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RESEARCH ARTICLE

Water Classification Using Convolutional Neural Network

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ABSTRACT The classification of water sources is a challenging task due to the low contrast texture features, the visual similarities between them, and the causes posed by image acquisition with different camera angles and placements. The various image enhancement techniques, i.e., Unsharp Masking (UM), Histogram Equalization (HE), Contrast Limited Adaptive Histogram Equalization (CLAHE), and Contrast Stretching, were used to highlight the contrast and texture features of water images. The enhanced image samples were then fed to the proposed Convolutional Neural Network (CNN)-based model named WaterNet (WNet) for classification. From all employed image enhancement techniques, Contrast Limited Adaptive Histogram Equalization (CLAHE) provides better results in terms of contrast and texture features of water. CLAHE also improved the classification performance of the proposed model, with an accuracy of 97%. For comparison, experiments have also been performed on state-of-the-art pre-trained models, which are DenseNet-201, Inception_ResNet_v2, Inception_v3, and Mobile-Net. Comparison shows that the proposed technique achieves better accuracy in comparison with the state-of-the-art methods.

INDEX TERMS Water sources, water source classification, water images, WaterNet (WNet), image processing, image enhancement techniques, computer vision, convolutional neural network, deep learning.

I. INTRODUCTION

Water is an important resource for human survival and development [1]. The most accessible form of water supply for living creatures is from various water sources like rivers, lakes, canals, streams, ponds, etc. Numerous efforts have been devoted to the detection, analysis, and monitoring of water sources because they have a significant impact on our daily life. Jan et al. [2] presented an Internet of Things (IoT)-based lake water level monitoring system. However, this technology was expensive and difficult to implement. To tackle the problems of Internet of Things (IoT) low-cost, visualized, and non-contact digital image processing approaches have been adopted.

As the use of digital image processing in research grows, the evaluation and analysis of water images and their prediction have received special attention from researchers. Such as, classification of water images is crucial for evaluating surface water for agriculture, monitoring river water quality, detecting water hazards, classifying rainwater, food production, constructing aerial water maps for safe zone detection using land drones, and residential water consumption [3], [4], [5], [6], [7], [8], [9]. For all of the above-discussed applications, analysis and classification of water source images significantly improve system performance. In the literature, numerous approaches were proposed to

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classify water sources through remote sensing images [1], [10], [11], [12], [13]. Contrarily, the classification of water source images captured from normal cameras is still considered challenging. To cope with this challenge, a deep learning-based [14] model called the Convolutional Neural Network (CNN) has been proposed, as deep CNNs are widely used in image classification because of their outstanding performance in comparison with other machine learning paradigms. In addition, the CNN automatically extracts an image's spatial and temporal properties.

The proposed technique involves two steps. In the first step, various techniques of image enhancement are employed for preprocessing to enhance the texture and contrast of water. Because texture and contrast are the most important features for representing various types of water sources. In the second stage, enhanced images are fed-forwarded to the proposed CNN model named WaterNet(WNet) for classification.

A. CONTRIBUTION OF STUDY

The following is an overview of the research contributions from the perspective of innovation:

- According to our knowledge, this is the first research that examines the effect of image enhancement techniques through the CNN for water source classification.
- Real-time dataset has been prepared by capturing the images from different water sources through smartphone camera.
- For the classification of different water sources, a deep learning based CNN model has been proposed.

B. ORGANIZATION OF STUDY

The remaining research is structured according to the following hierarchy: Section II discusses related work. Section III outlines the proposed methodology of water source classification as well as associated topics. In Section IV, dataset and evaluation measures are discussed. Section V discusses the results, and the discussion. Lastly, section VI ultimately summarizes this research with future directions.

II. RELATED WORK

Various methods of water image classification are reviewed here. Ulutas and Ustubioglu [15] introduced an approach to improving underwater images that contained two modules: color correction and contrast. The contrast correction module is utilized to enhance the contrast of test images in the RGB color space through the application of local and global contrast corrections using CLAHE and LDR. For 200 underwater images, the proposed model achieves the highest mean values of EMEE (32.06), EME (40.97) entropy (7.83), Sobel count (130393) and average gradient (152.55).

