

Original Article

Hyperspectral Image Classification based on Improved Whale Optimization Algorithm, Deep Convolution Network and Bidirectional Long Short-Term Memory

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Abstract - Hyperspectral Image Classification (HIC) is very crucial for the different remote sensing applications because of its rich spectral-spatial properties. In the last decade, various Machine Learning (ML) and Deep Learning (DL)-based HICs have been proposed to improve system accuracy. However, the effectiveness of HIC systems is highly challenging due to a greater number of spectral bands, complexity within each band, class imbalance, greater intricacy of DL frameworks, and poor spatial-spectral and temporal correlations across bands. This paper presents an HIC system based on a Deep Convolutional Neural Network and Bidirectional Long Short-Term Memory (DCNN-BiLSTM) to improve the spatial, spectral, and temporal representations of the spectral bands. Furthermore, it employs an Improved Whale Optimization Algorithm (IWOA) for spectral band selection, thereby minimizing the computational intricacy of the HIC system. The IWOA-DCNN-BiLSTM provides an Overall Accuracy (OA) of 99.39%, a recall of 99.31%, a precision of 99.40%, and an F1-score of 99.35% for the Indian Pines Dataset (IPD). The proposed IWOA-based band selection scheme offers lower computational complexity and higher HIC accuracy than traditional techniques.

Keywords - Hyperspectral Image Classification, Whale optimization algorithm, Deep Learning, Convolution Neural Network.

1. Introduction

Hyperspectral Image Classification is important for applications such as mineral identification, land mapping, urban planning, vegetation detection, crop monitoring, water quality analysis, object recognition, healthcare, and military systems [1-5]. The HSI contains rich spatial and spectral information about objects. The HSI consists of more than 100 spectral bands depicting precise information about objects. HSIs can distinguish objects based on their spectral signatures, including texture, color, and shape [6]. Hyperspectral Image Classification is the process of assigning a unique label to every pixel in an image based on the spectral-spatial signature of objects. Accurate HIC is very crucial for understanding the material type and composition of the objects [7].

However, the effectiveness of the HIC system is hindered by the spectral variability, high dimensionality, and data redundancy of HSIs [8, 9]. The larger bands increase the computational complexity of the HIC system. Obtaining correctly labeled data is a time-consuming and labor-intensive task. The limited availability of data and disparities in the training samples lead to class imbalance. Higher spatial

resolution increases the complexity of the overall HIC system [10, 11]. Various intelligent techniques based on ML and DL methods has been employed for HIC in recent years. These algorithms consider the multiband signature to classify objects in images [12].

However, the HIC's effectiveness is limited by numerous spectral bands and low spatiotemporal variation. HIC systems face data scarcity and class imbalance due to limited labeled samples. Sensor noise, material variations, and environmental factors reduce spectral distinctiveness, while complex architectures increase training time and the number of trainable parameters [13].

Thus, there is a need to minimize the computational complexity of the HIC system and improve its classification accuracy [14]. There is a need to enhance the distinctive power of HSIs' complex spectral signatures. This article presents a DL-based HIC using a DCNN-BiLSTM to improve spectral-spatial correlation and long-term connectivity in the spectral signatures of HSIs [15]. The major contributions of the article are summarized as follows:



- Development of the lightweight hybrid DCNN-BiLSTM framework for HIC, where DCNN provides the correlation in spectral signatures, and BiLSTM helps to acquire the long-term and temporal depiction of the spectral bands.
- Development of an improved WOA for spectral band selection to minimize computational complexity and improve the accuracy of the DL-based HIC model. The improved WOA dynamically tunes factor A, which determines whether a whale follows the leader, to ensure diversity in the whale population. Further, it uses a weak member to improve exploitation and search space. The IWOA helps improve convergence, solution diversity, parameter tuning, and the exploration-exploitation balance.

The article is organized as follows: Section 2 describes the proposed DCNN-BiLSTM-IWOA-based HIC system, Section 3 deliberates the experimental results of HIC, and Section 4 presents the inferences of the HIC system and future scope.

2. Review of Literature

Various ML and DL-based systems have been proposed for the HIC. The general framework for the HIC comprises band selection, feature representation, classification, and performance evaluation. Zhang et al. [15] explored a Graph-based Convolutional Network (GCN) to capture the spectral and spatial properties of hyperspectral images for the HIC. It provided superior spatial, inter-cluster, and intra-cluster feature depiction. It provided an OA of the 98.48% for WHU-Hi-HongHu, 98.33% for WHU-Hi-HanChuan, and 94.22% for the YRD-GF-5 dataset.

However, the results of the HIC system are challenging due to poor temporal representation, class imbalance, and difficulties in graph construction. Further, Wu et al. [16] presented the Spectral-Spatial Dual-Branch Fusion Transformer (S2DBFT), which employs a weighted fusion of the spatial and spectral attributes of hyperspectral images.

Although it has yielded promising results across various HIC datasets, its effectiveness is limited by the system's high computational complexity, which hinders standalone deployment on resource-constrained devices. Shang et al. [17] explored a DL model, ConvGRU, that combines a CNN and a Gated Recurrent Unit (GRU) with a spectral-spatial attention mechanism to enhance HIC performance. The suggested ConvGRU helps to improve the correlation between the local and global spatial-spectral attributes of hyperspectral images.

Transformer-based models, such as the tensor transformer [18], the Hybrid Conv-ViT Network (HCVN) [19], and the morphological transformer [20], have been extensively used in HIC to improve the representation of

spectral information. Transformer models provide superior spectral-spatial representation for hyperspectral object detection, but their high complexity, memory demands, and large training data requirements hinder real-time deployment on resource-constrained devices. Convolution-based DL models offer better spatial characterization but lack long-term spectral representation [21-24].

In recent years, various advanced DL techniques have been presented for HIC. Ahmad et al. [25] presented a Multiscale Transformer Model with Spatial Attention (MTSA-Net) to improve generalization capability and capture long-term dependencies in HSIs. It extracts the spatial features using 2D and 3D convolutions followed by a spatial attention mechanism. The multiscale transformer model helps to grab the local-global characteristics of the HSIs to improve the HIC accuracy. The MTSA-Net achieved mean accuracies of 95.87% for Houston-18, 97.84% for Houston-13, 99.80% for Salinas, 98.77% for Pavia, and 98.84% for Indian Pines. However, real-time deployment of the system is challenging due to the model's high computational complexity.

Zhang et al. [26] suggested the Kolmogorov-Arnold Network (KAN) along with Neural Ordinary Differential Equations (Neural ODEs) to capture complex patterns and spectral-spatial correlations in HSIs for HIC. The KANODE model helped acquire trajectories of feature variations and enhanced complex feature generalization. Gendy et al. [27] suggested that MAMBA techniques offer lower complexity than transformers and offer long-term depiction in latent data for HIC. The multi-kernel convolution used in MAMBA helps capture global and local spatiotemporal correlations.

Liao et al. [28] offered a Hybrid Attention Network (ATN-Hybrid) for depicting the intricate feature relationships in the spectral bands of HSIs. The ATN-Hybrid consists of deterministic and probabilistic branches. The deterministic branch offers normalization and channel mapping to prove stability in feature weights, whereas the probabilistic branch uses a soft attention scheme for feature selection. It offered improved accuracy of 96.01% for Indian Pines, 95.23% for Pavia, 97.37% for KSC, and 95.99% for Salinas.

