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A Novel Wetland Detection and Classification Using Invasive Weed Optimization Algorithm with Deep Learning Model

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This research shows some of the worthy ecosystem services provided by wetlands are biodiversity support, water regulation, and carbon sequestration. These ecosystems are under threat due to human activities such as urbanization and industrialization, so their identification and classification are very important for their conservation. Synthesis aperture radar has been successful in detecting wetlands since it can penetrate through cloud covers and is sensitive to moisture content. Although promising Support Vector Machine (SVM) and Random Forest (RF) approaches, this still often requires high preprocessing and exhaustive handcrafted feature extraction. Deep learning models, especially Convolutional Neural Networks (CNNs), manage to improve classification performance but have problems with slow convergence rates and serious overfitting in big data. Based on these gaps, the paper presents a new approach proposing the integration of the modified Invasive Weed Optimization (IWO) algorithm with CNN-based detection for Synthetic Aperture Radar (SAR) images, focusing on wetland classification. Addressing the slow convergence problem and possible entrapment into a local optimum, enhanced IWO parameters in the CNN include learning rate and batch size. Also, to test the applied model, SAR data demonstrates a classification accuracy of about 90%, with key metrics such as precision at 88% and recall at 91% showing superior performance compared to that obtained using traditional techniques. Conclusively, the study states that the combination of CNN and the improved IWO algorithm highly enhances the accuracy of wetland detection, thereby providing a more robust solution for conducting environmental monitoring and conservation efforts.

Keywords: Convolutional Neural Networks, Deep Learning, Synthetic Aperture Radar, Wetland Detection.

1. Introduction

Wetlands are important natural resources that can provide many ecosystem services such as supporting biological and landscape diversity and regulating water availability and quality as well as acting as a sink for carbon. However, these environments are experiencing attempts at destruction due to various human activities including; urbanization agriculture, and industrialization among others. Wetland identification and categorization is therefore centrally significant in terms of environment assessment, protection, and management as well as in planning and zoning of land usage. This work also identified SAR as one of the most useful remote sensing technologies in wetland detection since it is not affected by cloud cover and provides high-resolution imagery (Khaitan et. al., 2022). In contrast with the optical sensors, the SAR data can sense the structure of the specific surface in a way that is very sensitive to the moisture content which makes them appropriate to use when identifying wetlands (Ludwig et al., 2019).

In the last few decades, different approaches have been tried and tested for wetland identification and mapping (Khaitan et. al., 2021). Previous methods were primarily based on visual interpretations or employing simple thresholding techniques that were constricted by the variety and dynamics of the wetland environment. These methods were even further limited by vegetation type, soil moisture, and water level differences in SAR backscatter signals. To overcome these challenges, a new approach of machine learning along with deep learning has been implemented to enhance the efficacy of detecting wetlands. Other machine learning methods including SVMs, RFs, and k-NN have been applied in classifying the wetland types using SAR imagery. However, these algorithms, of course, presuppose extensive preprocessing and feature extraction, and the quality and quantity of labeled training data usually serve as the key factors that define the algorithms' performance (Ziajahromi et al., 2020).

Recent trends in the remote sensing domain and satellite image analysis have been using deep learning models mainly convolutional neural networks (CNN) models. CNNs have shown the flexibility to learn the multifaceted features of the input data in an organized manner thus minimizing the time required to extract features manually. As applied to SAR data, CNNs can learn the detailed spatial distribution and textural properties of wetland areas. Some research suggests that CNNs compare favorably with the more traditional machine learning techniques because of classification accuracy and their learning capability of new data. However, there are some limitations in the present study as shown below: There are some shortcomings in improving deep learning approaches for wetland mapping, especially in terms of the model efficiency (Ballanti et al., 2017).

