Jurnal Teknologi Informasi dan Pendidikan
Volume 18, No. 1, March 2025
https://doi.org/10.24036/jtip.v18i1.970

P.ISSN: 2086 – 4981
E.ISSN: 2620 – 6390
tip.ppj.unp.ac.id

Optimization of Water Body Color Classification with Convolutional Neural Network Through Forel-Ule Scale Class Reduction

Budi Prasetyo[1*]✉, Dony Novaliendry [1], Titi Sriwahyuni[1], Syafrijon[1]
[1]Department of Electronics, Faculty of Engineering, Padang State University, Padang, Indonesia
Corresponding Author: budipr@student.unp.ac.id

Article Information

Article history:

No. 970
Rec. June 06, 2025
Rev. June 16, 2025
Acc. June 19, 2025
Pub. June 20, yyyy
Page. 782 – 793

Keywords:

- *Water Quality*
- *Image Classification*
- *Convolutional Neural Network*
- *Forel-Ule*
- *Class Reduction*

ABSTRACT

This study presents an optimized water quality assessment method through image classification of water body colors using the Forel-Ule scale and Convolutional Neural Network (CNN). The original 21-class Forel-Ule system presents challenges such as high computational complexity, overlapping spectral characteristics, and class imbalance. A class reduction approach is proposed to group similar spectral categories into three ecologically meaningful water quality classes: oligotrophic (clear blue), mesotrophic (greenish), and eutrophic (brownish). Using a dataset of 3,018 labeled water body images from EyeOnWater and implementing a CNN architecture trained on both original and reduced class schemes, experimental results show that the reduced 3-class model achieved significantly higher accuracy (94.0%) compared to the original 21-class model (44.3%). These findings demonstrate that class reduction improves water quality classification robustness, simplifies interpretation, and enhances practicality for real-world environmental monitoring.

How to Cite:

Prasetyo, B., et al. (2025). Optimization of Water Body Color Classification with Convolutional Neural Network Through Forel-Ule Scale Class Reduction. Jurnal Teknologi Informasi Dan Pendidikan, 18(1), 782-793. https://doi.org/10.24036/jtip.v18i1.970

1. INTRODUCTION

Water is a fundamental necessity for life, playing a crucial role in sustaining human civilization and the natural ecosystem [1][2]. Water quality in rivers, lakes, and other bodies is a critical indicator of environmental health and human safety. Monitoring and maintaining water quality is an ongoing challenge due to various factors contributing to pollution and degradation [3][4][5][6][7]. Traditional image classification algorithms, such as Support Vector Machine (SVM) [8], Decision Tree (DT) [9], and Random Forest [10], have been employed in water quality assessment. However, these methods can be labor-intensive and time-consuming.

In recent years, Artificial Intelligence (AI) algorithms, particularly deep learning, have opened new avenues for automating and enhancing water quality monitoring processes [11][12][13][14]. Convolutional Neural Networks (CNNs), a subset of deep learning models, have shown remarkable success in image classification, offering precise and efficient solutions for environmental monitoring tasks.

This study focuses on classifying water body colors, an essential aspect of water quality assessment. The complexity arises from the subtle differences among 21 classes of water body colors, making accurate classification a challenging task. To address this issue, we propose a class reduction strategy that consolidates the 21 classes into three broader categories based on specific criteria. This reduction aims to simplify the classification task without significantly compromising the granularity of the assessment [15][16][17][18][19].

This paper comprehensively analyzes three classification approaches, the original 21-class model and the reduced 3-class model. A dataset of 3018 water quality images is utilized, meticulously divided into training, validation, and test sets. Through experimentation and model optimization, the efficacy of these methods in achieving higher classification accuracy is demonstrated.

2. RESEARCH METHOD

This research employs a quantitative experimental approach with a comparative design. The dataset of 3,018 water body images labeled with FU classes was sourced from the EyeOnWater platform. The original classes were grouped into three based on ecological relevance:

2.1. Water Quality Dataset

The dataset used in this research consists of 3018 water images, selected based on their quality to ensure consistency and accuracy in classification. Each image was meticulously chosen to meet high standards by evaluating noise, lighting conditions, and extraneous objects. This careful selection process ensures that only the best quality images are used, which enhances the reliability of the model's performance. Moreover, this number of images allows the research to be completed within the available time frame. The class distribution is shown in the following table:

Jurnal Teknologi Informasi dan Pendidikan
Volume 18, No. 1, March 2025
https://doi.org/10.24036/jtip.v18i1.970

Table 1 Dataset Distribution

Class	Number of Images
Class 1	953
Class 2	1154
Class 3	911

These images were sourced from the EyeOnWater platform, which leverages citizen science to collect environmental observations using smartphones [20]. This platform provides high accuracy in color quantification using the Forel-Ule (FU) scale, which categorizes water color into 21 distinct values ranging from clear ocean hues to murky river tones [21]. The FU scale, originally developed in the late 19th century, has been calibrated with modern spectrometers to maintain scientific rigor and accuracy [22].