Yan et al. [29] proposed a Semantic-Anchor-Enhanced Prototype Learning (SAEPL) model for developing the HIC system that works under sample-scarcity and cross-domain conditions. Data augmentation based on dynamic adaptive spatial occlusion is employed to model real-time spatial degradation. The SEPL achieved an OA of 81.35% for Houston, 80.49% for Indian Pines, and 93.22% for the Salinas dataset.

Traditional DL techniques fail to characterize the irregular spatial properties of natural HSIs. Zhang et al. [30] proposed the Hypergraph Cooperative Graph Convolutional Network (HCoGCN) to capture correlations among

heterogeneous regions of HSIs for HIC. It achieved OA of 95.49% for the QUH-Qingyun, 97.66% for the QUH-Pingan, and 98.75% for the QUH-Tangdaowan datasets. Wang et al. [31] suggested context-aware autoencoders for HIC to capture contextual information via contrastive learning. The autoencoders help to retain the topological structure and latent depiction of the HSIs.

The results of traditional transformer, CNN, and Mamba techniques for HIC are limited due to the loss of spatial correlation, increased complexity, and greater spectral redundancy. Yang et al. [32] proposed localized LMamba to improve local spatial correlation, minimize complexity, and reduce spectral redundancy by using multi-scale kernels.

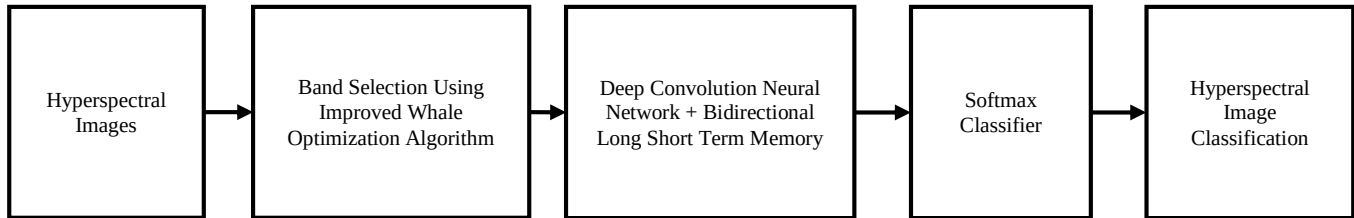


Fig. 1 Flow diagram of DCNN-BiLSTM-IWOA-based HIC system

Various band selection techniques have been proposed to minimize the computational complexity of DL-based HIC systems by selecting highly informative spectral bands. Shinde and Patidar [33] proposed a patch-based DCNN with PCA-based spectral band selection, achieving 98.20% accuracy on the IPD.

However, PCA considers only band variance, leading to low-entropy band selection, reduced spectral-spatial representation, and limited generalization capability. Further, Shinde and Patidar [34] proposed a Linear Discriminant Analysis (LDA)-based band selection method that considers intra-class and inter-class variance across spectral bands for a Lightweight Compact DCNN (LC-DCNN). The LDA-LC-DCNN achieved an OA of 99% on the IPD.

Thus, from the extensive survey of HIC techniques, the following major research gaps are analysed:

- Huge computational complexity of HIC systems because of larger spectral bands.
- Lower feature depiction because of the higher complexity on spectral pattern in the HSIs.
- Lower spectral-spatial correlation and long-term connectivity in spectral bands of HSIs leads to poor accuracy.
- Inferior band selection because of poor convergence, lower search space and limited balance in exploration-exploitation of optimization algorithms utilized for band selection [25, 26].
- Class imbalance issue due to uneven classes in HSIs leads to poor precision and F1-score.

3. Methodology

The proposed HIC system includes improved WOA-based band selection, DCNN-BiLSTM feature extraction, and Softmax classification, as shown in Figure 1. Band selection reduces computational complexity by removing redundant and non-essential spectral information, while DCNN-

BiLSTM captures strong spatiotemporal correlations and long-term spectral representations. The selected bands possess higher spectral quality, variance, and entropy, improving HIC performance.

3.1. Spectral Band Selection using Improved WOA

WOA is a metaheuristic that incorporates the social behavior of humpback whales in the ocean, as well as their bubble-hunting process. They are the largest animal in the world and one of seven unique whale species. Humpback whales are also the largest whales. More than anything else, they are famous for their hunting strategy, a bubble-net feeding scheme. The existence of spindle cells in whale brains is why they are considered intelligent aquatic animals.

They swim downside around 12 meters in the water, forming bubbles in spiralized shape around the prey. The leader whale, an experienced whale, hunts prey at random. Following the bubbles, they eventually swim upwards towards the surface [35]. The leader sends a synchronization request to the other whale.

- The leader whale is responsible for searching for the prey, diving around 12 meters below the prey, producing bubbles in the form of spirals to mislead the prey, and swimming in the direction of the bubbles in order to catch the prey.
- The leader whale is responsible for synchronizing the process of pursuing prey.
- The member whales attack their target while continuing to follow the leader.

The performance of the traditional WOA is limited due to the manual tuning of factor A, which governs the balance between exploration and exploitation.

The flow chart of the IWO-based band selection is provided in Figure 2.