Lee and Lee [16] employed long short-term memory (LSTM) model to determine algal blooms in four main South Korean rivers. They employed regression analysis and deep learning to construct one-week predictions utilizing a freshly generated water quantity and quality dataset from 16 river dammed pools. The LSTM model demonstrated the highest accuracy in predicting harmful blooms of algae, and all deep-learning methods surpassed OLS regression analysis.

In order to extract bodies of water from satellite imagery, Yuan et al. [10] developed an innovative method based on an efficient DCNN model. The data from the Sentinel-2 satellite has been utilized in experiments. The experimental outcomes show that the suggested model detects micro-water bodies better than previous DCNN models.

Wu et al. [17] suggested a method for the classification of clean and dirty water images. The proposed methodology investigates the utilization of Fourier transform-based characteristics to extract textural features from images of both clean and dirty water obtained from various sources. Support vector machine (SVM) classifiers were used to classify the data. Classification rate, recall, precision, and F-measures of clean and dirty water images reveal that the suggested method outperforms the existing method.

Wu et al. [18] build an attention neural network for the Internet of Things (IoT) that captures images of clean and polluted water and encodes channel-wise and multi-layer features to improve feature representation. The data was gathered from several water sources. The proposed system facilitates real-time monitoring of water pollution occurrences, encouraging users to take quick action.

Vignesh and Thyagharajan [19] employed Gabor filters, Fuzzy c-means, and an expert edge detection algorithm to identify water bodies in multispectral images. The method used Landsat-7 and Landsat-8 satellite images. The experimental findings demonstrated that the suggested methodology produces more accurate results for water identification.

Xue et al. [20] this study develops deep invariant texture features and a deep network for recognizing images of clean and dirty water. The proposed methodology has been evaluated through experiments conducted on a huge dataset comprising images of clean and polluted water. The results indicate that the suggested approach outperforms the current techniques in terms of both speed and accuracy.

Several methods have been proposed in literature, such as analyzing water sources via satellite, detecting clean and polluted water, and restoring underwater images. However, no research has looked into how CNN image enhancement affects the classification of water sources. Furthermore, instead of the complex techniques discussed in the literature, a simple and easy method has been proposed.

III. PROPOSED METHODOLOGY

The proposed methodology involves two phases. In the first phase, image preprocessing has been performed using different image enhancement techniques to enhance the texture and contrast features of water images. In the second stage, enhanced images from preprocessing are fed forwarded

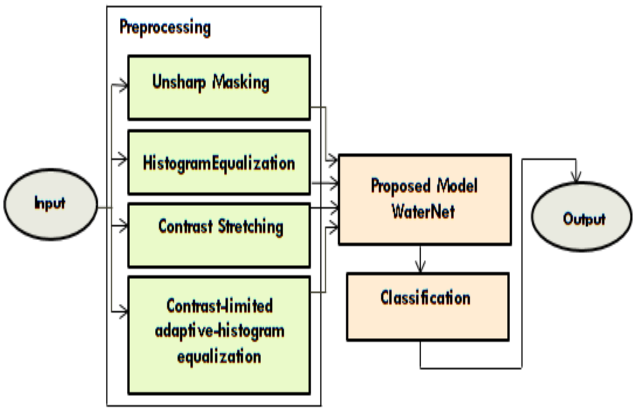

FIGURE 1. Overall flow of proposed methodology.

to the proposed WNet for classification. The flow of proposed methodology is explained in Fig. 1.

A. PREPROCESSING

The images captured from water sources contain noise, poor resolution, low texture, and contrast, which degrade the image quality. Effective image preprocessing techniques can be used to generate training and testing data for Deep-CNN, which could help solve this problem. According to Koo and Cha, image pre-processing is crucial before training CNN models, as it improves the accuracy of the models' classification [21]. Consequently, the primary objective of this research is to employ effective image pre-processing techniques to generate datasets that reduce the computational time needed by the neural network and improve accuracy and classification rates. In order to accomplish this, preprocessing techniques such as image enhancement have been selected to increase the quality of the input images for the neural network, which may lead to better results when the model is applied in the real world. Various image enhancement techniques, including contrast stretching, unsharp masking, histogram equalization, and contrast-limited adaptive histogram equalization (CLAHE), were used to achieve the best results for contrast and texture features.