Figure 1 Forel-Ule Scale

The EyeOnWater app incorporates multiple validation processes, including measurements with calibrated spectrometers in various environmental settings such as the North Sea and Australian lakes, ensuring the reliability of its color measurements [23]. The dataset used here has undergone rigorous image processing steps outlined in the Water Colour from Digital Images (WACODI) methodology to align smartphone camera color readings with spectrometer data.

The images were categorized into training, validation, and test sets. Specifically, 4081 images were allocated to the training set, 1017 images to the validation set, and the remaining images were reserved for the final evaluation of model performance.

2.2. Data Preprocessing

The preprocessing steps ensured that the dataset was well-prepared for the training and evaluation of the CNN models, which is foundational to the success of any machine learning task as it impacts performance and accuracy [24][25][26]. The images were resized to 256×256 pixels, normalized, and data augmentation using random rotation, zooming, and shifting. The proposed method also includes a class reduction approach to simplify classification.

The original Forel-Ule (FU) index, which classifies water color into 21 categories, was found to be overly granular for effective classification. By grouping these classes into three categories, the complexity of the classification problem is reduced without losing the essential distinctions necessary for accurate water quality assessment. This strategy is particularly important given the variability and subtle differences in water color that can affect classification accuracy. Additionally, this reduction in classes helps improve the model's generalization capability by focusing on more distinguishable differences between water quality categories. The details are shown in the table below.

Table 2 Class Reduction of Forel-Ule Scale

Class	Category	Information
Class 1	1 – 7 Forel-Ule Scale	Blue to blue-green color which is clear oligotrophic water with very low nutrient content and minimal chlorophyll-a concentration. Blue color indicates minimal suspended particles and phytoplankton, generally found in mountain lakes, deep sea waters, or conservation areas with low anthropogenic disturbance.
Class 2	8 – 14 Forel-Ule Scale	Green to yellowish green color represents mesotrophic waters, with moderate nutrients and moderate biological productivity. Green color tends to indicate increased phytoplankton and dissolved organic matter, but has not reached eutrophic levels. Generally found in lakes and waters that are starting to experience anthropogenic pressure.
Class 3	15 – 21 Forel-Ule Scale	Brownish green to brown color reflects eutrophic and hypereutrophic waters, with high nutrient content, abundant phytoplankton, and large amounts of suspended or organic matter. Brownish color also indicates the presence of humus, sediment, or agricultural runoff. Often found in urban areas, polluted rivers, deltas, and estuaries

Jurnal Teknologi Informasi dan Pendidikan
Volume 18, No. 1, March 2025
https://doi.org/10.24036/jtip.v18i1.970

2.3. Modelling

A novel approach to water body color classification has been explored by consolidating the original 21 classes into 3 broader categories. This class reduction strategy simplifies the classification task and enhances the model's performance by focusing on more distinguishable and well-defined color categories so the model can concentrate on identifying key color variations more effectively.