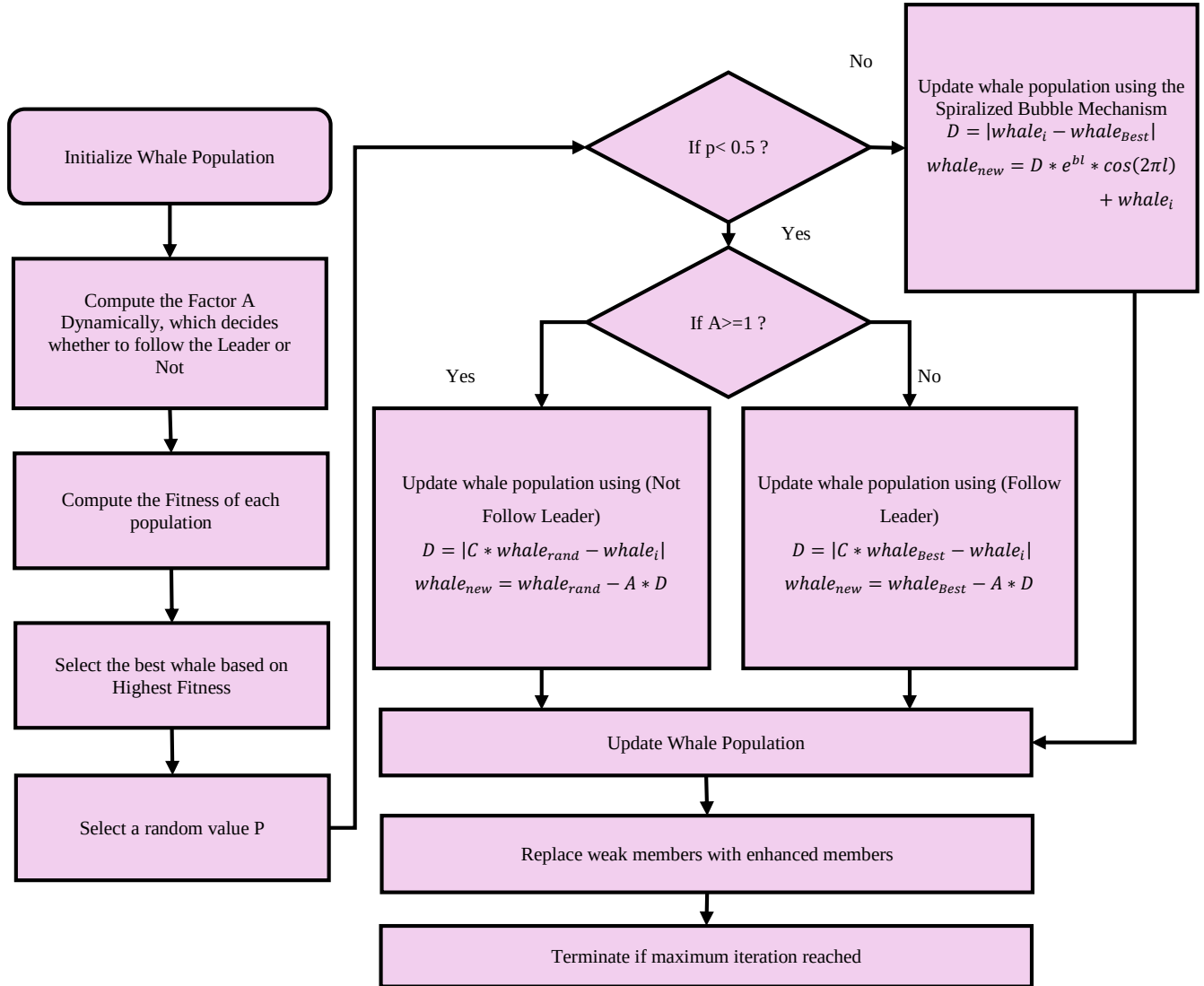


Fig. 2 Flow diagram of IWOA-based band selection for HIC

The steps in the band selection using WOA are summarized as follows:

Step 1: Initialize the whale population as $whale_i \in \{X_1, X_2, X_3, \dots, X_{NB}\}$ using Equations (1) and (2).

$$Whale_i = w_i = LB + r_1 * (UB - LB) \quad (1)$$

$$pop = \begin{bmatrix} w11 & w12 & w13 & \dots & w1n \\ w21 & w22 & w23 & & \dots & w2n \\ & & \dots & & & \\ & & \dots & & & \\ wN1 & wN2 & wN3 & \dots & \dots & wNn \end{bmatrix} \quad (2)$$

Here, LB is lower bound, UB is upper bound (denotes total bands in HIS), r_1 is a random number between 0 and 1.

Step 2: Compute A dynamically, which denotes the whale following factor (Traditionally chosen between 0 and 2 randomly) using Equation (3).

$$A = 2 * \left(1 - \left(\frac{iter}{maxIter}\right)^2\right) \quad (3)$$

Step 3: Compute the fitness for each population using Equation (4) based on Variance (V), Entropy (E), Spectral Dissimilarity (D) and Penalty (R).

$$Fitness = w_1 * V + w_2 * H + w_3 * D + w_4 * (1/R) \quad (4)$$

Here, $w_1 + w_2 + w_3 + w_4 = 1$ such that $w_1=0.35$, $w_2=0.30$, $w_3=0.25$, $w_4=0.10$, where higher weightage is given to variance and entropy of the spectral bands to get a distinctive spectral signature for HIC.

The variance (V) measures spatial intensity variations and texture richness within each selected band (X_k) among K bands as given in Equation (5).

$$V = \frac{1}{K} \sum_{k=1}^K \text{var}(X_k) \quad (5)$$

The entropy (H) quantifies the information content and uncertainty of each band, favoring informative spectral bands as given in Equation (6).

Here $p_k(i)$ denotes the probability of the i^{th} intensity level in the k^{th} band, and L represents the number of histogram bins.

$$H = -\frac{1}{K} \sum_{k=1}^K \left(\sum_{i=1}^L -p_{k(i)} \log_2 p_{k(i)} \right) (X_k) \quad (6)$$

The spectral dissimilarity encourages the selection of spectrally diverse bands by maximizing inter-band distance as given in Equation (7).

$$D = \frac{2}{K(K-1)} \sum_{i < j} \|X_i - X_j\|^2 \quad (7)$$

The penalty factor penalizes highly correlated bands to reduce redundant spectral information using Equation (8). Here, ρ_{ij} denotes the Pearson correlation coefficient between bands i and j .

$$R = \frac{1}{K(K-1)} \sum_{i < j} |\rho_{ij}| \quad (8)$$

Step 4: Exploration phase: Encircling the prey

During the hunting process, humpback whales will circle the prey. Following that, they consider the current best contender as the best possible answer.

By using Equations (9) and (10), the whales circumnavigate the target and launch their assault from the most advantageous position offered by the leader whale.

In the event that the value of A is less than one, the whale will follow the leader; otherwise, it will swim away from the leader.

$$D = \begin{cases} |C * \text{whale}_{\text{Best}} - \text{whale}_i| & \text{if } A < 1 \\ |C * \text{whale}_{\text{rand}} - \text{whale}_i| & \text{if } A \geq 1 \end{cases} \quad (9)$$

$$\text{whale}_{\text{new}} = \begin{cases} \text{whale}_{\text{Best}} - A * D & \text{if } A < 1 \\ \text{whale}_{\text{rand}} - A * D & \text{if } A \geq 1 \end{cases} \quad (10)$$

In this context, D denotes the distance between the whale and its prey. The term $\text{whale}_{\text{Best}}$ refers to the current best solution, whale_i represents the current location of the whale, and the values of the variables C and A are initialized arbitrarily in between $[-2, 2]$.

Step 5: Exploitation phase: Spiralized bubble formation mechanism

This level illustrates how the spiralized bubble formation approach may be used to assault the target.

By creating new bubbles, it combines the techniques of shrinking, encircling, and spiral updating to capture the target as given in Equation (11).

$$\text{whale}_{\text{new}} = D \otimes e^{bl} * \cos(2\pi l) + \text{whale}_i \quad (11)$$

In this context, the letter D denotes the disparity between the prey and the whale, the letter b represents the random variable range between 0 and 1, the letter l represents the random variable range between -1 and 1, and the symbol $\otimes$ denotes element-wise multiplication. Between 0 and 1, the probability of randomness determines which exploration and exploitation options are chosen, as given in Equation (12).

$$\text{whale}_{\text{new}} = \begin{cases} \text{whale}_{\text{Best}} - A * D & p \geq 0.5 \\ D \otimes e^{bl} * \cos(2\pi l) + \text{whale}_i & p < 0.5 \end{cases} \quad (12)$$

Step 6: Update the whale population and compute fitness for the updated population.

Step 7: Replace weak whales by stronger whales as given in Equation (13).

$$\text{whale}_{\text{new}} = \text{whale}_{\text{worst}} + \text{Rand}(1) * \text{Whale}_{\text{worst}} * \text{Whale}_{\text{Best}} \quad (13)$$

Step 8: Repeat steps 2-6 until all iterations exceed.

3.2. DCNN-BILSTM

The DCNN-BILSTM framework uses a 3-layer 1D-DCNN followed by 2 BiLSTM layers. The DCNN uses 64, 128, and 256 filters in three layers, followed by a Rectified Linear Unit (ReLU) layer and a Batch Normalization (BN) layer to enhance nonlinearity and standardize deep features, thereby enabling the learning of spatial correlations across different spectral bands. Furthermore, two BiLSTM layers with 50 units are employed after the third BN layer to enhance temporal and long-term modeling of the spectral signatures in hyperspectral images. Further, the fully connected layer enhances connectivity among different deep features by interlinking them. The softmax classifier maps the deep features to the HIC categories.

