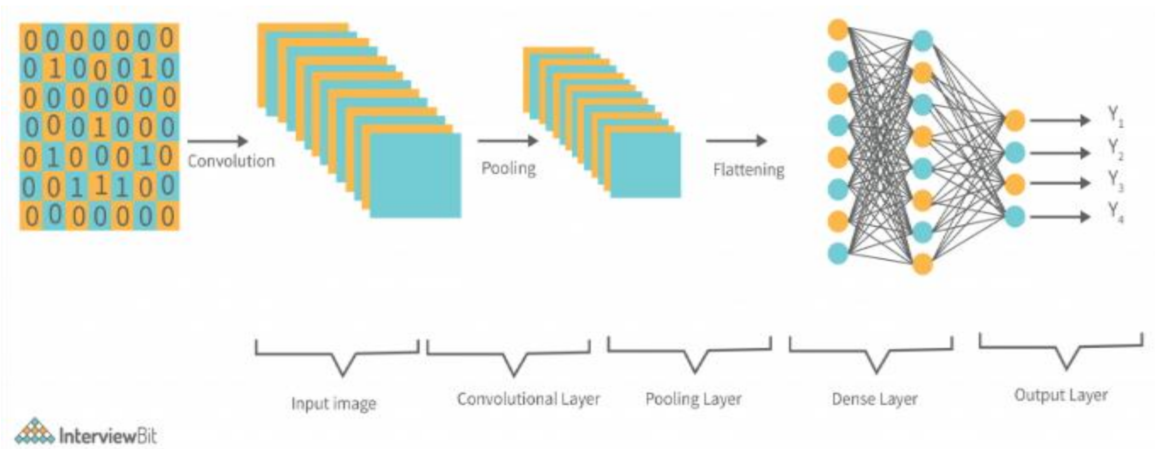


Fig 2: CNN architecture.

Convolutional Layer:

At the core of the CNN lies the convolutional layer. This pivotal layer applies convolutional filters, also known as kernels, to the input data in order to detect features such as edges, textures, and patterns. Each filter is relatively small in size compared to the input data and slides over the entire input using a specified stride. At each position, the filter performs element-wise multiplication with the corresponding input elements and sums the results to produce a feature map. The feature map can be represented as follow:

$$f(i, j) = \Sigma\Sigma(l(i + m, j + n) * k(m, n)$$

Where:$f(i, j)$ is the value at position (i, j) in the feature map.

$l(i+m, j+n)$ is the value at position $(i+m, j+n)$ in the input data.

$K(m,n)$ is the value at position (m,n) in the convolutional filter.

$\Sigma\Sigma$ represents the summation of overall spatial positions (m, n) in the convolutional filter.

Pooling Layer:
In order to reduce the feature maps' spatial dimensions while maintaining important information, pooling layers are needed. These layers help manage overfitting and lower computing complexity. Max pooling is a popular method in which the maximum value within a small area (the pooling window) is kept and the remainder is discarded. The most notable elements of the feature map are preserved through this down sampling procedure.
Fully Connected Layer:
One or more fully connected layers are frequently included in the CNN model after a number of convolutional and pooling layers. In order to create a conventional neural network architecture, these layers connect each neuron in the current layer to every other neuron in the layer above. Using the features that the preceding layers have learnt, fully linked layers help discover global relationships and make predictions.
Output Layer:
The output layer represents the final layer of the CNN model. In classification tasks, it typically consists of neurons equal to the number of classes to predict. The values of these neurons indicate the model's confidence in assigning the input data to each class.
In the process of training, these layers collaborate through forward propagation to learn the optimal set of weights and biases that optimize the model's performance on the given task. The learning process is facilitated through backpropagation and the optimization algorithm, which iteratively updates the model's parameters based on the inclines of the loss function with deference to the model's parameters.
IV. Some notable CNN Architectures:
LeNet:
LeNet, introduced in 1989 by Yann LeCun [72], stands out as one of the earliest deep neural network (DNN) models, characterized by its straightforward architecture. This model gained prominence for its capacity to execute computations more rapidly compared to its contemporaries. The LeNet architecture encompasses several layers, incorporating both convolutional and fully connected layers. These components play a pivotal role in extracting features from images. When applied to hyperspectral image processing, the LeNet framework can be adjusted to address the unique complexities of hyperspectral data. Hyperspectral imagery holds extensive spectral data, with each pixel encompassing information from numerous spectral bands. This abundant data can be effectively harnessed by modifying LeNet's structure to encompass the spectral dimension. The convolutional layers can be configured to accommodate the distinct spectral bands, enabling the capture of spectral features.

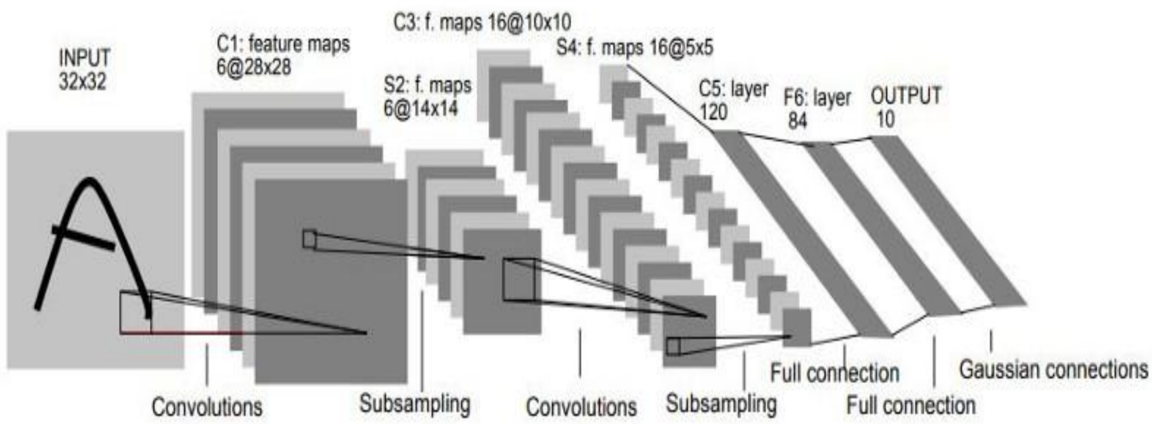


Fig 3: LeNet-5 Architecture
Furthermore, LeNet's convolutional layers' capacity for hierarchical feature learning is beneficial in identifying intricate spectral patterns that signify specific land cover categories. These acquired features can be employed in classification jobs, anywhere the objective to allocate individual pixel to a particular land cover class. LeNet architecture, featuring its convolutional layers and feature extraction capabilities,

can be customized for handling hyperspectral image data. Through adaptation and training on hyperspectral datasets, LeNet emerges as a respected resource for tasks such as land cover arrangement, detection of spectral-based patterns, and various other applications within hyperspectral image analysis.