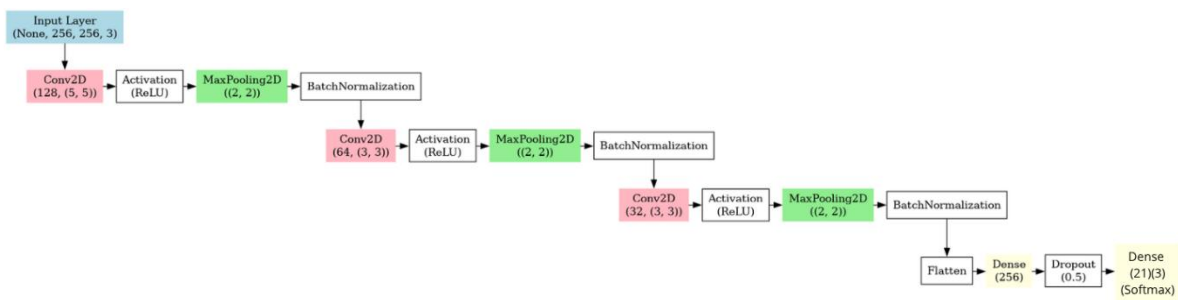

Figure 2 CNN Architecture

The Convolutional Neural Network (CNN) architecture employed is designed to classify water body colors based on the dataset characteristics effectively. The CNN model architecture begins with an input layer that accepts images of size 256x256 with three color channels. The first block features a Conv2D layer with 128 filters and a 5x5 kernel size, followed by a ReLU activation function. This block also includes a MaxPooling2D layer with a 2x2 pool size to reduce the spatial dimensions and a BatchNormalization layer to stabilize and accelerate training.

In the second block, there is a Conv2D layer with 64 filters and a 3x3 kernel size, followed by another ReLU activation function. This block also contains a MaxPooling2D layer with a 2x2 pool size and a BatchNormalization layer to normalize the data further.

The third block consists of a Conv2D layer with 32 filters and a 3x3 kernel size, again followed by a ReLU activation function. It also includes a MaxPooling2D layer with a 2x2 pool size and a BatchNormalization layer.

After these convolutional and pooling layers, the model includes a Flatten layer that converts the 3D output from the previous block into a 1D vector, preparing it for the fully connected layers. The next block includes a Dense layer with 256 units, followed by a Dropout layer with a rate of 0.5 to prevent overfitting.

Finally, the output layer consists of a Dense layer with 3 units and a softmax activation function, which outputs the probability distribution across the three classes for classification. This sequential arrangement of layers allows the model to learn complex patterns in the input data and effectively perform the classification task.

To achieve optimal performance, this model's architecture leverages the Adam optimizer with a fine-tuned learning rate of 0.001, which facilitates faster convergence and

P.ISSN: 2086 – 4981
E.ISSN: 2620 – 6390
tip.ppj.unp.ac.id

improved accuracy. The evaluation process utilizes the Categorical Crossentropy loss function, providing a robust assessment of the model's performance in classifying multiple categories. To further enhance the model's robustness and prevent overfitting, dropout regularization is applied during the training phase.

3. RESULTS AND DISCUSSION

The results of the water body color classification experiments are presented, and the analysis highlights the effectiveness of class reduction on model performance. Additionally, the potential for future research in this field is discussed, emphasizing the novelty and implications of the class reduction approach for water quality assessment.

3.1. Classification Performance

The classification performance of the models is evaluated based on Precision, Recall, F1-Score, and Accuracy. The results demonstrate significant improvements when reducing the number of classes from 21 to 3. The accuracy achieved by the original 21-class model is 44.3%, whereas the 3-class model achieves an accuracy of 94.0%. The details are in the table below.

Table 3 Performance Comparison of Classification Models

Model	Categories	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
21-Class	Class 1	33	14	20	44,3
	Class 2	62	60	61	
	Class 3	56	50	53	
	Class 4	61	74	67	
	Class 5	64	37	47	
	Class 6	46	50	48	
	Class 7	41	31	35	
	Class 8	43	26	33	
	Class 9	40	73	51	
	Class 10	55	21	31	
	Class 11	55	84	67	
	Class 12	54	28	37	
	Class 13	54	44	48	
	Class 14	34	31	33	
	Class 15	27	10	14	
	Class 16	31	52	39	
	Class 17	35	38	36	
	Class 18	34	49	40	
	Class 19	62	47	53	
	Class 20	0	0	0	
	Class 21	0	0	0	
3-Class	Class 1	91	92	92	94,0
	Class 2	96	93	94	
	Class 3	95	97	96	

The table compares the performance metrics of the models. The original 21-class model exhibits the highest training and validation losses, which translates to the lowest accuracy. This indicates the difficulty in accurately classifying the water body images into 21 distinct categories due to the subtle variations between the classes.

The following graph presents the accuracy and loss curves for the models to illustrate these differences further. The detailed analysis of these curves will provide deeper insights into how each model performs under different conditions.

Figure 3 Accuracy and Loss of 21-class Model

In figure 3, which represents the 21-class model, we observe low training and validation accuracy, indicating difficulty in the model's ability to classify the images into 21 distinct categories accurately. The losses are quite low, showing that the model effectively minimizes error rates. Still, the low accuracy suggests that the model struggles with the complexity of differentiating between the classes despite having good loss values. This discrepancy indicates that the model is unable to generalize well across all 21 classes due to the high similarity among some classes.