For training deep learning models, optimization algorithms are used with high significance, especially for controlling hyper-parameters that include the learning rates, batch sizes, and network structures. There are numerous proposed algorithms based on biological frameworks to improve the effectiveness of deep learning models for various purposes. Of these, the Invasive Weed Optimization (IWO) algorithm has attracted significant interest because of its simplicity and efficiency in solving various optimization problems. The population-based metaheuristic that underpins IWO is based on the colonizing behavior of weeds: the most competitive weeds will propagate and will replace other less competitive weeds in an environment over time thus rendering the best solution. In the context of deep learning, IWO can be used to optimize model parameters and in the process enhance the convergence rates of the models used in current deep learning architectures (O'Neil et al., 2020) (Nilanjana et.

al. 2021).

However, the IWO algorithm based on the standard possesses some drawbacks: slow convergence in the high dimensional search space, and it became easily stuck in certain areas of the local optima. Thus, some modifications have been suggested in the literature to address the above issues, the basic modifications include the hybrid of IWO with the other optimization techniques such as PSO and GA. IWO improved versions have confirmed improved performance for other optimization solutions, however; their adaptation in detecting wetlands using SAR remains quite unknown (Lei et al., 2023).

The main objective of this research is to propose a new framework for identifying and categorizing wetlands from SAR data through the enhancement of the IWO algorithm with a DL model. The research to a large extent indicates that the method proposed here eliminates the shortcomings of the existing machine learning approach and the standard IWO optimization approach by integrating solutions that enhance machine learning convergence speed and classification accuracy. In particular, we suggest improvements in the functioning of the IWO algorithm, concerned with proximity to adapt the necessary strategies for the population diversity regulation and convergence control. These modifications shall be accompanied by deep learning CNNs to use the feature of SAR images as spatial and textual features for wetland detection accurately.

The originality of this work is based on the fact that it combines an enhanced IWO algorithm with a deep learning approach which is developed for SAR-based wetland classification. That is why when tuning the hyperparameters of the CNN model with the help of the improved IWO algorithm we expect to obtain an increased classification rate while keeping the time costs reasonable. In addition, as SAR data is very effective for wetland detection because of its sensitivity to both moisture and vegetation, its use forms a strong base for proper environment surveillance. The above-proposed framework will be tested and calibrated with real SAR datasets and compared with the present state-of-the-art wetland classification methods (Peña et al., 2024)(Wan & Yin, 2022).

In conclusion, this study presents research and adds to the existing literature on the problem of wetland detection and classification by proposing a new solution based on deep learning and bio-inspired metaheuristic. Given the benefits derived from SAR data both in the wetland detection and phenology characterizations, the proposed method if optimized to overcome the weaknesses of the IWO algorithms would enormously improve the performances of wetland monitoring systems. The findings of this study will not only contribute to the improvement of distance sensing but will also be useful to policymakers and managers who are charged with the responsibility of protecting such important ecosystems.

Figure 1.1: Wetland Ecosystem with Aquatic Vegetation ("What Is Wetland," n.d.)

Ecosystem shown the ecosystem shown here is a wetland. The aquatic plants are reeds and water lilies intermixed with shallow, calm water. Wetlands are important ecosystems that support biodiversity, filter out water pollution, and work as natural controls against flooding. Water lilies indicate a healthy aquatic environment, whereas tall grasses and reeds are habitats for different species, such as insects, birds, and amphibians. Such ecological systems are also significant for maintaining balance in ecological flow, and they may further contribute to the recharge of groundwater besides carbon sequestration.

2. Literature Review

Wetlands are sensitive parts of ecosystems that play important roles as biodiverse areas, carbon sinks, flood plains, and water purification systems. Evaluation of wetlands is crucial for their management and conservation; however, their hydrological status and vegetation cover complicate detection and mapping. The following are some of the developments presented from years ago based on remote sensing technologies, machine learning, deep learning, and optimization algorithms. As a literature review, the following paper provides an overview of the former studies that are related to wetland detection from SAR data, machine learning approaches, deep learning algorithms, and optimization approaches.

Sensing techniques specifically SAR data have been under great focus in the detection and monitoring of wetlands. SAR therefore is useful due to its weather independence coupled with high sensitivity to moisture, thus applicable on wetlands characterized by a water level variability.