AlexNet:

Image recognition is accomplished with AlexNet. It was first presented by Alex Krizhevsky in 2012. The architecture of AlexNet has served as a foundation for numerous different CNNs. It is a novel structure of a convolutional neural network (CNN), originally designed for picture organization persistence in computer vision. The principles and features of AlexNet have prompted adaptations and applications in a variety of domains, including hyperspectral image analysis, despite its primary focus on RGB images. In order to automatically extract layered characteristics from input photos, AlexNet's convolutional layers are built to capture several degrees of abstraction, from simple edges and textures to complex patterns. In hyperspectral images, where each pixel contains many spectral bands, these convolutional layers can be used to extract important spectral and spatial information. For identifying subtle patterns and differentiating across land cover types based on their spectral characteristics, this is very helpful.

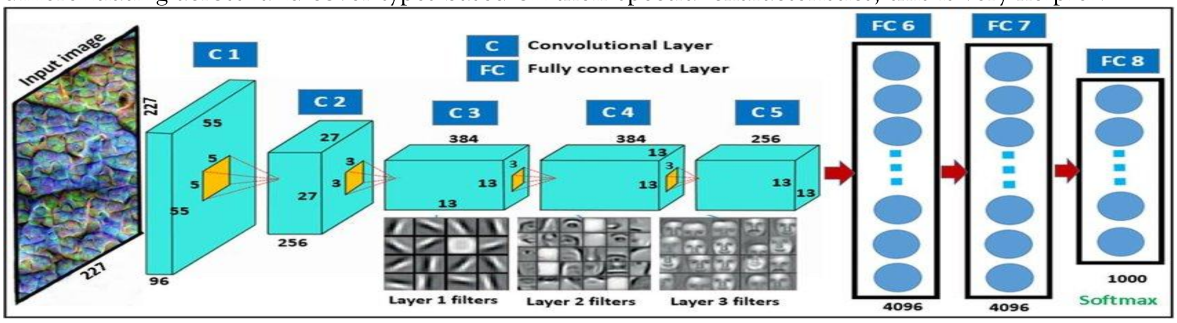


Fig 4: Architecture of AlexNet

Visual Geometry Group - VGG:

Visual Geometry Group members Andrew Zisserman and Karen Simonyan of the University of Oxford developed the VGG convolutional neural network (CNN) architecture. The CNN design is simple and effective, utilizing small 3x3 convolutional filters and max pooling layers. DenseNet, ResNet, Inception, and many other CNN designs have been built on top of VGG. VGG remains a popular CNN architecture for several purposes as object recognition, picture classification, and semantic segmentation. They use miniature 3x3 convolutional filters. Training is made easier and the network's computational efficiency is increased. Following each convolutional layer are max pooling layers. This lessens the feature maps' size and keeps overfitting from happening. It is made up of many layers. This enables the network to extract increasingly intricate elements from the pictures.

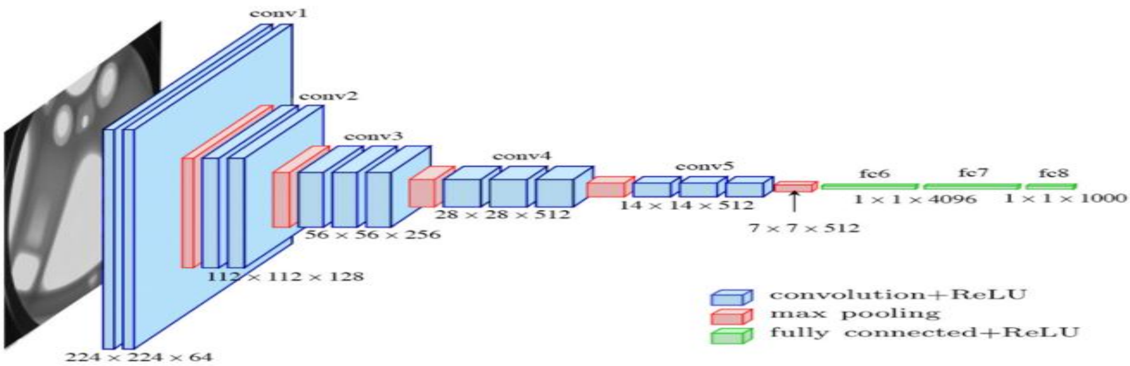


Fig 5: VGG 16 architecture

It is computationally costly to deploy and train. It can be challenging to adjust for particular tasks. Compared to some more recent CNN architectures, it is less efficient.

GoogLeNet:

GoogLeNet,, is a CNN planning that was developed by researchers at Google in the year 2014. On a number of tasks, such as semantic segmentation, object detection, and picture classification, GoogLeNet has produced state-of-the-art results. Even now, a lot of people still employ this strong CNN architecture. Uses inception modules to combine different sized convolutional filters. More efficient than previous

CNN architectures. Can learn more complex features from images. obtained cutting-edge outcomes on a range of challenges.