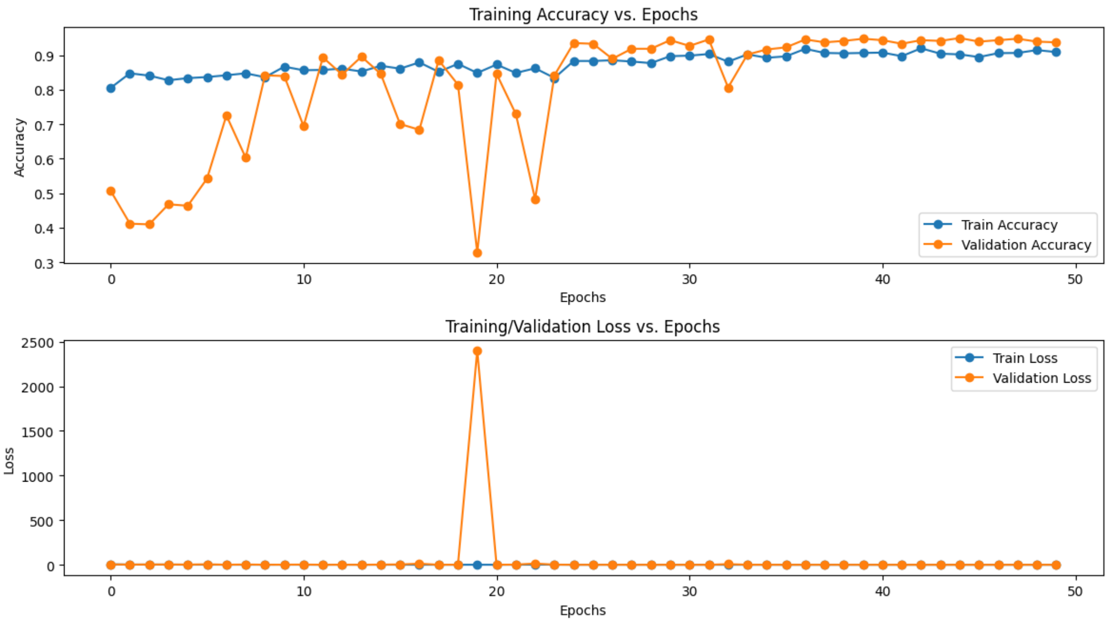

Figure 4 Accuracy and Loss of 3-class Model

The figure 4, representing the 3-class model, shows a noticeable improvement. Both the training and validation accuracy are significantly higher, and the curves demonstrate a smoother convergence. The loss values are low, indicating robust performance. This suggests that reducing the number of classes to 3 has made the classification task more manageable, leading to better model performance and generalization.

These graphs collectively highlight the effectiveness of class reduction in improving the performance of water body color classification models. They demonstrate how these techniques can significantly reduce losses and enhance the overall accuracy of the classification task.