1) CONTRAST STRECHING

It is a technique for stretching contrast by increasing the dynamic range of an image's intensity value [22]. It enhances the image's contrast by making bright pixels brighter and dark pixels darker. To normalize or enhance the image's contrast, it's crucial to determine the image's lower and upper values. Image lower and upper values will be denoted as L and U, respectively. The next phase is to generate and analyze the original image's histogram in order to identify the image's value limits (lower = l, upper = u). Finally, the function shown in Eq. (1) is used to map the original value X of each pixel to the output value Y.

$$Y = (X - 1)\left(\frac{U - L}{u = l}\right) + u \tag{1}$$

2) UNSHARP MASKING

Unsharp masking [23] is a standard technique for enhancing sharpness. The enhancement framework can be summarized as follows: By using a linear shift-invariant low-pass filter (e.g., the Gaussian filter), the original image is divided into two layers. The image that is obtained as a result is commonly denoted as the "base layer" and consists of the main structure of the image. The layer that reveals the finer details of the original image is commonly referred to as the "detail layer", which differentiates it from the base layer. It can be defined as in Eq. (2):

$$i = \lambda(I - \emptyset_L(I)) + I \tag{2}$$

3) HISTOGRAM EQUALIZATION

Histogram equalization is a widely used technique for images enhancement. This technique involves the uniform distribution of image intensities, resulting in an increased contrast from low to high. Due to its effectiveness and simplicity, histogram equalization [24] produces an output image with a uniform histogram, which flattens and stretches the dynamic range of the image's intensity levels. Furthermore, it will change the image's brightness and may result in an increase in contrast. The basic equation of histogram equalization for an image is shown in Eq. (3):

$$New\_intensity = T(original\_intensity) \tag{3}$$

In Eq. (3), new intensity is the value after equalization, original intensity is the original pixel intensity, and T is the transfer function that transfers the original intensity values to the new intensity values, determined using the function defined in Eq. (4):

$$T(i) = \left(\frac{c}{L} - 1\right) * (p(f) <= i) \tag{4}$$

where i is the intensity value, c is a constant that controls image contrast, L is the number of intensity levels (*often L = 256 for 8-bit images*), and $p(j)$ is the probability density function of image intensity values.

4) CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALIZATION (CLAHE)

CLAHE is a method for enhancing the texture and contrast of different objects. CLAHE has generated accurate statistical estimations for medical, computing, and real-time applications [25]. It's an extension of adaptive histogram equalization (AHE) however, it distinguishes itself from standard AHE due to its utilization of contrast limiting. CLAHE reduces amplification by cutting off the histogram at the 'clip limit' set by the user. The clipping level decides the amount of histogram noise smoothing and contrast enhancement. Moreover, a histogram clip (AHC) can be used. AHC automatically moderates the over-enhanced background region of images and adjusts clipping. A common AHC that results in a bell-shaped histogram is Rayleigh

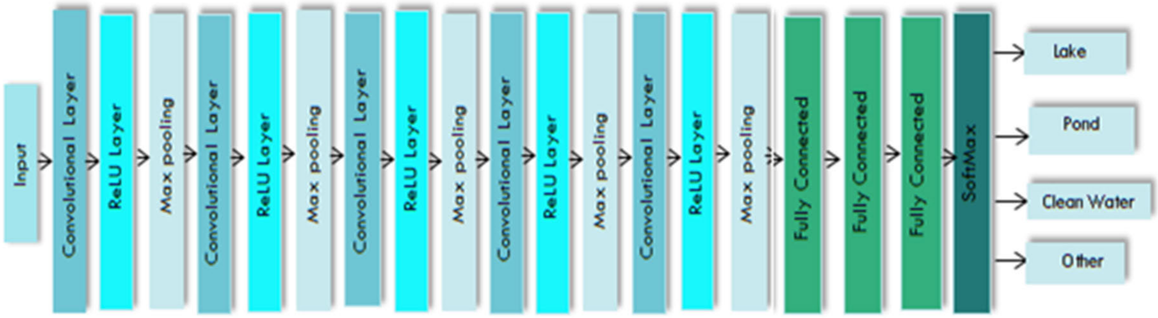

FIGURE 2. Architecture view of proposed CNN model Water Net(WNet).