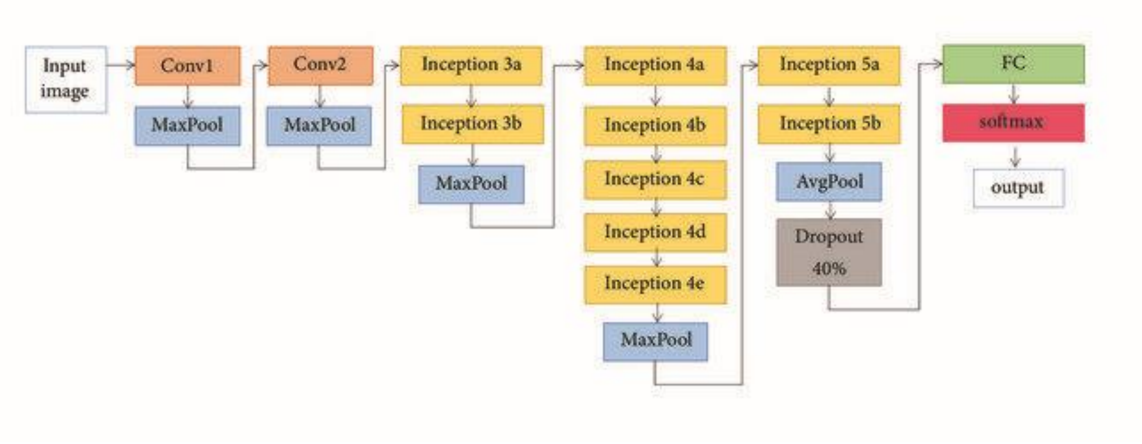


Fig 6: GoogLeNet Framework

GoogLeNet can be computationally spendy to train and deploy. It can be difficult to fine-tune for specific tasks. Not as efficient as some newer CNN architectures.

ResNet:

Researchers at Microsoft Research unveiled the Residual Network, a convolutional neural network (CNN) architecture, in 2015. It has served as a foundation for numerous different CNN designs and was the winner of the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) that year. ResNet's utilization of residual connections is one of its distinguishing features. The output of one layer can be added to the input of the subsequent layer via residual connections. This aids in avoiding the vanishing gradient issue, which arises when the loss function's gradients get progressively smaller as the network gets deeper. ResNet has a very deep architecture. The original ResNet architecture has 152 layers, but there are also smaller versions of ResNet with 50, 101, and 182 layers. The first few layers of ResNet are liable for mining low-level structures from the images, such as edges and textures.

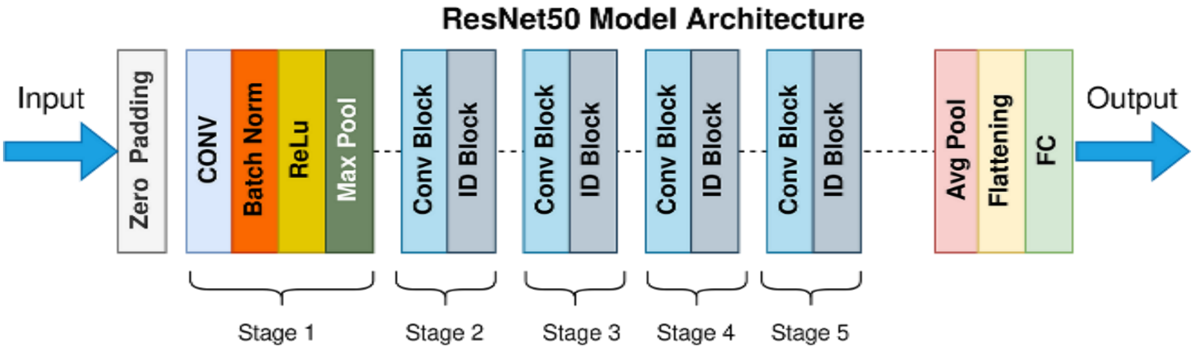


Fig 7: ResNet Architecture

DenseNet:

Researchers from Hong Kong University of Science and Technology unveiled DenseNet, a convolutional neural network architecture, in 2016. It has served as a foundation for numerous different CNN designs and was the winner of the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) that year. The usage of dense connections is what distinguishes DenseNet.

All of the network's layers can be directly connected to one another using dense connections. By doing this, the network's information flow is enhanced and the vanishing gradient issue is avoided. DenseNet's architecture is incredibly small. Although there are lesser versions of DenseNet with 169 and 201 layers, the original DenseNet architecture has 121 layers. Low-level elements like edges and textures are extracted from the images by DenseNet's initial layers. High-level information like object components and objects themselves are extracted by DenseNet's later layers. On a number of tasks, such as semantic segmentation, object detection, and picture classification, DenseNet has produced state-of-the-art results. It is a prevailing CNN construction that is still widely used today.

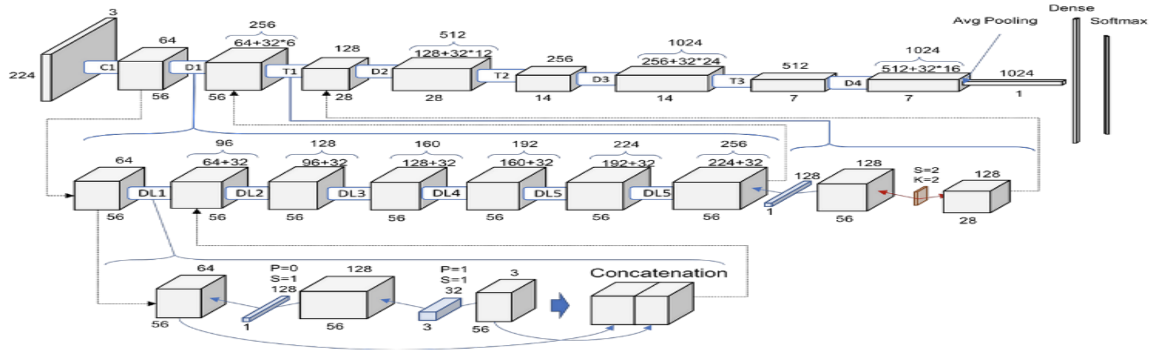


Fig 8: DenseNet Architecture

UNet:

UNet (short for Universal Network) also a convolutional neural network architecture is used for image segmentation. It was first introduced in the paper "U-Net: Convolutional Networks for Biomedical Image Segmentation" by Olaf Ronneberger in 2015. UNet makes it more efficient for image segmentation tasks, as fully connected layers are not able to handle the spatial information of images. The architecture of UNet is U-shaped, with a decreasing path and an expanding path. The contracting path is responsible for extracting features from the input image, while the expanding path constructs the output segmentation map by up sampling the features. The contracting route consists of a series of convolutional and max pooling layers. The max pooling layers reduce the feature maps in the input image, while the convolutional layers extract features. The expanding path is composed of convolutional layers and a series of up sampling. The convolutional layers up sample the features at the same time that the up-sampling layers enlarge the feature maps. Concatenation is performed between the features extracted from the contracting path and the up-sampled features from the expanding path. This allows the input image's local and global characteristics to be learned by UNet. UNet has demonstrated state-of-the-art performance on a variety of image segmentation tasks, such as sequence segmentation, biological image segmentation, and instance segmentation. Because of its strength and versatility, this CNN design is still in use today.

V. Evolutionary Algorithms:

The genetic representation can be customized to suit the particular problem domain, offering adaptability in managing different types of variables. EAs utilize a selection mechanism to pick individuals from the population based on their fitness. Individuals with superior performance have a greater probability of being chosen, emulating the thought of "survival of the fittest" in normal choice. Crossover is a genetic operator that involves merging two parent solutions to produce new offspring. This process fosters exploration and facilitates the exchange of advantageous traits between solutions, potentially leading to improved solutions. As seen in figure 2, mutation introduces random changes to the candidate solutions, protecting against early convergence to poor solutions and maintaining population variety. Until a predetermined termination condition is met, such as reaching a maximum number of generations or achieving a certain degree of solution quality, EAs continue to evolve the population.

Feature extraction and feature selection are two popular techniques for reducing the number of dimensions in hyperspectral datasets. Principal component analysis (PCA) [50], independent component analysis (ICA) [49], and local linear embedding (LLE) [51] are examples of feature extraction approaches that convert the original data into a feature space that is less redundant and has fewer dimensions. But in the process of compression, they may lose some physical information [52]. However, feature selection, a prominent technique for dimension reduction, keeps the most important characteristics while maintaining the physical meaning of the original data [53]. Conventional filter approaches use metrics like distance, correlation, and information to evaluate the feature subset, which is chosen independently of the classifier or classification algorithm [54]. Wrapper methods, on the other hand, employ the classifier model to estimate feature subsets, resulting in more accurate selections [55]. Although filter methods are computationally efficient, they tend to be less accurate than wrapper methods since they lack classifier guidance [56]. The availability of example tags determines whether feature-selection techniques are supervised or unsupervised [57]. Although bands without class labels can be chosen using unsupervised approaches, the lack of prior knowledge may make them unstable and biased [58]. On the other hand, supervised approaches, which use class labels to help, produce better feature-selection outcomes.

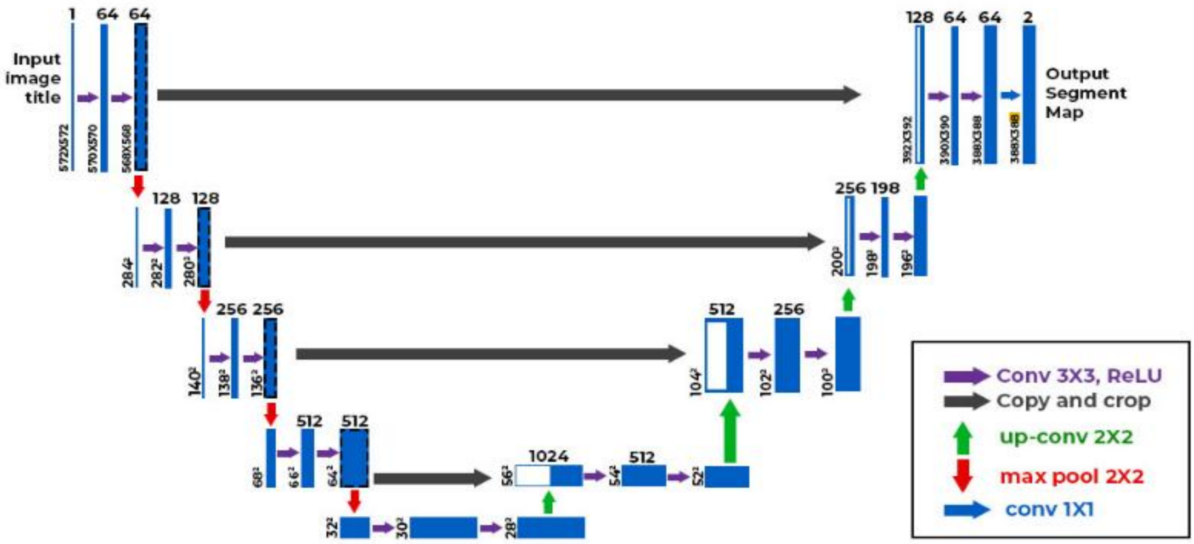


Fig 9: U-Net Architecture

IV. Summery :

CNN Architecture	Dataset Focus	Remote Sensing Applications
AlexNet	ImageNet	Land cover classification with hyperspectral data
VGGNet	ImageNet	Land use classification, feature extraction
GoogLeNet (Inception)	ImageNet	Land cover classification, multi scale feature extraction
ResNet	ImageNet	Object detection, feature extraction
DenseNet	ImageNet	Land cover classification, feature reuse
MobileNet	It is not dataset specific	Real time object detection, classification with resource constraints
UNet	Biomedical Image Segmentation	Road Extraction, building segmentation
Fully Convolutional Networks (FCN)	Semantic Segmentation	Land cover classification, detailed image labelling.
SegNet	Road Scene understanding	Semantic Segmentation in aerial and satellite imagery
DeepLab	Semantic Segmentation	Land cover mapping, precise segmentation in high-resolution energy.