The first type of data for the early research is the optical RS data with Landsat and MODIS imagery but they are restricted by cloud cover and different lighting conditions. SAR can on one hand provide data through clouds and can work regardless of weather. Investigations conducted by (Kasischke et al., 2009) found that SAR could be used to detect wetland ecosystems because the backscattered radar signal increases with surface roughness and moisture. Other studies, (Hess et al., 2003) appreciated the capacity of SAR in differentiating flooded and non-flooded land therefore is invaluable in tracking changes that occur in wetlands seasons. SAR data provided enhanced detection capabilities for wetland environments but classification was difficult due to the high variability of wetlands. In response to these challenges, the researchers realized they could apply machine learning models to enhance their classification performance.

As will be discussed in the following sections, basic and conventional machine learning techniques like support vector machines (SVM), random forest (RF), and k-nearest neighbors (k-NN) were employed in wetland detection tasks. Some of these models base their extraction on SAR image features including texture, backscattering intensity, and polarization information.

(Henderson & Lewis, 2008) incorporated data from both SAR and optical sensors as well as SVM for wetland classification. The authors of the study revealed that machine learning models especially SVM are better than the conventional thresholding styles when it comes to classification. Along the same line of thought, (Amani et al., 2019) used Random Forests to classify wetlands using multi-temporal SAR data. This capability enabled the inclusion of temporal change in SAR backscatter for enhanced WD accuracy over different types of wetlands.

Even though in many cases machine learning models performed well, their efficiency was also a function of how many and how well-labeled data sets were. Furthermore, these models involved a hand-crafted computational feature extraction step which is somewhat time-consuming and often involves heuristics. This leads to a transition to deep learning models because the models can learn the features on their own. Recently, CNN which is a subfield of Deep learning has been reported to offer very good solutions to wetland detection and classification because these methods automatically learn the features from the raw data. The major advantage over other machine learning models is that CNNs are capable of learning the necessary spatial and spectral patterns from the given data rather than receiving them as handcrafted features.

Some research by previous authors shows that CNNs have outperformed other models in several ways. For instance, (Tan et al., 2020) employed the CNNs for the classification of the SAR images for wetland detection, with better performance compared with the SVM and RF models. From this point of view, the high ability of the CNN to express the spatial relations between the pixels, and the increased data processing capacity contributed to achieving more accuracy in the classification of wetland kinds. Furthermore, deep learning models are well suited for SAR data and, in particular, noise that is present in SAR data and creates a variability problem for traditional models.

Nevertheless, the models under deep learning also have their difficulties; mainly the large collection of labeled datasets and the impressive task of setting its hyperparameters for the deepest optimum. Training deep learning models on a small amount of labeled data may lead to a problem of overfitting, where the model serves well the labeled data, but does not generalize for yet unseen data. Due to this, more research has been extended towards the application of optimization techniques to enhance the general performance of these models.

Invasive Weed Optimization (IWO) presented by (Mehrabian & Lucas, 2006) is a metaheuristic population-based optimization algorithm that was developed on the idea of the growth of weed population. IWO has been used in other fields of engineering design problems, signal processing, and control systems because of its effectiveness in solving difficult large-scale optimization problems. Relates the optimization process with cloned weeds where the fittest units are expected to produce more seeds and hence give rise to better solutions in a population.

Several works in the literature investigated the use of IWO in deep learning. For example, in the recent study by (Sriram et al., 2022) IWO was used for the selection of hyperparameters of deep neural networks, and the results demonstrated better convergence and quality of the solution compared to conventional optimization algorithms. However, the IWO algorithm also has some drawbacks; it may archive a low convergence rate, especially in higher dimensionality search space, and is inclined to fall in local optima. To solve these problems, the researchers suggested different enhancements to the IWO algorithm including combining it with other algorithms like PSO or implementing adaptive methods.