4. Results and Discussions

The suggested HIC system is simulated in MATLAB R2025b on a personal laptop with 20 GB of RAM and a Core i7 processor with 4GB of graphics memory. The parameter specifications of the DCNN-BiLSTM are summarized in Table 1.

Table 1. Parameter specification of the DCNN-BiLSTM

Parameter	Specification
Optimizer	Adam
Batch Size	16
Epoch	100
Momentum	0.8
Learning rate	0.001
Dropout	0.5
Loss Function	Cross-entropy
Train-Test Split	70:30

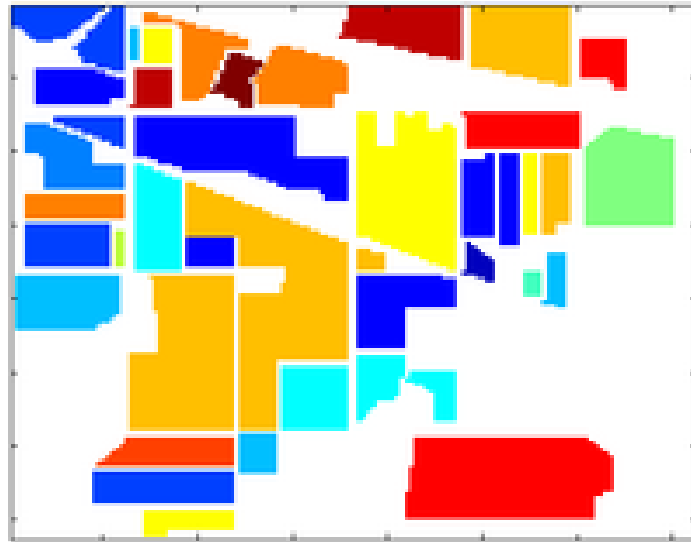
4.1. Dataset: Indian Pines

The experiments are conducted on the IPD, which consists of 220 spectral bands and 16 classes [36]. The images are available at 145×145 pixels, with a wavelength range of $0.4\text{--}2.5 \times 10^{-6}$ meters.

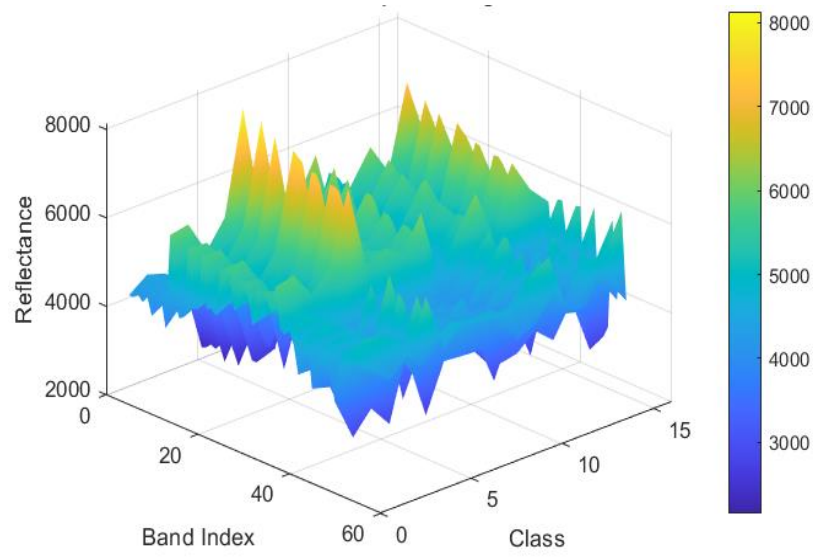
Figure 3 shows the original Indian Pines image, its ground truth, and spectral signature. Figure 4 provides several sample bands IPD.



(a)



(b)



(c)

Fig. 3 Visualizations of the IPD (a) IPD image, (b) Ground truth of IPD, and (c) Spectral signatures of IPD.

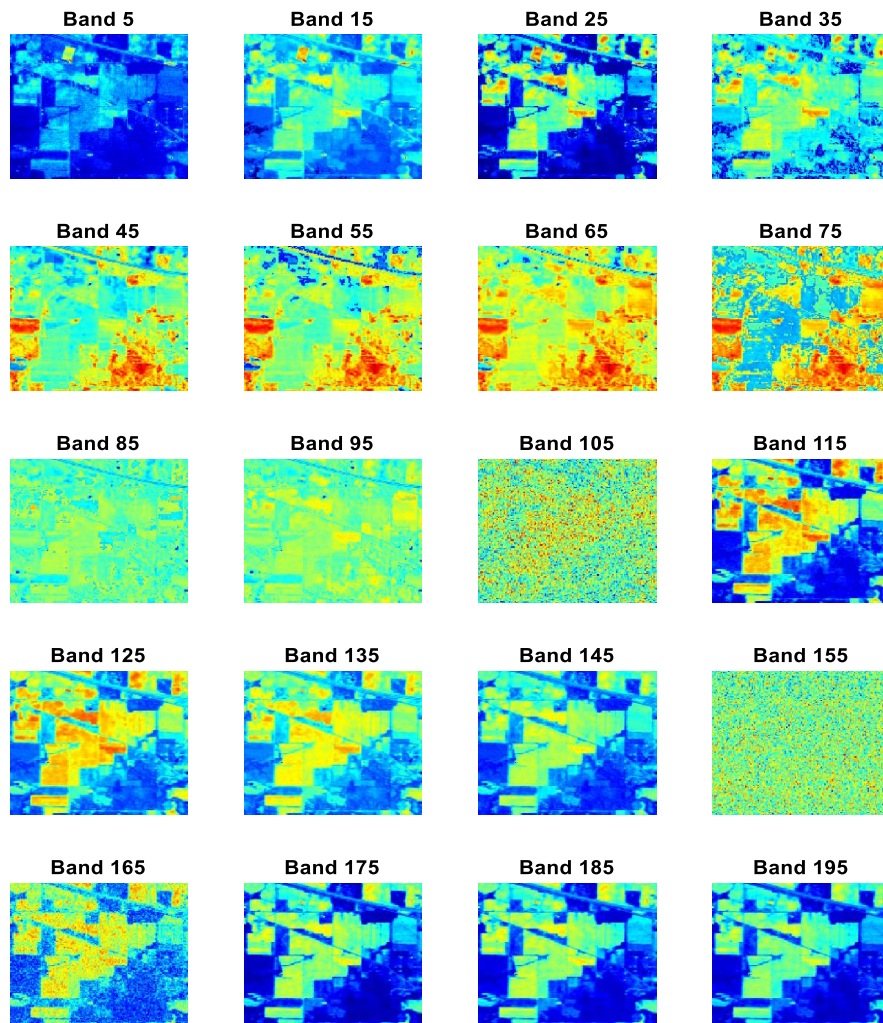


Fig. 4 Sample spectral bands from the IPD

4.2. Discussions and Results

Table 2 and Figures 5-8 show the comparative performance analysis of the WOA-DCNN-BiLSTM and the proposed IWOA-DCNN-BiLSTM models for Hyperspectral Image Classification using 100 selected spectral bands. The WOA-DCNN-BiLSTM-based model performed well on the alfalfa class with 85.70% accuracy, 100% precision, and 92.30% F1-score. The performance is significantly enhanced after incorporating the improved band selection strategy using IWOA, obtaining 96.20% accuracy, 93.00% recall, 95.00% precision, and an F1-score of 93.99%. This improvement shows that the optimal spectral bands selected by IWOA can effectively capture discriminative spectral information for challenging and low-sample classes. For agricultural crop classes such as corn-no-till, corn-min-till, and corn, both models achieved very high results. The WOA-DCNN-BiLSTM model achieved the accuracy of 99.80%, 99.60%, and 100%, respectively. The proposed IWOA-based framework maintained similar superior performance. In particular, the corn class was perfectly classified, with 100% accuracy, recall, precision, and F1-score for both methods, indicating the robustness of deep spectral-spatial feature extraction. The proposed IWOA method also achieved significant improvements for vegetation-related classes such as grass-pasture, grass-trees, and grass-pasture-mowed. The traditional method achieved 96.20% accuracy for the Grass-pasture-mowed class, while the improved method increased accuracy to 98.00% (with 99.00% recall and precision). This demonstrates that the band selection based on IWOA can effectively reduce the spectral redundancy and improve the class separability for vegetation categories.