distribution; define in Eq. (5):

$$Rayleighg = g_{min} + [2\left(\alpha^2\right) ln\left(\frac{1}{1-P(f)}\right)]^{0.5} \tag{5}$$

where g_{min} is the minimum possible value for a pixel in the water image, $P(f)$ is a cumulative probability distribution, and α is a nonnegative real scalar representing the parameter of the distribution. In this research, the clip limit is set to 0:01, whereas the value of the Rayleigh distribution function is 0:04.

B. CNN-BASED MODEL WATERNET (WNET)

In this research, deep learning-based CNN-model WNet has been proposed for the classification of different water sources. The architecture of the proposed WNet is shown in Fig. 2. CNN operates similarly to the human visual system and is built on the concept that raw data consists of two-dimensional images, allowing certain properties to be encoded. The purpose of its development was to construct a neural network with less parameter that could be stored in computer memory more easily. It is important to note that the proposed model includes only 19 layers, as indicated in Table 1, which is too low in comparison to state-of-the-art models. The following subsections provide an extensive explanation of all the layers of WNet.

1) CONVOLUTIONAL LAYER

Convolution is performed by the convolutional layer, which is then followed by the normalizing and pooling processes. Using a series of filters with trainable weights, the main objective of convolution operations is to make feature maps from the input dataset. Given an image *Img* with dimensions (*M, N*) and a filter F with dimensions (*p, q*), the convolution process is defined by the Eq. (6). ∈

$$\begin{aligned} conv &= (Img * F)(x, y) \\ &= \sum_{M}\sum_{N} I(x-p, y-q)\,F(p, q) \end{aligned} \tag{6}$$

These filters begin the convolution process from the upper left of the input image to the bottom-right. As a result, feature maps are generated.

2) POOLING LAYER

The pooling layer receives the output of the convolutional layer and minimizes the features' dimensionality. The result of a pooling operation is a feature map with local perceptual fields. Pooling can be done in two ways: max pooling and mean pooling. In the proposed CNN design, we use "max pooling", which takes the maximum response from the convolutional process.

3) ACTIVATION FUNCTION

When training a network, matrix multiplication might lead to a linear network if the activation function is not used. There are various types of activation functions, but in the proposed model, *ReLU* activation has been used, which is calculated using Eq. (7).

$$ReLU(x) = max(x, 0) \tag{7}$$

The main reason for preferring the *ReLU* function over other activation functions is that it is computationally efficient, requiring only a simple threshold operation as compared to other activation functions like sigmoid or *tanh*, which require more computation.

4) FULLY CONNECTED LAYERS

These layers are often found at the end of CNN models that are used to classify and detect the desired objects. These layers are often found at the end of CNN models, which are used for the classification and detection of the targeted objects. These layers are connected to all the activities that were previously connected in a hierarchical way. This enables CNN to extract more discriminating feature representations from the lower to higher layers.

IV. DATASETS AND EVALUATION MEASURES

This section discusses datasets and the evaluation measures that are used for validation of WNet.

A. DESCRIPTION OF DATASETS

Under uniform illumination conditions, 308 images from different water bodies, including lakes, ponds, and clean water, were captured over three weeks. All images were

TABLE 1. The detail of Water Net(WNet) layers.