Table 1: Summery of various CNN architectures, their dataset focuses and their application in remote sensing.

Evolutionary Algorithm	Datasets	Applications
Genetic Algorithms (GA)	Hyperspectral, Multispectral	➢ Feature Selection for classification. ➢ Optimization of remote sensing parameters. ➢ Land cover classification ➢ Change Detection
Differential Evolution (DE)	Multispectral, Hyperspectral	➢ Feature Selection for classification.

		➢ Spectral Unmixing. ➢ Land use classification.
Particle Swarm Optimization (PSO)	Satellite, Aerial Imagery	➢ Feature Selection for classification. ➢ Object Detection. ➢ Sensor Network Optimization.
Artificial Bee Colony (ABC)	Multispectral, Hyperspectral	➢ Selecting features for classification. ➢ Optimization for Image segmentation and clustering.
Cuckoo Search (CS)	Hyperspectral, SAR	➢ Feature Selection for classification. ➢ Image registration for remote sensing tasks.
Evolutionary Strategies (ES)	Multispectral, Hyperspectral	➢ Parameter optimization for remote sensing algorithms.
Genetic Programming (GP)	Hyperspectral	➢ Feature Generation for improved classification and analysis.

Table 2: Summery of evolutionary algorithms used in remote sensing

V. RESULTS COMPARISON:

In the domain of hyperspectral image (HSI) band selection, various algorithms have been explored by different researchers. Nagasubramanian et al.[59] utilized Genetic Algorithm [GA] to identify the optimum subgroup of bands in addition SVM for classifying infested and vigorous trials. They replaced the cataloguing accuracy with F1-Score to address the issue of unstable datasets, and their results demonstrated that the selected bands provided more informative data related to RGB pictures. A band selection technique for HSI classification was presented by Xie et al. [60] and was based on the Artificial Bee Colony (ABC) algorithm and enhanced subspace decomposition. After achieving subspace decomposition by calculating the importance between adjacent bands, they optimized the combination of chosen bands by guiding the ABC algorithm with increased subspace decomposition and maximum entropy. Their approach outperformed six related techniques, achieving high classification accuracy. Wang et al. [61] suggested a wrapper feature-selection method that reduced the dimension of HSI by combining wavelet SVM with an enhanced Ant Lion Optimizer (ALO). To help ALO escape local optima, they used Lévy flight, and wavelet SVM improved the stability of the classification outcomes. With fewer frequency bands, their approach showed acceptable categorization accuracy. Using chaos operation to generate matching indices for the top three gray wolves, Wang et al. [62] further developed a new band selection technique that enhanced the Grey Wolf Optimizer's (GWO) optimization capabilities. Experimental results showed that this approach had a high classification accuracy and generated a good band subset. Using a Discrete Wavelet transform with eight and four taps for feature extraction, Kavitha and Jenifa [63] used Particle Swarm Optimization (PSO) to identify the optimal band subsets. SVM was then employed as a classifier for effective HSI categorization. A new band selection framework based on the binary Cuckoo Search (CS) algorithm was presented by Medjahed et al. [64]. By using a few examples for training, they tested CS's optimization abilities under two distinct objective functions and showed that it performed better than pertinent methods. By optimizing the objective function's minimal values, Su et al. [65] suggested a modified version of the Firefly Algorithm (FA) to address the band selection issue. Their approach outperformed PSO and Sequential Forward Selection (SFS) in terms of performance. Even with these algorithms' advancements, band selection is still a difficult NP-hard task.

The aforementioned algorithms may experience early convergence and optimization stagnation as the number of bands rises.
Some of the false colour and ground truth hyperspectral images are shown below:

(a) (b)

Fig 10: (a) Botswana HIS. (b) Ground Truth

In northwest Indiana, the AVIRIS sensor collected the Indian pines dataset.

(a) (b)

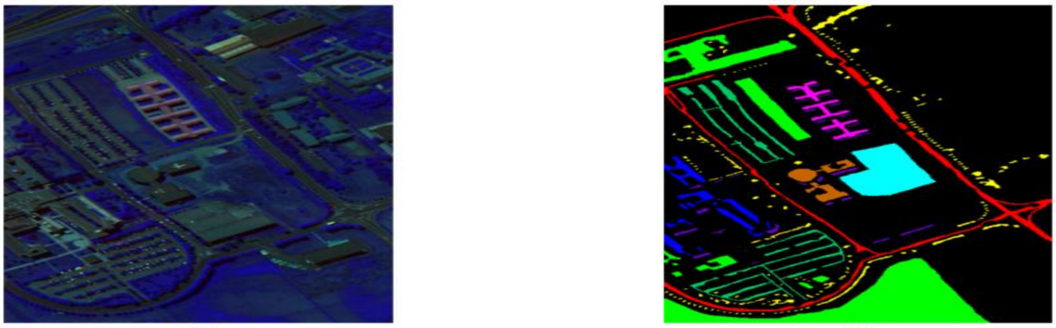
Fig 11: (a) Indian Pines. (b) Ground Truth

The Salinas dataset remained found by an AVIRIS sensor on Salinas valley.

(a) (b)

Fig 12. (a) Salinas HIS. (b) Ground Truth

Pavia university dataset is a 610x340 pixels image, collected from Pavia University in 2002.



(a) (b)

Fig 13. (a) Pavia University. (b) Ground Truth

Algorithm	Parameters	Value
GA	Crossover Rate C_R Mutation Rate C_M	0.8 0.01
PSO	Acceleration coefficients c1, c2. Smallest inertia weightiness w_{min} Extreme inertia weightiness w_{max}	2 0.2 0.9
CS	Detection Probability p_a β	0.25 1.25
FA	Absorption coefficient γ Initial attraction β_0 Randomization Parameter α	1 1 0.5

Table 4: Parameters of standard evolutionary algorithms and their values.