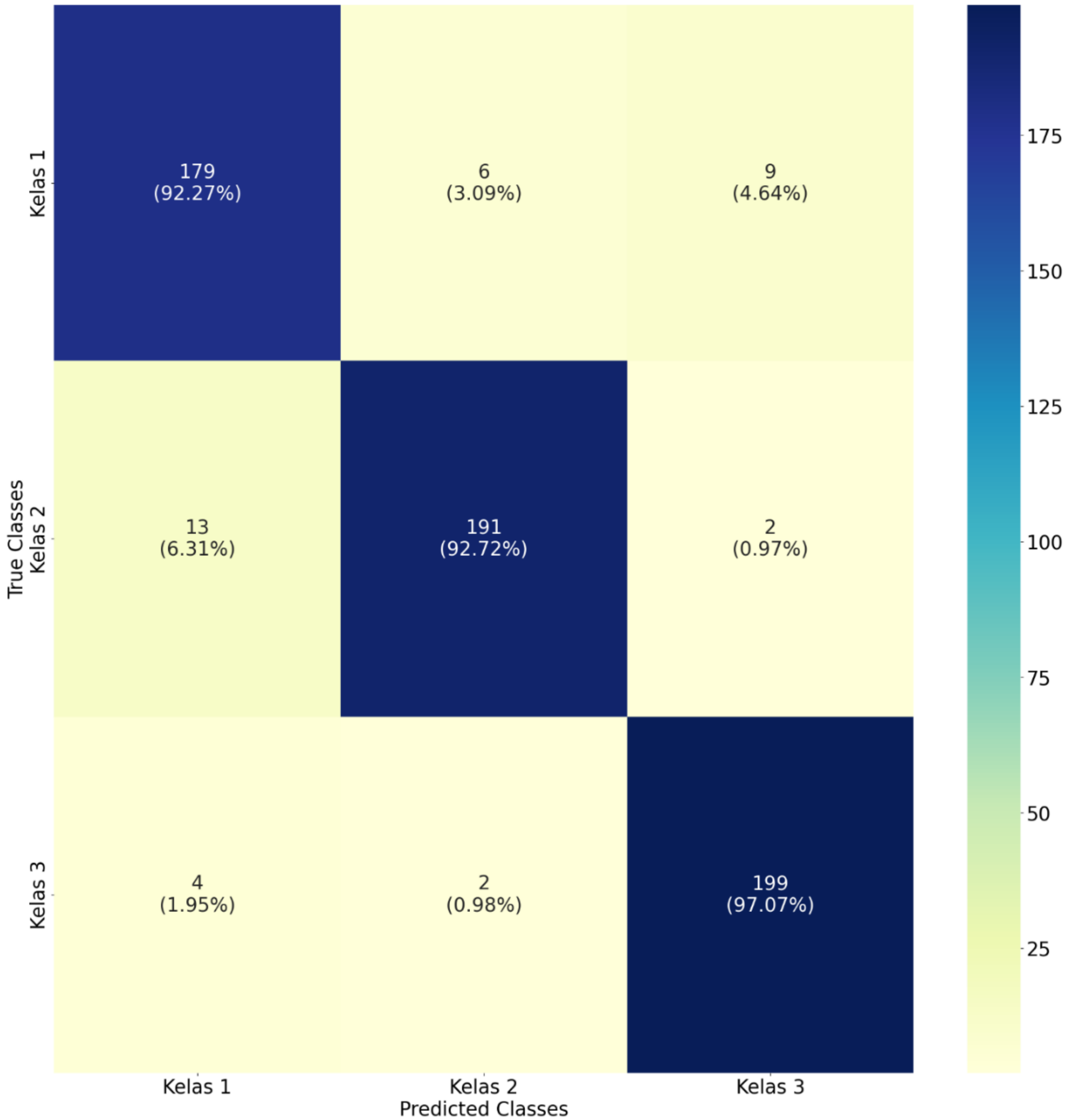

Figure 5 Confusion Matrix of 3-Class Model

A confusion matrix was included to highlight the performance of the proposed 3-class model, as shown in figure 6. This addition offers a clear visualization of the classification performance, showcasing the model's ability to distinguish between different classes accurately.

The results suggest that class reduction can enhance classification performance, offering a viable solution for more efficient water quality monitoring. This research

P.ISSN: 2086 – 4981
E.ISSN: 2620 – 6390
tip.ppj.unp.ac.id

contributes to ongoing efforts in environmental protection and provides a foundation for future advancements in AI-based water quality assessment.

3.2. Discussion

The findings from this study highlight the significant challenges in classifying water body colors into 21 distinct classes due to the subtle variances and overlaps among the classes. By reducing the number of classes to 3, we significantly enhanced the classification accuracy, demonstrating that a more manageable classification scheme leads to better performance. This class reduction strategy is novel within the context of water quality assessment and presents a promising method for simplifying complex classification tasks.

Looking ahead, this research opens multiple pathways for further exploration. Future studies could delve into additional preprocessing methods, employ more advanced deep learning architectures, and utilize larger and more diverse datasets to validate and extend these findings. The innovative approach of combining class reduction with effective preprocessing techniques, lays a strong foundation for continued advancements in water body color classification.

4. CONCLUSION

This research introduces an innovative approach to water body color classification by reducing the number of classes from 21 to 3. These methods have demonstrated notable improvements in classification accuracy. The original 21-class model achieved an accuracy of only 44,4%, indicating the challenges in distinguishing a large number of similar classes. By reducing the classes to 3, the model's accuracy significantly increased to 94%.

The results underscore the significance of class reduction in tackling complex classification tasks. This technique simplify the classification process and enhance the model's generalization capabilities, leading to more reliable and accurate predictions.