The performance for hay-windrowed and oats classes also improved significantly. The WOA-based framework achieved 94.00% accuracy and 96.99% F1-score in the Oats class, while the proposed IWOA-DCNN-BiLSTM has achieved the perfect classification of 100% accuracy, recall, precision, and F1-score. The proposed framework outperformed the conventional method in soybean-related categories of soybean-no-till, soybean-minimum-till, and soybean-clean. Specifically, the soybean-mintill class increased from 93.20% accuracy and 94.50% F1-score under WOA to 98.00% accuracy and 99.00% F1-score using IWOA. Similarly, Soybean-clean achieved 100% accuracy across all metrics using the proposed method, demonstrating the effectiveness of improved band selection in handling highly correlated spectral information. The remaining classes, such as Wheat, Woods, Buildings-Grass-Trees-Drives, and Stone-Steel-Towers, also achieved great performance. Some classes obtained nearly perfect or perfect scores, indicating the high capability of the deep hybrid DCNN-BiLSTM classifier to extract spatial and sequential spectral features from hyperspectral data. Overall, the average performance values strongly support the superiority of the proposed IWOA-based framework. The classical WOA-DCNN-BiLSTM model achieved an average accuracy, recall, precision, and F1-score of 97.70%, 97.67%, 98.54%, and 98.07%, respectively. Conversely, the suggested IWOA-DCNN-BiLSTM model achieved significantly better average values of 99.39% accuracy, 99.31% recall, 99.40% precision, and 99.35% F1-score. The results verify the feasibility of the IWOA for selecting the most informative 100 spectral bands to mitigate redundancy and enhance the overall performance of HIC.

Table 2. DCNN-BiLSTM-based HIC performance for the different classes

S. No	Hyperspectral Class	WOA-DCNN-BiLSTM				IWOA-DCNN-BiLSTM			
		Accuracy	Recall	Precision	F1-Score	Accuracy	Recall	Precision	F1-Score
1	Alfalfa	85.70	85.70	100.00	92.30	96.20	93.00	95.00	93.99
2	Corn-notill	99.80	99.80	100.00	99.90	99.80	99.80	100.00	99.90
3	Corn-mintill	99.60	99.60	100.00	99.80	99.60	99.60	100.00	99.80
4	Corn	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
5	Grass-pasture	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
6	Grass-trees	99.50	99.50	100.00	99.75	99.50	99.50	100.00	99.75
7	Grass-pasture-mowed	96.20	93.00	95.00	93.99	98.00	99.00	99.00	99.00
8	Hay-windrowed	100.00	100.00	99.30	99.65	100.00	100.00	100.00	100.00
9	Oats	94.00	98.00	96.00	96.99	100.00	100.00	100.00	100.00
10	Soybean-notill	100.00	100.00	99.30	99.65	100.00	100.00	99.30	99.65
11	Soybean-mintill	93.20	95.00	94.00	94.50	98.00	99.00	99.00	99.00
12	Soybean-clean	96.10	93.00	95.00	93.99	100.00	100.00	100.00	100.00
13	Wheat	100.00	100.00	98.40	99.19	100.00	100.00	98.40	99.19
14	Woods	100.00	100.00	99.70	99.85	100.00	100.00	99.70	99.85
15	Buildings-Grass-Trees-Drives	99.10	99.10	100.00	99.55	99.10	99.10	100.00	99.55
16	Stone-Steel-Towers	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Average		97.70	97.67	98.54	98.07	99.39	99.31	99.40	99.35