Layer No.	Layer Name	Filter Size	Stride	No. of filters
1.	Convolutional layer	3x3	2x2	8
2.	ReLU layer	-	-	-
3.	Max Pooling	2x2	2x2	-
4.	Convolutional layer	3x3	2x2	16
5.	ReLU layer	-	-	-
6.	Max Pooling	2x2	2x2	-
7.	Convolutional layer	3x3	2x2	32
8.	ReLU layer	-	-	-
9	Max Pooling	2x2	2x2	-
10.	Convolutional layer	3x3	2x2	64
11.	ReLU layer	-	-	-
12.	Max Pooling	2x2	2x2	-
13.	Convolutional layer	3x3	2x2	128
14.	ReLU layer	-	-	-
15.	Max Pooling	2x2	2x2	-
16.	Fully Connected layer	-	-	-
17.	Fully Connected layer	-	-	-
18.	Fully Connected layer	-	-	-
19.	Softmax Layer	-	-	-

TABLE 2. Datasets detail.

Total Images	Location	Water Depth	Distance of camera from water	Camera	Resolution
308	South Korea (Seoul)	1.5m	0.2m	16megapixal	5312x2988

captured in natural light during the morning, afternoon, and evening. Additional information about the dataset is shown in Table 2.

The captured images have been saved as image processing supported format JPEG. Then resized to 224×224 pixels.

B. EVALUATION MEASURES

Evaluation measures including accuracy, sensitivity, and F1-Score will be used to evaluate the classification's results, and these evaluation measures are represented in the following equations: 8, 9, and 10, respectively.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}$$

$$ReCall = \frac{TP}{TP + FN} \tag{9}$$

$$F1 - Score = \frac{2TP}{2TP + FN + FP} \tag{10}$$

In the above equations, true positive (TP) represents the number of correctly classified images in the positive class; true negative (TN) represents the number of correctly classified images in the negative class; and false positive (FP) and false negative (FN) represent the number of incorrectly classified images in the positive and negative classes, respectively.

V. RESULTS AND DISCUSSION

For experiments, image preprocessing work was conducted using Matlab and other tools, the main algorithm was performed using Anaconda3 (Python 3.6). The experimental hardware environment utilized for model training and testing comprises an Intel ®Xeon(R) E5-2620 v4 central processing unit, which operates at a frequency of 2.10 GHz and is equipped with 64 GB of memory. Additionally, an NVIDIA GeForce RTX 2080 graphics card (CUDA 10.2) is also employed. The dataset was split into three sections: 70% for training, 15% for validation, and 15% for testing. Due to the lack of data, different data augmentation techniques like rotation, shifting, 90° rotation, zooming, random cropping, horizontal flipping, and translation are used during model training, and at least 200 images per category are guaranteed. The dataset has four classes such as lake, pond, clean-water, and others. The proposed methodology has two phases: (I) improving image quality with different image enhancement techniques during preprocessing, (II) classifying the preprocessed water source images. Adam optimizer was used for training with a batch size of 4, a learning rate of 0.001, and a maximum of 50 epochs.

To exhibit usefulness of the proposed methodology, a detailed discussion on: Effects of various image enhancement techniques on water images during preprocessing, Effects of various enhancement techniques on WNet accuracy, Effects of various epochs on WNet accuracy, and comparison with state-of-the-art methods are presented in following sub-sections.

A. EFFECTS OF VARIOUS IMAGE ENHANCEMENT TECHNIQUES ON WATER IMAGES AFTER PREPROCESSING

By using different image enhancement techniques; this research enhanced the appearance of water images before DL classification stage. Each technique was executed and evaluated independently. The Fig. 3 shows how image enhancement techniques make the images more informative for WNet. This will enhance the WNet's performance when deployed in the real world. The proposed model gives more accurate classification results for images of various water sources.