VI CONCLUSION:

In conclusion, the incorporation of deep-learning methods with evolutionary algorithms in hyperspectral image processing marks a significant leap forward in our ability to extract meaningful insights from complex data. This powerful combination enhances our capacity for precise material characterization and classification, with applications spanning agriculture, environmental monitoring, and Défense. The dynamic and evolving nature of this field underscores the need for ongoing research and exploration. As we continue to unlock the full potential of hyperspectral imaging, we open new doors to understanding and leveraging the rich spectrum of electromagnetic frequencies for a multitude of scientific and technological advancements.

REFERENCES:

[1] K. Makantasis, K. Karantzalos, A. Doulamis and N. Doulamis, "Deep supervised learning for hyperspectral data classification through convolutional neural networks," 2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Milan, Italy, 2015, pp. 4959-4962, doi: 10.1109/IGARSS.2015.7326945.

[2] X. Jia, B.-C. Kuo, and M. Crawford, "Feature mining for hyperspectral image classification," Proc. IEEE, vol. 101, no. 3, pp. 676–697, Mar. 2013.

[3] B. Pan, Z. Shi, Z. An, and Z. Jiang, "A novel spectral-unmixingbased green algae area estimation method for GOCI data," IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens., vol. 10, no. 2, pp. 437–449, Feb. 2017.

[4] Grewal, R., Kasana, S.S. & Kasana, G. Hyperspectral image segmentation: a comprehensive survey. Multimed Tools Appl **82**, 20819–20872 (2023). https://doi.org/10.1007/s11042-022-13959-w.

[5] P. Liu, H. Zhang and K. B. Eom, "Active Deep Learning for Classification of Hyperspectral Images," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 10, no. 2, pp. 712-724, Feb. 2017, doi: 10.1109/JSTARS.2016.2598859.

[6] E. Aptoula, M. C. Ozdemir and B. Yanikoglu, "Deep Learning With Attribute Profiles for Hyperspectral Image Classification," in IEEE Geoscience and Remote Sensing Letters, vol. 13, no. 12, pp. 1970-1974, Dec. 2016, doi: 10.1109/LGRS.2016.2619354.

[7] G. Licciardi, P. R. Marpu, J. Chanussot, and J. A. Benediktsson, "Linear versus nonlinear PCA for the classification of hyperspectral data based on the extended morphological profiles," IEEE Geosci. Remote Sens. Lett., vol. 9, no. 3, pp. 447–451, May 2011.

[8] A. Villa, J. A. Benediktsson, J. Chanussot, and C. Jutten, “Hyperspectral image classification with independent component discriminant analysis,” IEEE Trans. Geosci. Remote Sens., vol. 49, no. 12, pp. 4865–4876, Dec. 2011.
[9] T. V. Bandos, L. Bruzzone, and G. Camps-Valls, “Classification of hyperspectral images with regularized linear discriminant analysis,” IEEE Trans. Geosci. Remote Sens., vol. 47, no. 3, pp. 862–873, Mar. 2009.
[10]L. M. Bruce, C. H. Koger, and J. Li, “Dimensionality reduction of hyperspectral data using discrete wavelet transform feature extraction,” IEEE Trans. Geosci. Remote Sens., vol. 40, no. 10, pp. 2331–2338, Oct. 2002.
[11]D. Lunga, S. Prasad, M. M. Crawford, and O. Ersoy, “Manifold-learningbased feature extraction for classification of hyperspectral data: A review of advances in manifold learning,” IEEE Signal Process. Mag., vol. 31, no. 1, pp. 55–66, Jan. 2014.
[12]T. Han, and D. Goodenough, “Investigation of nonlinearity in hyperspectral imagery using surrogate data methods,” IEEE Trans. Geosci. Remote Sens., vol. 46, no. 10, pp. 2840–2847, Oct. 2008.
[13]A. Krizhevsky, I. Sutskever, and G. Hinton, “ImageNet classification with deep convolutional neural networks,” in Proc. Neural Inf. Process. Syst., Lake Tahoe, NV, USA, 2012, pp. 1106–1114.
[14]G. Hinton and R. Salakhutdinov, “Reducing the dimensionality of data with neural networks,” Science, vol. 313, no. 5786, pp. 504–507, Jul. 2006.
[15]M. Sivaram, S. J. Shobana, M. Khan, J. Ramakrishnan, P. M. Goel and A. Maseleno, "Various Deep Learning Methods for Hyperspectral Images," 2020 International Conference on Computing and Information Technology (ICCIT-1441), Tabuk, Saudi Arabia, 2020, pp. 1-4, doi: 10.1109/ICCIT-144147971.2020.9213763.
[16] C. Rodarmel and J. Shan, “Principal Component analysis for hyper-spectral image classification,” ACM Surveying and Land Information Science, vol. 62, no. 2, pp. 115-122, 2002.
[17] A. Shabna, and R. Ganesan, “HSEG and PCA for Hyper-spectral Image Classification,” IEEE International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT), 2014.
[18]Paoletti, M.E., Haut, J.M., Plaza, J. and Plaza, A., 2018. A new deep convolutional neural network for fast hyperspectral image classification. ISPRS journal of photogrammetry and remote sensing, 145, pp.120-147.
[19]E. Aptoula, M. C. Ozdemir and B. Yanikoglu, "Deep Learning With Attribute Profiles for Hyperspectral Image Classification," in IEEE Geoscience and Remote Sensing Letters, vol. 13, no. 12, pp. 1970-1974, Dec. 2016, doi: 10.1109/LGRS.2016.2619354.
[20]Wang, J.; Tang, C.; Li, Z.; Liu, X.; Zhang, W.; Zhu, E.; Wang, L. Hyperspectral band selection via region-aware latent features fusion based clustering. Inf. Fusion **2022**, 79, 162–173.
[21]Xie, S. Feature extraction of auto insurance size of loss data using functional principal component analysis. Expert Syst. Appl. **2022**, 198, 116780.
[22] Hubel, D.H. and Wiesel, T.N., 1962. Receptive fields, binocular interaction and functional architecture in the cat's visual cortex. The Journal of physiology, 160(1), pp.106-154.
[23] Yu, S., Jia, S. and Xu, C., 2017. Convolutional neural networks for hyperspectral image classification. Neurocomputing, 219, pp.88-98.
[24] Gao, H., Yang, Y., Li, C., Zhou, H. and Qu, X., 2018. Joint alternate small convolution and feature reuse for hyperspectral image classification. ISPRS International Journal of Geo-Information, 7(9), p.349.
[25] Wu, H. and Prasad, S., 2017. Convolutional recurrent neural networks forhyperspectral data classification. Remote Sensing, 9(3), p.298.
[26] Huang, Q., Li, W. and Xie, X., 2018, June. Convolutional neural network for medical hyperspectral image classification with kernel fusion. In BIBE 2018; International Conference on Biological Information and Biomedical Engineering (pp. 1-4). VDE.
[27] Li, J., Zhao, X., Li, Y., Du, Q., Xi, B. and Hu, J., 2018. Classification of hyperspectral imagery using a new fully convolutional neural network. IEEE Geoscience and Remote Sensing Letters, 15(2), pp.292-296.
[28] Haut, J.M., Paoletti, M.E., Plaza, J., Plaza, A. and Li, J., 2019. Hyperspectral image classification using random occlusion data augmentation. IEEE Geoscience and Remote Sensing Letters, 16(11), pp.1751-1755.
[29] Ding, C., Li, Y., Xia, Y., Wei, W., Zhang, L. and Zhang, Y., 2017. Convolutional neural networks based hyperspectral image classification method with adaptive kernels. Remote Sensing, 9(6), p.618.
[30] Chen, Y., Zhu, L., Ghamisi, P., Jia, X., Li, G. and Tang, L., 2017. Hyperspectral images classification with Gabor filtering and convolutional neural network. IEEE Geoscience and Remote Sensing Letters, 14(12), pp.2355-2359.
[31] Ran, L., Zhang, Y., Wei, W. and Zhang, Q., 2017. A hyperspectral image classification framework with spatial pixel pair features. Sensors, 17(10), p.2421.
[32] Paoletti, M.E., Haut, J.M., Plaza, J. and Plaza, A., 2018. A new deep convolutional neural network for fast hyperspectral image classification. ISPRS journal of photogrammetry and remote sensing, 145, pp.120-147.
[33] Li, S., Zhu, X., Liu, Y. and Bao, J., 2019. Adaptive spatial-spectral feature learning for hyperspectral image classification. IEEE Access, 7, pp.61534-61547.
[34] Li, Y., Zhang, H. and Shen, Q., 2017. Spectral–spatial classification of hyperspectral imagery with 3D convolutional neural network. Remote Sensing, 9(1), p.67.
[35] Zhang, H., Li, Y., Zhang, Y. and Shen, Q., 2017. Spectral-spatial classification of hyperspectral imagery using a dualchannel convolutional neural network. Remote sensing letters, 8(5), pp.438-447.
[36] Dong, H., Zhang, L. and Zou, B., 2019. Band attention convolutional networks for hyperspectral image classification. arXiv preprint arXiv:1906.04379.
[37] Cheng, G., Li, Z., Han, J., Yao, X. and Guo, L., 2018. Exploring hierarchical convolutional features for hyperspectral image classification. IEEE Transactions on Geoscience and Remote Sensing, 56(11), pp.6712-6722.