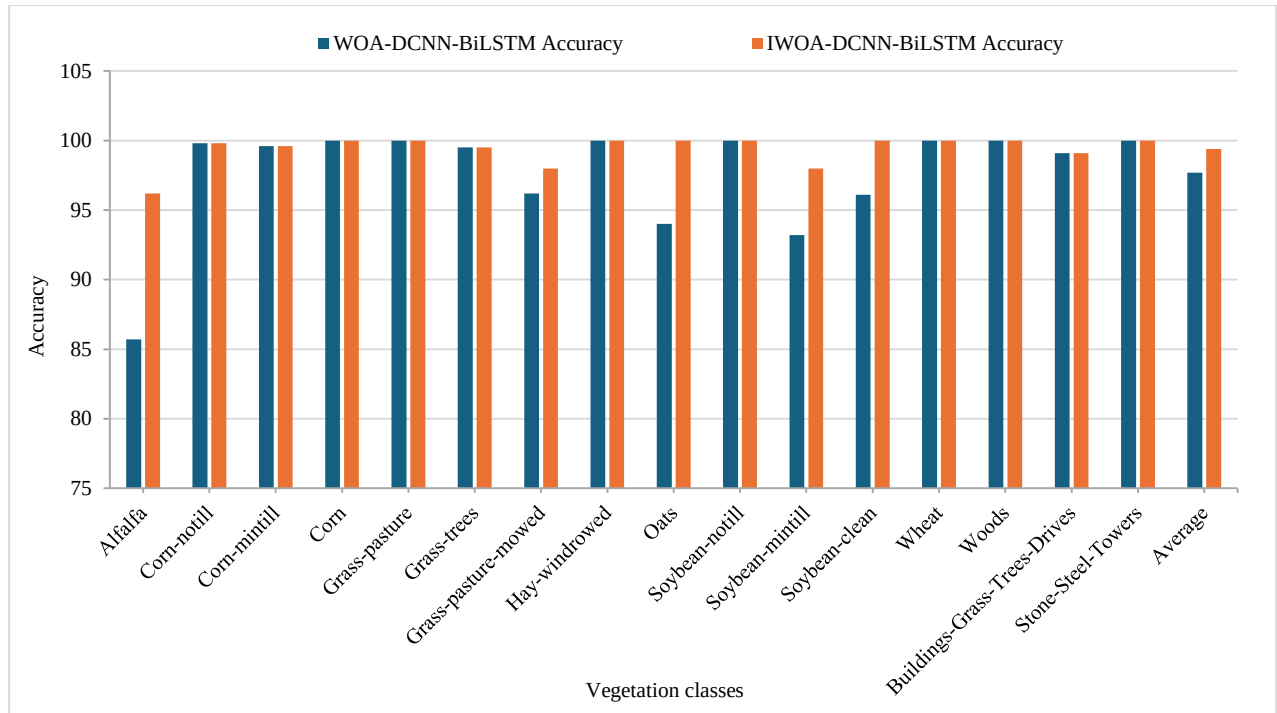


Fig. 5 Accuracy comparison for different vegetation classes for DCNN-BiLSTM

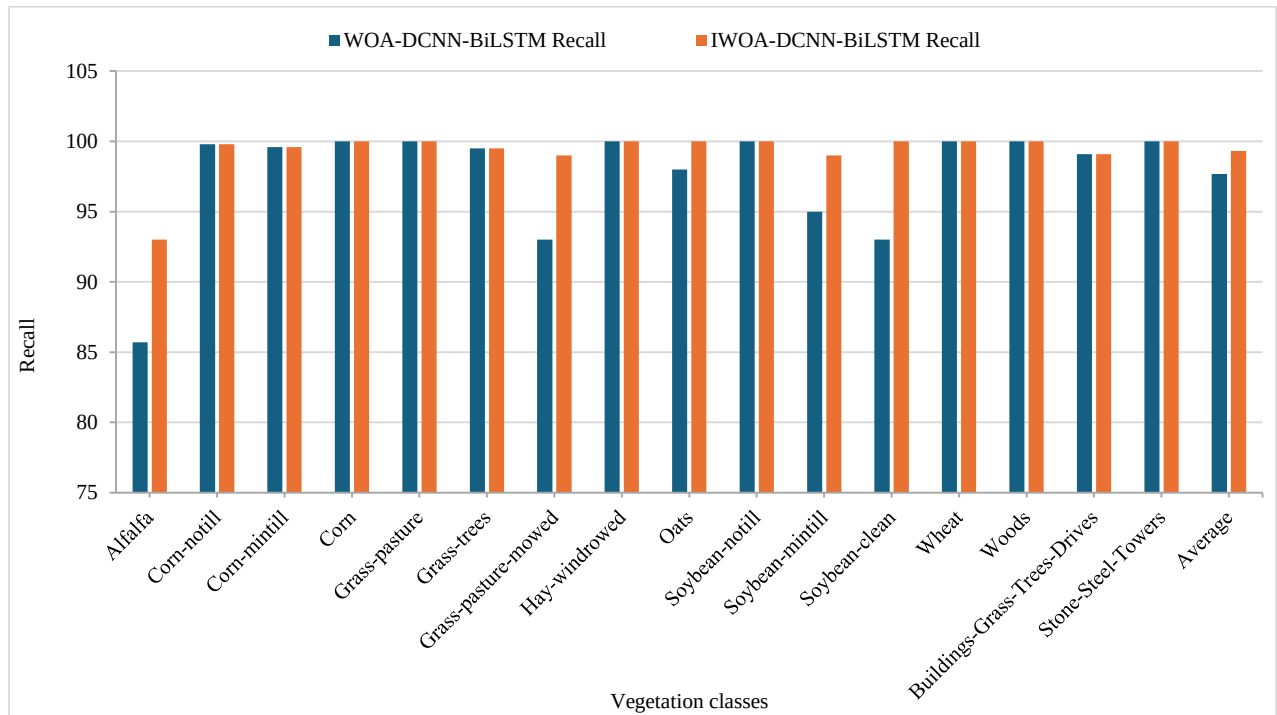


Fig. 6 Recall comparison for different vegetation classes for DCNN-BiLSTM

The comparison results for DCNN-BiLSTM-based Hyperspectral Image Classification across various spectral band selections, as given in Table 3 and Figure 9, show that the proposed model, IWOA-DCNN-BiLSTM, consistently outperforms the conventional model, WOA-DCNN-BiLSTM. At a smaller band selection like 10 bands, the WOA-based

model achieved 75.17% accuracy and 74.24% F1-score. The proposed IWOA method achieved 78.56% accuracy and 77.86% F1-score. An increase in the number of selected bands led to a significant improvement in classification performance for both methods. For the 50 bands, WOA-DCNN-BiLSTM achieved an accuracy of 92.44% and an F1-score of 93.37%,

while IWOA-DCNN-BiLSTM achieved an accuracy of 95.96% and an F1-score of 96.97%. The best overall performance was observed with 100 selected bands, where the proposed IWOA-DCNN-BiLSTM achieved 99.39% accuracy, 99.31% precision, 99.40% recall, and 99.35% F1-

score, outperforming the WOA-based model, which obtained 97.70% accuracy and 98.07% F1-score. Even with band selections beyond 100 bands, the proposed IWOA framework remains superior and more stable than the conventional WOA approach.