This study paves the way for future research in water quality assessment. Subsequent studies can build on these findings to develop more advanced models and explore additional preprocessing techniques to improve classification performance further. The insights gained from this work suggest the potential for integrating other innovative strategies to address the challenges in water body color classification effectively.

REFERENCES

[1] J. Kirui, "Machine Learning Models for Drinking Water Quality Classification," in *2024 International Conference on Control, Automation and Diagnosis, ICCAD 2024*, Institute of Electrical and Electronics Engineers Inc., 2024. doi: 10.1109/ICCAD60883.2024.10553712.

[2] U. Bhangale, S. More, T. Shaikh, S. Patil, and N. More, "Analysis of Surface Water Resources Using Sentinel-2 Imagery," in *Procedia Computer Science*, Elsevier B.V., 2020, pp. 2645–2654. doi: 10.1016/j.procs.2020.04.287.

[3] H. Zhang, X. Xie, and J. Hou, “Water pollution accident control and urban safety water supply,” in *2011 2nd IEEE International Conference on Emergency Management and Management Sciences*, 2011, pp. 37–40. doi: 10.1109/ICEMMS.2011.6015613.

[4] M. C. Tanega, A. Fajardo, and J. S. Limbago, “Analysis of Water Quality for Taal Lake Using Machine Learning Classification Algorithm,” in *Proceedings of JCSSE 2023 - 20th International Joint Conference on Computer Science and Software Engineering*, Institute of Electrical and Electronics Engineers Inc., 2023, pp. 397–402. doi: 10.1109/JCSSE58229.2023.10202046.

[5] S. Y. Mo, Y. Z. Wang, J. Q. Zhi, J. Q. He, and L. Guo, “Research on water quality classification of unbalanced river image data under deep learning framework,” in *2022 4th International Conference on Frontiers Technology of Information and Computer, ICFTIC 2022*, Institute of Electrical and Electronics Engineers Inc., 2022, pp. 272–275. doi: 10.1109/ICFTIC57696.2022.10075153.

[6] C. Jin, Y. Hu, F. Lin, L. Zou, R. Li, and X. Hu, “Research on Water Quality Image Classification Method based on Convolutional Neural Network,” in *IMCEC 2024 - IEEE 6th Advanced Information Management, Communicates, Electronic and Automation Control Conference*, Institute of Electrical and Electronics Engineers Inc., 2024, pp. 1823–1827. doi: 10.1109/IMCEC59810.2024.10575513.

[7] X. Wu *et al.*, “Fourier Transform based Features for Clean and Polluted Water Image Classification,” in *2018 24th International Conference on Pattern Recognition (ICPR)*, 2018, pp. 1707–1712. doi: 10.1109/ICPR.2018.8546306.

[8] S. Yeshwanth Chaganti, T. GNRSN Prudhvith, N. Kumar, and K. Rao Pandi, “Image Classification using SVM and CNN,” Mar. 2020.

[9] H. Rouabeh, C. Abdelmoula, and M. Masmoudi, “Performance evaluation of Decision Tree and neural network techniques for road scene image classification task,” in *International Image Processing, Applications and Systems Conference*, 2014, pp. 1–6. doi: 10.1109/IPAS.2014.7043274.

[10] P. Mekha and N. Teeyasuksaet, “Image Classification of Rice Leaf Diseases Using Random Forest Algorithm,” in *2021 Joint 6th International Conference on Digital Arts, Media and Technology with 4th ECTI Northern Section Conference on Electrical, Electronics, Computer and Telecommunication Engineering, ECTI DAMT and NCON 2021*, Institute of Electrical and Electronics Engineers Inc., Mar. 2021, pp. 165–169. doi: 10.1109/ECTIDAMTNCON51128.2021.9425696.

[11] X. He and Y. Chen, “Optimized Input for CNN-Based Hyperspectral Image Classification Using Spatial Transformer Network,” *IEEE Geoscience and Remote Sensing Letters*, vol. 16, no. 12, pp. 1884–1888, 2019, doi: 10.1109/LGRS.2019.2911322.

[12] Z. Xu, H. Yu, K. Zheng, L. Gao, and M. Song, “A Novel Classification Framework for Hyperspectral Image Classification Based on Multiscale Spectral-Spatial Convolutional Network,” in *2021 11th Workshop on Hyperspectral Imaging and Signal Processing: Evolution in Remote Sensing (WHISPERS)*, 2021, pp. 1–5. doi: 10.1109/WHISPERS52202.2021.9483998.