[38] Zhong, P., Peng, N. and Wang, R., 2015. Learning to diversify patch-based priors for remote sensing image restoration. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 8(11), pp.5225-5245.
[39] Liu, L., Shi, Z., Pan, B., Zhang, N., Luo, H. and Lan, X., 2020. Multiscale deep spatial feature extraction using virtual RGB image for hyperspectral imagery classification. Remote Sensing, 12(2), p.280.
[40] Sellami, A., Farah, M., Farah, I.R. and Solaiman, B., 2019. Hyperspectral imagery classification based on semisupervised 3-D deep neural network and adaptive band selection. Expert Systems with Applications, 129, pp.246-259.
[41] Mei, S., Ji, J., Geng, Y., Zhang, Z., Li, X. and Du, Q., 2019. Unsupervised spatial–spectral feature learning by 3D convolutional autoencoder for hyperspectral classification. IEEE Transactions on Geoscience and Remote Sensing, 57(9), pp.6808-6820
[42]Chen, C., Li, Y., & Liao, W. (2016). Deep feature extraction and classification of hyperspectral images based on convolutional neural networks. IEEE Transactions on Geoscience and Remote Sensing, 54(10), 6232-6251.
[43]Ma, L., Cheng, G., Li, J., & Zhao, D. (2016). Hyperspectral image classification using deep pixel-pair features. IEEE Transactions on Geoscience and Remote Sensing, 54(8), 4808-4822.