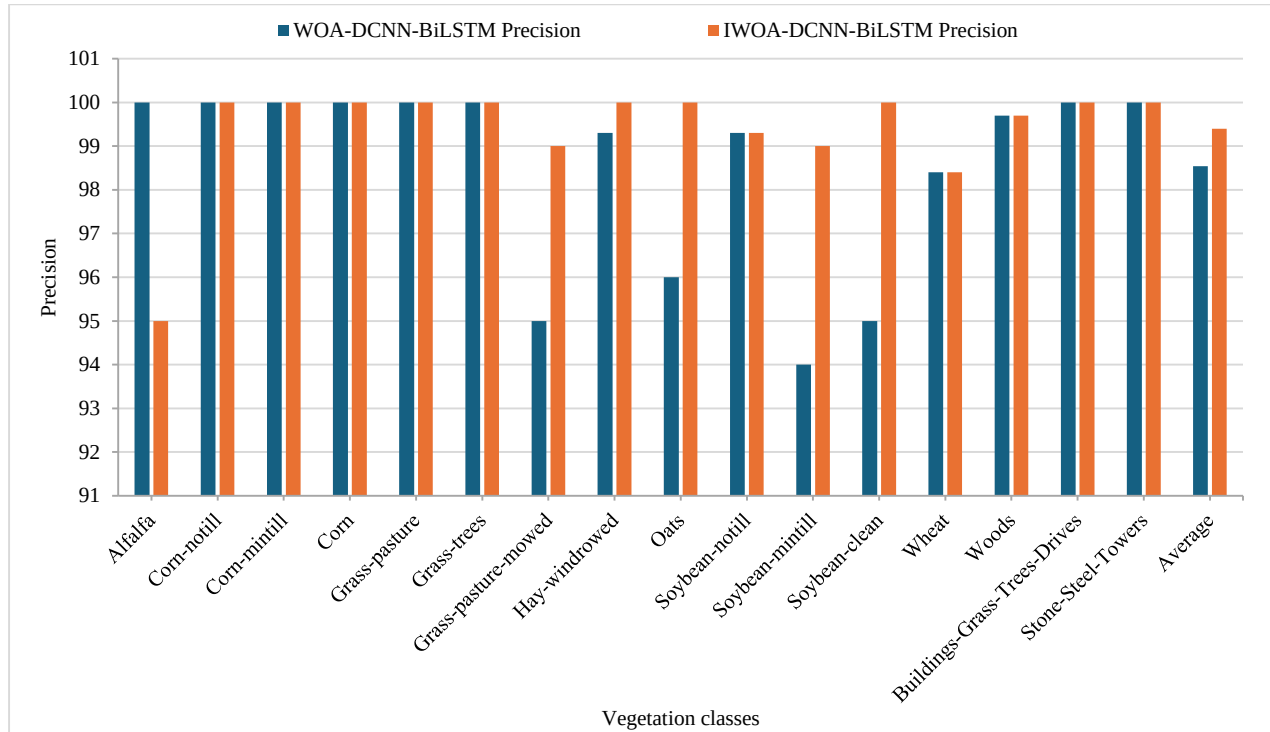


Fig. 7 Precision comparison for different vegetation classes for DCNN-BiLSTM

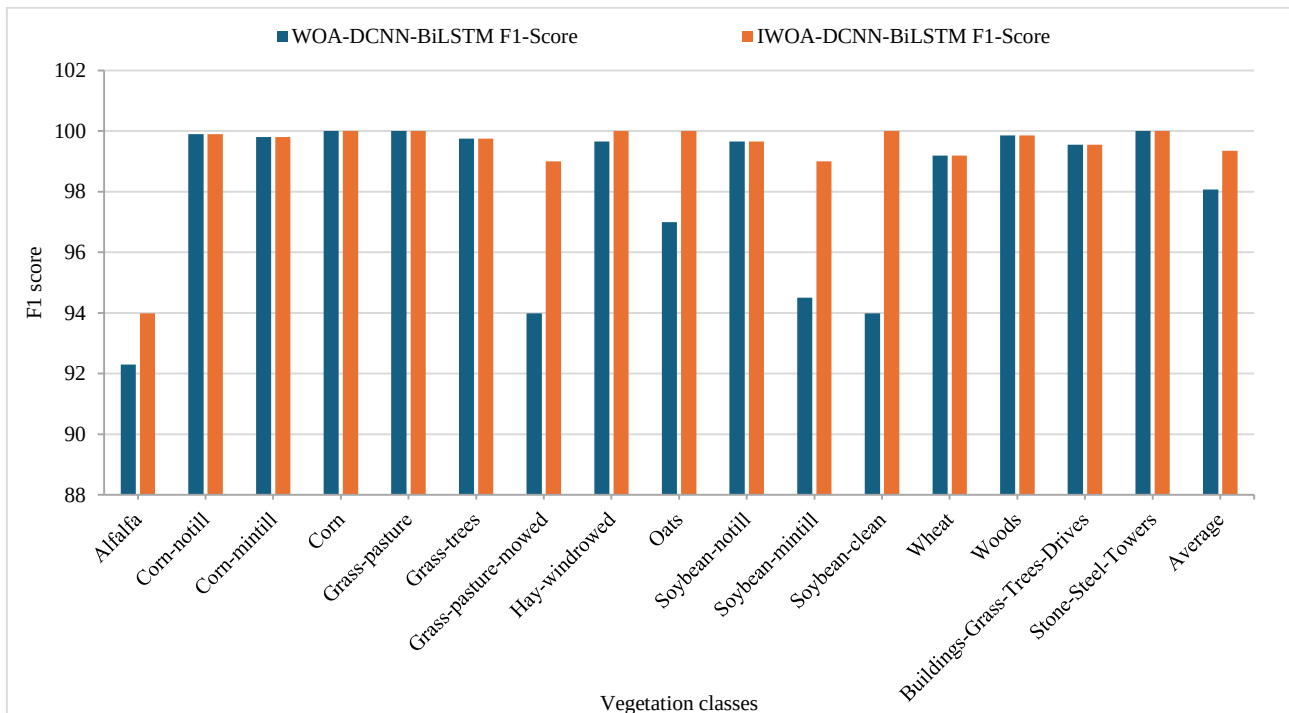


Fig. 8 F1-score comparison for different vegetation classes for DCNN-BiLSTM

Table 3. DCNN-BiLSTM-based HIC results comparison for different spectral band selection

Number of Bands	WOA-DCNN-BiLSTM				IWOA-DCNN-BiLSTM			
	Accuracy	Precision	Recall	F1-score	Accuracy	Precision	Recall	F1-score
10	75.17	73.13	75.39	74.24	78.56	76.17	79.62	77.86
20	89.57	88.82	84.83	86.78	92.62	93.00	88.63	90.77
30	94.98	97.54	95.42	96.47	91.26	93.90	90.03	91.92
40	90.94	95.73	91.50	93.57	95.03	99.60	95.59	97.55
50	92.44	94.37	92.40	93.37	95.96	97.67	96.28	96.97
60	91.59	95.19	88.25	91.59	95.82	98.22	91.77	94.88
70	88.60	94.54	87.81	91.05	92.84	97.53	91.67	94.51
80	90.29	90.64	87.34	88.96	93.54	93.73	90.85	92.26
90	93.81	89.92	87.26	88.57	97.48	93.04	90.86	91.94
100	97.70	97.67	98.54	98.07	99.39	99.31	99.40	99.35
110	92.38	88.58	89.91	89.24	98.08	100.00	99.65	100.00
120	89.05	93.35	88.31	90.76	97.46	92.86	91.49	92.17
130	91.79	88.65	87.77	88.21	95.59	95.17	92.47	93.80
140	89.90	93.49	90.86	92.16	96.37	91.72	92.89	92.30
150	90.10	89.06	84.69	86.82	95.54	97.18	91.32	94.16
160	92.83	87.75	87.42	87.58	95.28	92.76	92.06	92.41
170	91.20	90.75	88.23	89.47	94.17	96.44	93.73	95.07
180	92.64	97.11	88.54	92.63	93.03	93.13	87.73	90.35
190	90.75	82.19	81.71	81.95	96.92	91.83	90.95	91.39
200	88.40	91.84	87.05	89.38	94.48	93.76	92.09	92.92
210	87.68	90.16	86.73	88.41	96.32	100.00	91.43	95.69
220	91.79	91.50	89.34	90.41	94.45	85.72	85.37	85.54

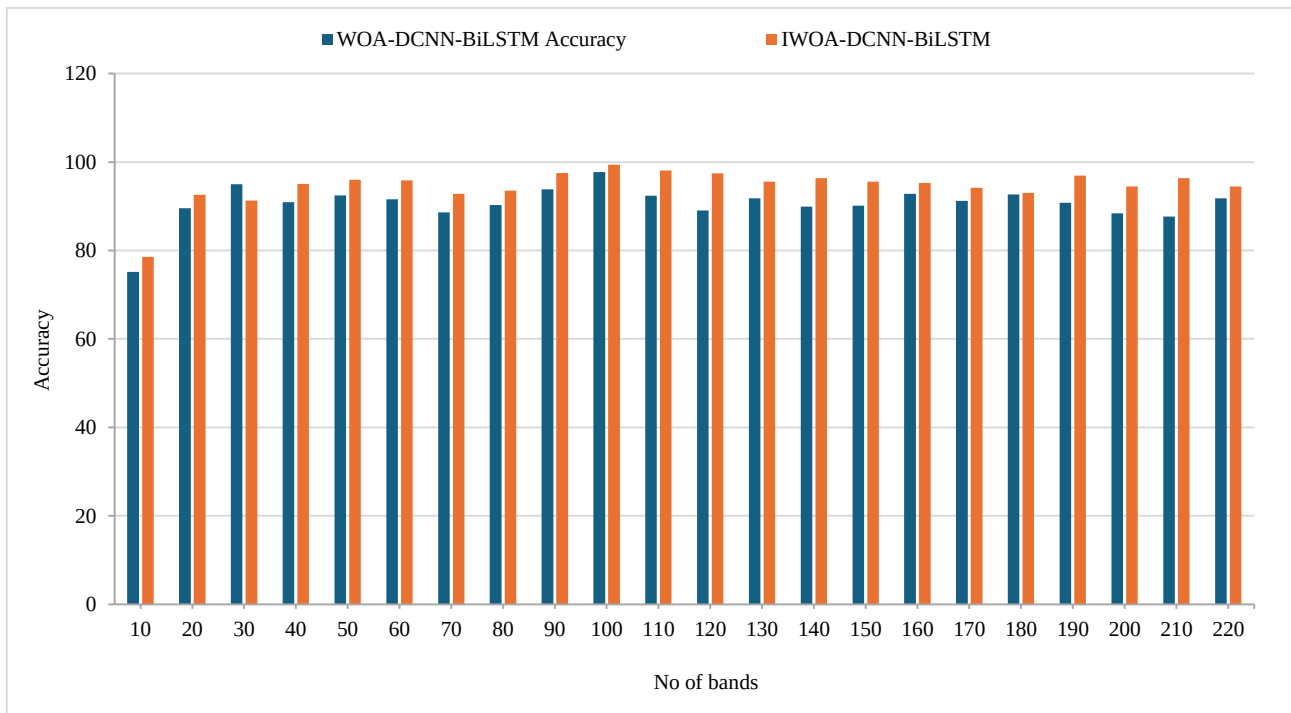
**Fig. 9 Accuracy comparison of DCNN-BiLSTM-based HIC for different band selection using WOA and IWOA**