[13] M. A. Merchant, “Classification of Open Water Features Using OBIA and Deep Learning,” in *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS*, 2021, pp. 104–107. doi: 10.1109/IGARSS47720.2021.9554400.

[14] H. Ouchra and A. Belangour, “Satellite image classification methods and techniques: A survey,” in *2021 IEEE International Conference on Imaging Systems and Techniques (IST)*, 2021, pp. 1–6. doi: 10.1109/IST50367.2021.9651454.

[15] V. Poliyapram, N. Imamoglu, and R. Nakamura, “Deep Learning Model for Water/Ice/Land Classification Using Large-Scale Medium Resolution Satellite Images,” in *IGARSS 2019 - 2019 IEEE International Geoscience and Remote Sensing Symposium*, 2019, pp. 3884–3887. doi: 10.1109/IGARSS.2019.8900323.

[16] A. Agnihotri and N. Kohli, “A Hybrid Deep Neural approach for multi-class Classification of novel Corona Virus (COVID-19) using X-ray images,” in *2023 International Conference on Advancement in Computation & Computer Technologies (InCACCT)*, 2023, pp. 1–5. doi: 10.1109/InCACCT57535.2023.10141782.

[17] S. Chethana, S. S. Charan, V. Srihitha, A. Thakur, and N. P. T V, "Multi-Class classification of Different Cancer Types Using CNN," in *2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, 2023, pp. 1–5. doi: 10.1109/ICCCNT56998.2023.10306850.
[18] D. D. Pandya, S. K. Patel, A. H. Qureshi, A. J. Goswami, S. Degadwala, and D. Vyas, "Multi-Class Classification of Vector Borne Diseases using Convolution Neural Network," in *2023 2nd International Conference on Applied Artificial Intelligence and Computing (ICAAIC)*, 2023, pp. 1–8. doi: 10.1109/ICAAIC56838.2023.10140654.
[19] C. Junliang, "CNN or RNN: Review and Experimental Comparison on Image Classification," in *2022 IEEE 8th International Conference on Computer and Communications (ICCC)*, 2022, pp. 1939–1944. doi: 10.1109/ICCC56324.2022.10065984.
[20] L. Ceccaroni *et al.*, "Citclops: A next-generation sensor system for the monitoring of natural waters and a citizens' observatory for the assessment of ecosystems' status," *PLoS One*, vol. 15, no. 3, p. e0230084, Mar. 2020, doi: 10.1371/journal.pone.0230084.
[21] M. Wernand, A. Hommersom, and H. Woerd, "MERIS-based ocean color classification with the discrete Forel–Ule scale," *Ocean Science Discussions*, vol. 9, pp. 2817–2849, Jun. 2012, doi: 10.5194/osd-9-2817-2012.
[22] S. Novoa, M. R. Wernand, and H. J. Van der Woerd, "The Forel-Ule scale revisited spectrally: Preparation protocol, transmission measurements and chromaticity," *Journal of the European Optical Society*, vol. 8, 2013, doi: 10.2971/jeos.2013.13057.
[23] S. Novoa, M. Wrnand, and H. J. van der Woerd, "WACODI: A generic algorithm to derive the intrinsic color of natural waters from digital images," *Limnol Oceanogr Methods*, vol. 13, no. 12, pp. 697–711, Dec. 2015, doi: 10.1002/lom3.10059.
[24] X. Li, W. Huang, D. K. Peters, and D. Power, "Assessment of Synthetic Aperture Radar Image Preprocessing Methods for Iceberg and Ship Recognition with Convolutional Neural Networks," in *2019 IEEE Radar Conference (RadarConf)*, 2019, pp. 1–5. doi: 10.1109/RADAR.2019.8835807.
[25] Y. Wu, X. Zhang, Y. Xiao, and J. Feng, "Attention Neural Network for Water Image Classification under IoT Environment," *Applied Sciences*, vol. 10, no. 3, 2020, doi: 10.3390/app10030909.
[26] N. T. Singh, C. Kaur, A. Chaudhary, and S. Goyal, "Preprocessing of Medical Images using Deep Learning: A Comprehensive Review," in *2023 Second International Conference on Augmented Intelligence and Sustainable Systems (ICAISS)*, 2023, pp. 521–527. doi: 10.1109/ICAISS58487.2023.10250462.