[44]Luo, H., Zhang, Y., Tao, D., & Huang, H. (2018). Hyperspectral image classification with deep learning models. IEEE Transactions on Geoscience and Remote Sensing, 56(9), 5408-5423.
[45]Li, S., He, J., Zhang, Y., & Chen, C. (2019). Hyperspectral image classification with deep spectral-spatial feature extraction and stacked sparse autoencoder. IEEE Transactions on Geoscience and Remote Sensing, 57(11), 8475-8490.
[46]Zhang, Z., Zhang, C., Du, B., & Liu, Q. (2018). Deep convolutional neural networks for hyperspectral image classification. Remote Sensing, 10(11), 1722.
[47]B. Xue, M. Zhang, W. N. Browne and X. Yao, "A Survey on Evolutionary Computation Approaches to Feature Selection," in IEEE Transactions on Evolutionary Computation, vol. 20, no. 4, pp. 606-626, Aug. 2016, doi: 10.1109/TEVC.2015.2504420.
[48]J. Zhang et al., "Evolutionary Computation Meets Machine Learning: A Survey," in IEEE Computational Intelligence Magazine, vol. 6, no. 4, pp. 68-75, Nov. 2011, doi: 10.1109/MCI.2011.942584.
[49]Li, R.; Zhang, H.; Chen, Z.; Yu, N.; Kong, W.; Li, T.; Wang, E.; Wu, X.; Liu, Y. Denoising method of ground-penetrating radar signal based on independent component analysis with multifractal spectrum. Measurement **2022**, 192, 110886.
[50]Xie, S. Feature extraction of auto insurance size of loss data using functional principal component analysis. Expert Syst. Appl. **2022**, 198, 116780.
[51]Liu, Q.; He, H.; Liu, Y.; Qu, X. Local linear embedding algorithm of mutual neighborhood based on multi-information fusion metric. Measurement **2021**, 186, 110239.
[52]Ding, X.; Li, H.; Yang, J.; Dale, P.; Chen, X.; Jiang, C.; Zhang, S. An improved ant colony algorithm for optimized band selection of hyperspectral remotely sensed imagery. IEEE Access **2020**, 8, 25789–25799.
[53]Zhang, A.; Ma, P.; Liu, S.; Sun, G.; Huang, H.; Zabalza, J.; Wang, Z.; Lin, C. Hyperspectral band selection using crossover-based gravitational search algorithm. IET Image Processing **2019**, 13, 280–286.
[54]Ambusaidi, M.A.; He, X.; Nanda, P.; Tan, Z. Building an intrusion detection system using a filter-based feature selection algorithm. IEEE Trans. Comput. **2016**, 65, 2986–2998.
[55]Wah, Y.B.; Ibrahim, N.; Hamid, H.A.; Abdul-Rahman, S.; Fong, S. Feature Selection Methods: Case of Filter and Wrapper Approaches for Maximising Classification Accuracy. Pertanika J. Sci. Technol. **2018**, 26, 329–340.
[56]Ghosh, M.; Guha, R.; Sarkar, R.; Abraham, A. A wrapper-filter feature selection technique based on ant colony optimization. Neural Comput. Appl. **2020**, 32, 7839–7857.
[57]Wang, J.; Tang, C.; Li, Z.; Liu, X.; Zhang, W.; Zhu, E.; Wang, L. Hyperspectral band selection via region-aware latent features fusion based clustering. Inf. Fusion **2022**, 79, 162–173.
[58]Shi, J.; Zhang, X.; Liu, X.; Lei, Y.; Jeon, G. Multicriteria semi-supervised hyperspectral band selection based on evolutionary multitask optimization. Knowl. -Based Syst. **2022**, 240, 107934.
[59]Nagasubramanian, K.; Jones, S.; Sarkar, S.; Singh, A.K.; Singh, A.; Ganapathysubramanian, B. Hyperspectral band selection using genetic algorithm and support vector machines for early identification of charcoal rot disease in soybean stems. Plant Methods **2018**, 14, 86.
[60]Xie, F.; Li, F.; Lei, C.; Yang, J.; Zhang, Y. Unsupervised band selection based on artificial bee colony algorithm for hyperspectral image classification. Appl. Soft Comput. **2019**, 75, 428–440.
[61]Wang, M.; Wu, C.; Wang, L.; Xiang, D.; Huang, X. A feature selection approach for hyperspectral image based on modified ant lion optimizer. Knowl. -Based Syst. **2019**, 168, 39–48.
[62]Wang, M.; Liu, W.; Chen, M.; Huang, X.; Han, W. A band selection approach based on a modified gray wolf optimizer and weight updating of bands for hyperspectral image. Appl. Soft Comput. **2021**, 112, 107805.
[63]Kavitha, K.; Jenifa, W. Feature Selection Method for Classifying Hyper Spectral Image Based on Particle Swarm Optimization. In Proceedings of the 2018 International Conference on Communication and Signal Processing (ICCSP), Chennai, India, 3–5 April 2018; pp. 119–123.
[64]Medjahed, S.A.; Saadi, T.A.; Benyettou, A.; Ouali, M. Binary cuckoo search algorithm for band selection in hyperspectral image classification. IAENG Int. J. Comput. Sci. **2015**, 42, 183–191.
[65]Su, H.; Yong, B.; Du, Q. Hyperspectral band selection using improved firefly algorithm. IEEE Geosci. Remote Sens. Lett. **2015**, 13, 68–72.
[66]Turky, A.; Sabar, N.R.; Dunstall, S.; Song, A. Hyper-heuristic local search for combinatorial optimisation problems. Knowl. -Based Syst. 2020, 205, 106264.

[67]P. R. Sekhar and B. Sujatha, "A Literature Review on Feature Selection using Evolutionary Algorithms," 2020 7th International Conference on Smart Structures and Systems (ICSSS), Chennai, India, 2020, pp. 1-8, doi: 10.1109/ICSSS49621.2020.9202257.
[68]Ye Z, Cai W, Liu S, Liu K, Wang M, Zhou W. A Band Selection Approach for Hyperspectral Image Based on a Modified Hybrid Rice Optimization Algorithm. Symmetry. 2022; 14(7):1293. https://doi.org/10.3390/sym14071293.
[69]Nagasubramanian, K.; Jones, S.; Sarkar, S.; Singh, A.K.; Singh, A.; Ganapathysubramanian, B. Hyperspectral band selection using genetic algorithm and support vector machines for early identification of charcoal rot disease in soybean stems. Plant Methods 2018, 14, 86.
[70]X. Ding et al., "An Improved Ant Colony Algorithm for Optimized Band Selection of Hyperspectral Remotely Sensed Imagery," in IEEE Access, vol. 8, pp. 25789-25799, 2020, doi: 10.1109/ACCESS.2020.2971327.
[71]Pablo Ribalta Lorenzo, Jakub Nalepa, Luciano Sanchez Ramos, and José Ranilla Pastor. 2017. Hyper-parameter selection in deep neural networks using parallel particle swarm optimization. In Proceedings of the Genetic and Evolutionary Computation Conference Companion (GECCO '17). Association for Computing Machinery, New York, NY, USA, 1864–1871. https://doi.org/10.1145/3067695.3084211
[72]Y. Lecun, L. Bottou, Y. Bengio and P. Haffner, "Gradient-based learning applied to document recognition," in Proceedings of the IEEE, vol. 86, no. 11, pp. 2278-2324, Nov. 1998, doi: 10.1109/5.726791.