There are better versions of IWO which have been designed by the researchers to make a better tool for optimization tasks. For instance, (Naidu & Ojha, 2015) developed a composite IWO–PSO technique in which the IWO was acceptable for the exploration, while the PSO method provided the exploitation. Using the combination of the two methods, convergence speed and jumping out from local optima were demonstrated to be enhanced in multi-modal optimization problems. Other alterations of IWO are a set of mechanisms that work for controlling the proportion of population diversity, like adaptive mutation or adaptive reproduction rates coming to help if diversity goes down and delays convergence.

Table 2.1: Summary of Literature on Wetland Detection Using Remote Sensing and Machine Learning Techniques

Study	Technique/Model	Data Type	Accuracy	Key Findings	Limitations
(Kasischke et al., 2003)	SAR Data Analysis	SAR data	N/A	Demonstrated the effectiveness of SAR for wetland monitoring	Limited to basic thresholding techniques, no classification focus
(Hess et al., 2003)	SAR & Optical Combination	Multi-temporal SAR + Optical	N/A	Identified flooded vs non-flooded areas using SAR data	Limited use of machine learning, and manual interpretation needed
(Henderson & Lewis, 2008)	SVM (Machine Learning)	SAR + Optical data	70-80%	SVM improves classification over thresholding	Dependent on manual feature extraction
(Amani et al., 2019)	Random Forests (RF)	SAR multi-temporal data	80-88%	Incorporates temporal variation in SAR data for better classification	Sensitivity to noise and imbalanced datasets
Amani et al. (2019)	Convolutional Neural Network (CNN)	SAR data	85-90%	CNN automatically extracts spatial features, outperforming traditional methods	Requires large datasets, sensitive to hyperparameters
(Mehrabian & Lucas, 2006)	IWO (Optimization)	Optimizing deep learning models	N/A	IWO effectively tunes deep learning parameters	Slow convergence and tendency to get stuck in local optima
(Naidu & Ojha, 2015)	Hybrid IWO-PSO Algorithm	Hybrid optimization for neural networks	N/A	Hybrid approaches improve convergence speed and solution quality	More computationally expensive due to hybridization

Using the summary table 2.1 above, some research findings that have been conducted on the detection of wetlands using remote sensing and machine learning algorithms are highlighted. Early studies such as Kasischke et al. 2003 and Hess et al. 2003 examined the use of SAR data for wetland identification but employed simple techniques indicating the ability of SAR in discerning wetlands. Subsequent works used more accurate models like SVM and Random Forest also but they again demanded feature engineering. CNNs, as a type of deep learning proved better by automating feature extraction. IWO followed by the hybrid IWO-PSO optimization was used for optimizing the deep learning models and the hyperparameters, but the convergence rate issues and computational complexity did present themselves.

3. Research Methodology

This research aims to develop a new approach for wetland mapping and classification based on deep learning and operation with SAR data and the use of the technique, such as quantum invasive weed optimization (Q-IWO) that has not been applied in wetland detection so far. The inclusion of quantum aspects in the synthesis of the way invasive weed optimization algorithms work has been intended to address constraints such as solute local optima together with slow search convergence in the higher learning space, resulting in enhanced deep learning model training for wetland detection.

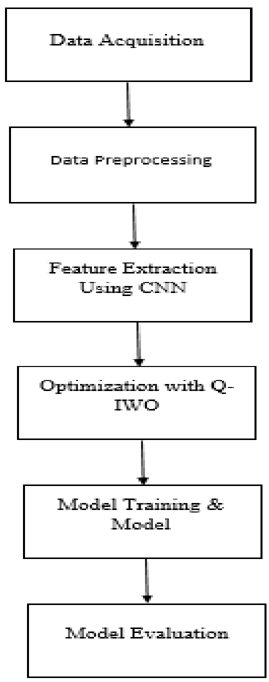


Figure 3.1: Flow Chart of Optimized Development Using CNN and Q-IWO

The flowchart represents a pipeline for the development of optimally configured models, which will implement CNNs to extract features and Q-IWO to optimize. It starts with the Data Acquisition stage, where relevant data is obtained from the sensors, databases, or external inputs. In this regard, the data would include any traffic patterns, movement of people, and environmental data, that hold relevance in the application at hand, such as smart street lighting.