Table 4 presents the training and testing times for the IP dataset across selected bands. Using all 220 bands, the system achieved 95.45% accuracy with 547.7 sec training and 0.087 sec testing time. Optimal performance was obtained with 100

bands, achieving 99.39% accuracy with 386.3 sec training and 0.078 sec testing time. Using 10 bands reduced training and testing times to 134.23 sec and 0.045 sec, respectively, but lowered accuracy to 78.56%.

Table 4. Training and testing time comparison for IWOA-DCNN-BiLSTM-based HIC for different bands

No of Bands	Accuracy	Training time (sec)	Testing time (sec)
10	78.56	134.23	0.045
50	95.96	259.38	0.067
100	99.39	386.3	0.078
150	94.45	487.6	0.081
220	95.54	545.7	0.087

Table 5. Results comparison of DCNN-BiLSTM-based HIC for Indian Pines

Method	Accuracy	Recall	Precision	F1-score
PCA-DCNN [25]	98.20	-	-	-
PCA-LC-DCNN [26]	98.5	98.0	100	98.9
LDA-LC-DCNN [26]	99.00	99.00	99.8	99.4
PSO-DCNN	89.01	91.91	87.46	89.63
PSO-BiLSTM	90.49	93.13	89.15	91.10
PSO-DCNN-BiLSTM	93.45	93.20	93.60	93.40
WOA-DCNN	90.31	90.69	90.50	90.58
IWOA-DCNN	93.00	95.00	94.00	94.50
WOA-BiLSTM	91.56	91.44	91.44	91.43
IWOA-BiLSTM	94.00	96.00	96.00	96.00
WOA-DCNN-BiLSTM	97.70	97.67	98.54	98.1
IWOA-DCNN-BiLSTM	99.39	99.31	99.40	99.35

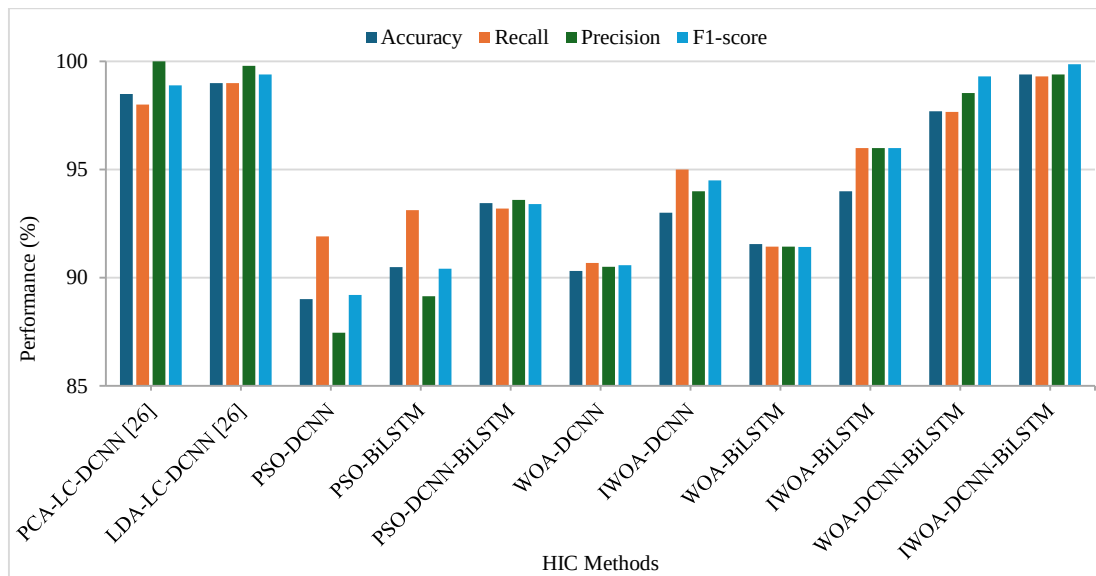
The results are compared with the traditional HIC techniques as given in Table 5 and Figure 10.

The PCA-based band selection achieved OA of 98.20% and 98.5% with the DCNN [25] and LC-DCNN [26], respectively, on the IP dataset. The LDA-based band selection achieves 99% accuracy, 99% recall, 99.4% F1-score, and 99.8% precision on the IP dataset.

The effectiveness of band selection is assessed for both the traditional PSO- and WOA-based approaches. The POS-based band selection provides OA of 93.45%, 90.49%, and 89.015%

for the DCNN-BiLSTM, BiLSTM, and DCNN, respectively, with 100 spectral bands. The WOA-based band selection achieves OA of 97.70% for the DCNN-BiLSTM, 91.56% for the BiLSTM, and 90.31% for the DCNN with 100 bands, compared to the PSO-based feature selection.

The IWOA achieves a recall of 99.31%, accuracy of 99.39%, and an F1-score of 99.87% on the IP dataset with 100 bands, representing a significant improvement over the traditional technique. The IWOA achieves an OA of 99.395% for DCNN-BiLSTM, 94% for BiLSTM, and 93% for DCNN on the IP dataset.

**Fig. 10 Results comparison for HIC for different algorithms**

5. Conclusion

Thus, this chapter presents the HIC based on the DCNN-BiLSTM, which helps improve the effectiveness of vegetation detection in hyperspectral images. The WOA-DCNN-BiLSTM achieves an OA of 97.70%, precision of 98.54%, recall of 97.67%, and F1-score of 98.07% for 16-class vegetation detection on the IPD. The IWOA-DCNN-BiLSTM achieves an OA of 99.39%, a recall of 99.31%, a precision of 99.40%, and an F1-score of 99.35%. The band selection significantly reduces computational complexity, training time, and testing time, and improves the HIC system's classification accuracy. The hybrid DCNN-BiLSTM model captures spectral, spatial, temporal, and long-term dependencies across spectral bands, achieving higher accuracy than either DCNN or BiLSTM-based HIC.

In the future, the system's effectiveness can be improved by incorporating a data augmentation scheme to mitigate data scarcity. Also, the model's generalization, explainability, and interpretability can be improved to enhance the HIC system's reliability.

Conflicts of Interest

The authors declare no conflict of interest.

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Data Availability Statement

Data will be made available on reasonable request.

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