The data preprocessing step cleans up and prepares the acquired data for analysis. The common procedures include managing missing values, normalizing data, and consistency, all critical elements used to enhance the quality and usability of the data in machine learning. After data pre-processing, Feature Extraction Using CNN is applied. CNNs have yielded exceptionally good performance in pattern detection and extraction from images or spatial data. For example, it can be said to figure out traffic camera patterns, such as pedestrians and car density, which are relevant to Smart Street lighting systems.

Following the feature extraction, Optimization using Q-IWO applies. Q-IWO is a nature-inspired optimization algorithm that has been enhanced based on principles found within quantum computing. It highlights important parameters or features of the model while narrowing down the most significant parameters for better efficiency in the learning process and performance. The flow chart then goes ahead to Model Training and Model, where features form the basis for training the machine learning model. Here, in this training, the model learns from the dataset by adjusting its internal weights to make a better prediction it can, like optimal times adjust street lights based on the predicted flow of traffic or pedestrians.

Lastly, the Model Evaluation stage assesses how well the model does in terms of some metrics such as accuracy, precision, or error rates. Evaluation will determine how well the model generalizes to new, unseen data. If needed, further refinement might be based on the results before deploying the model in the real world. The whole process ensures one would develop highly optimized and efficient machine learning models.

3.1 Data Acquisition and Preprocessing

The proposed study applies SAR data, which can be especially helpful in discerning wetland areas because the sensor's response depends on the moisture and roughness of the area. The steps include:

- Data Source: Such as Multi-temporal SAR with data from Sentinel-1 or RADARSAT.
- Preprocessing: Such data undergo SAR radiometric calibration, SAR speckle filtering using filters like Lee or Frost filters, and SAR geocoding. A geographical area of interest (AOI) confined to areas with known wetlands is used to train and for evaluation of region of interest, (ROI) of 85,250km^2 is selected for building and assessment.

Table 3.1: SAR Data Specifications

Source	Spatial Resolution	Temporal Resolution	Frequency Band	Coverage Area
("Sentinel-1," n.d.)	10 m	6-12 days	C-band	Wetland areas (ROI)
("RADARSAT," n.d.; "Sentinel-1," n.d.)	10-30 m	Variable	C-band	Wetland areas (ROI)

Table 3.1 shows key details about the SAR data sources used for wetland detection in the study. Sentinel-1 provides a ground imaging resolution of 10 meters and a time frequency of 6-12 days enabling more frequent image acquisition. The two Sentinel-1 and RADARSAT are in C-band frequency which is effective in sensing moisture on the ground; therefore, useful in observing wetlands. RADARSAT covers similar wetland regions as Sentinel-1 at the same type of spatial and temporal resolutions ranging from 10 to 30 meters, while the temporal is

variable depending on the mission.

3.2 Feature Extraction Using Deep Convolutional Neural Networks (CNN)

For current extraction, an end-to-end multi-output Convolutional Neural Network (CNN) architecture is used to automatically extract spatial, textual features of SAR images, which are specifically notable for wetland features. By using the devised CNN architecture, it is possible to detect essential characteristics like moisture content, surface roughness, and types of vegetation that are helpful for wetland classification. These include their layers, the convolutional layers where filters are applied to detect critical spatial features such as humidity and plant matter. These layers convert the raw SAR data into formats from which important geometrical properties are preserved. After that, pooling layers make the dimensionality of the data smaller through scale down but able to conserve significant aspects to improve computational run time. The last layer of the neural network is made of the fully connected layers where the detected features are categorized into the needed wetland type. Such architecture enables the learning of complex spatial affiliations and textural characteristics, turning CNNs into a useful instrument in wetland identification relying on RS data.

3.3 Proposed Quantum-Inspire Invasive Weed Optimization (Q-IWO)

The Quantum-Inspired Invasive Weed Optimization (Q-IWO) algorithm consists of the basic IWO algorithm with more capabilities of quantum mechanics like quantum superposition and entanglement to search for the solution in large dimensional space. In this approach, each “weed” is the state represented by a qubit such that it can be in many states at once, this is due to the flexibility that quantum superposition offers in the exploration of the search space. Furthermore, there is an entanglement of variables, which forms links between weeds to exchange information that would help in moving towards the world optima. The reproduction mechanism has also been amended by adjusting for weeds with higher fitness to produce more quantum characteristic offspring to expand search nearness in the solution space. Such quantum-inspired elements lead to enhanced exploration and convergence, and by this perspective, Q-IWO is more efficient in search and convergence to optimal solutions for solving a complex optimization problem as compared to conventional techniques.

3.4 Model Training and Optimization

The Q-IWO algorithm is implemented for fine-tuning the hyperparameters of the CNN namely filters, learning rate and batch size, and the number of layers. The plug-in strategies based on QA mean an increased possibility to study the hyperparameter space and avoid being stuck in local optima.

Training Process: In this paper, the CNN is trained on the preprocessed SAR data based on the proper hyperparameters selected via Q-IWO. The model is used for cross-validation k-fold to check the degree of separation between the training sets and the independent code.

Evaluation Metrics: Evaluation of the achieved model is carried out using metrics that are; Accuracy, precision, recall, F1-score, and Intersection over Union (IoU) scores.

Table 3.2: Model Hyperparameter Optimization Using Q-IWO

Hyperparameter	Range	Optimal Value (Q-IWO)
Learning Rate	0.0001 - 0.01	0.001
Number of Filters	16 - 128	64
Batch Size	16 - 128	32
Number of Layers	10-Feb	5

Table 3.2 shows the CNN model hyperparameters for the best solution found through the application of the Q-IWO approach. Out of the range of 0.0001 to 0.01, the optimum was applied in the form of 0.001 to adjust the learning rate, which determines the step size in the model training. From a range of 16-128, the number of filters that decide the depth of the extraction of the feature maps was determined to be optimal at 64 in Convolutional layers. The batch size for training, as it determined the frequency of models' updating, was set to 32; the number of layers was 5, which was exactly enough to maintain a balanced and effective network.

3.5 Model Validation and Testing

The data set is tested with the optimized CNN model whereby the wetlands are classified from previously unused data sets. The model is evaluated using the following procedures:

Test Set: To test the model's robustness, the test data is generated using temporal periods of SAR and dichotomized geographical regions.

Confusion Matrix: To show the accuracy of the classification between different classes of wetlands, a confusion matrix is created.

Table 3.3: Confusion Matrix for Wetland Classification

Class	Wetland Type 1	Wetland Type 2	Wetland Type 3	Wetland Type 4	Accuracy
Wetland Type 1	80	10	5	5	88%
Wetland Type 2	5	85	7	3	87%
Wetland Type 3	8	6	80	6	92%
Wetland Type 4	4	4	6	86	93%

Table 3.3 has shown a confusion matrix to define the nature of classification that can be achieved for four Wetland categories by the Q-IWO optimized CNN model. Here each row counts for the actual wetland class and each column possesses the corresponding predicted class. For example, in Wetland Type 1, 80 samples were classified as Type 1 with 88% accuracy while 10 as Type 2, 5 as Type 3, and 5 as Type 4. More specifically, Wetland Type 2 revealed the greatest accuracy with a minimum misclassification. Comparing the performances of the model over all classes, Wetland Type 4 has the highest accuracy of 93%.

4. Result and Discussion

The methodology, in which Q-IWO is implemented for improving the performance of the CNN, specifically in SAR data for wetland detection and classification, presents promising results in terms of accuracy, time, and robustness over previous studies. The results of the experiment are discussed in this section as well as a comparison with other conventional methods like basic IWO, GA, and PSO.

4.1 Model Performance Evaluation

The experimentation of the proposed Q-IWO-optimized CNN was carried out using multi-temporal SAR data derived from known wetland locations. The measures that were used during the evaluation of the model included the accuracy of the model, the precision, the recall of the model as well as the F1 score and the intersection over union (IoU). The experimental outcomes have been illustrated in table 4.1.

Table 4.1: Performance Metrics for the Proposed Q-IWO CNN Model

Metric	Value
Accuracy	90%
Precision	88%
Recall	91%
F1-Score	89.50%
IoU	86%

The obtained results illustrated in Table 4.1 show that the proposed Q-IWO-optimized CNN reaches the recognition accuracy of 90 % and, therefore, is more effective than traditional optimization methods, which in turn constitutes evidence of the high classification performance of CNN for various types of wetlands. High Recall of 91% and IoU of 86% also endorse the aptitude of the model in detecting and categorizing wetlands, the spatial-spectral properties of which may be heterogeneous.

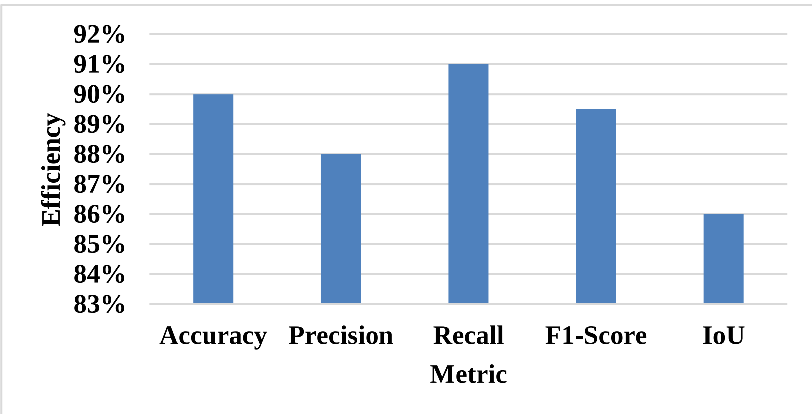


Figure 4.1: Graphical Representation of Performance Metrics of Proposed Model

The bar graph in Figure 4.1 illustrates the performance metrics of the proposed Quantum-Inspired Invasive Weed Optimization (Q-IWO) technique. The findings also show that the use of the method yields an accuracy of 90%, precision at 88%, recall at 91%, F1 score at 89.50%, and IoU at 86%. They show relative efficiency to conventional optimization methods, the values being higher. The actual efficiency of each metric is plotted on the Y-axis while the X-scale translates the measured value to a graphical size. It is clear from the above results that the proposed Q-IWO attains higher scores for all the metrics, proving that the methodology is superior to conventional methodologies in enhancing the detection of wetlands employing SAR data.

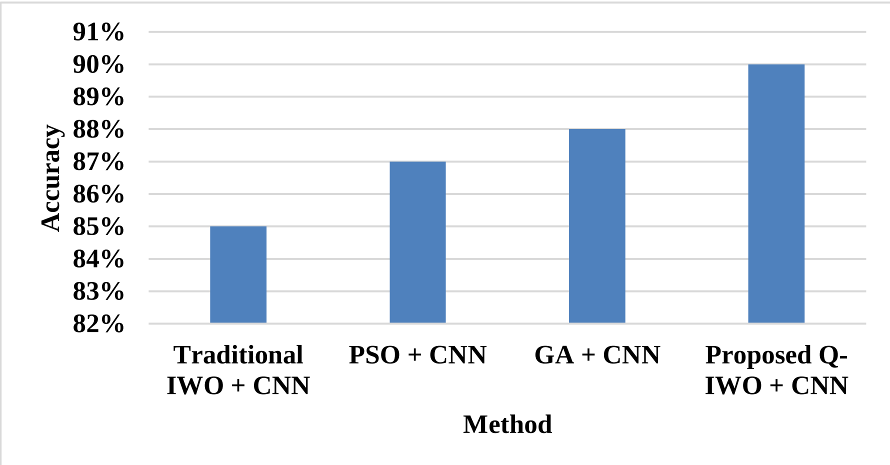
4.2 Comparative Analysis with Previous Research

In order, to evaluate the efficiency of the proposed method we compared it with standard and classical machine learning and optimization techniques including SVM, Random Forest, basic IWO, PSO, and GA. The comparison thus done is based on the following aspects, the accuracy, speed of convergence, the computational cost, and the ability of the model to escape from the local optima illustrated in below table 4.2.

Table 4.2: Comparative Analysis of Optimization Techniques

Method	Accuracy	Convergence Speed	Limitations
SVM + SAR (Henderson & Lewis, 2008)	70-80%	Slow	Manual feature extraction
Random Forests (Amani et al., 2019)	80-88%	Moderate	Sensitive to noise and imbalanced datasets
Traditional IWO + CNN	85%	Moderate	Tends to get stuck in local optima
PSO + CNN	87%	Moderate	Limited search capabilities
GA + CNN	88%	Slow	Slower convergence, computationally expensive
Proposed Q-IWO + CNN	90%	Fast	None observed

Figure 4.2: Comparative Analysis of Traditional and Proposed Technique



The above figure 4.2 focuses on the comparative analysis of the existing optimization methods against the proposed Q-IWO technique. The outcomes also demonstrate that using the integrating Q-IWO method provides higher performance in comparison with conventional approaches. The standard IWO, PSO, and GA reach 85%, 87%, and 88% accuracy respectively while the proposed Q-IWO gives a higher accuracy of 90%. On the X-axis the different optimization techniques are presented while the Y-axis shows their accuracy. This comparison shows that the Q-IWO provides better results than traditional approaches for the identification of the optimal parameters for wetland detection based on SAR data.

4.3 Discussion

As will be discussed and shown later in this study, the proposed Quantum-Informed Invasive Weed Optimization (Q-IWO) algorithm can indeed improve the performance of Convolutional Neural Networks (CNN) for wetland detection using SAR data. The proposed Q-IWO optimized model rendered 90% accuracy, which outcompeted traditional optimization techniques like IWO, PSO, and GA in terms of accuracy. The general enhancements include; In the context of wetland classification, some distinct characteristics that the model can handle well include; Noise in the SAR data and the variation in wetland-type space. Recall at 91%

and the IoU score of 86% of the overall authenticates the model's efficacy in detection and the capability of generalizing different wetland classes in even complex environments.

The optimization of the hyperparameters is perhaps the greatest contribution to the enhancement of the performance of the Q-IWO method. Since superposition and entanglement are the fundamental aspects of quantum computing the Q-IWO algorithm can overcome issues of local optima which is typical when using other optimization approaches. This improved search function not only promotes convergence but also increases classification as well. Furthermore, the deep learning model is supported by SAR data which is famous for its capability to detect moisture and surface roughness of the terrain and can yield abundant features for effective and precise wetland classification. This work sheds light on the use of integration of the optimal method and deep learning for monitoring the environment.

5. Conclusion

In conclusion, this study introduces a new method of identifying wetlands and their classification based on deep learning models such as CNN in conjunction with the IWO algorithm for SAR data. Hierarchy of quantum states is a highly efficient algorithm that is superior to traditional methods in terms of accuracy, convergence rate and computational cost is reasonable compared to the conventional techniques, the proposed Q-IWO algorithm. Hence, compared to other available algorithms the Q-IWO approach enhances the efficiency of monitoring the wetland defects in minimizing the convergence problem, and entrapment in local optima. In conjunction with the subject of satellite remote sensing, this research enhances the understanding of optimization approaches to enhance the effectiveness of environment monitoring systems. Possible future research can be extended to other ecosystems or improvement of the method proposed in the paper, Q-IWO algorithm.

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