B. EFFECTS OF VARIOUS IMAGE ENHANCEMENT TECHNIQUES ON WNET ACCURACY

Four different image enhancement techniques: histogram equalization (HE), contrast limited adaptive histogram equalization (CLAHE), unsharp masking, contrast stretching have varying effects on WNet accuracy. The WNet achieves different levels of accuracy for each image enhancement technique shown in Fig. 4. The Fig. 4 shows with histogram equalization WNet receives an accuracy of 90% because histogram equalizations it doesn't provide high contrast and texture in water images due to some limitations, including contrast limitation, weighted adjustment, and brightness preservation. Unsharp masking achieves an accuracy of

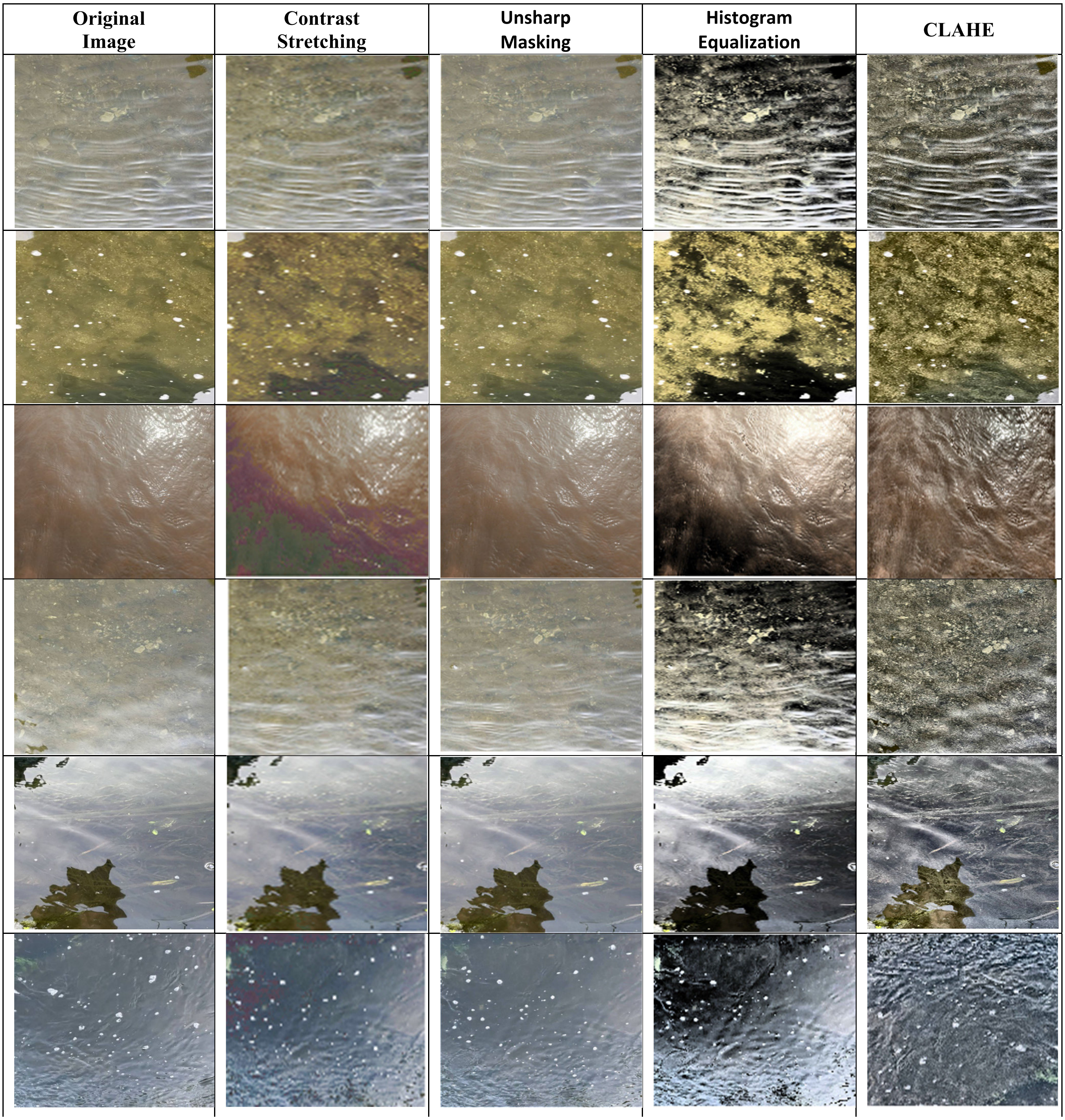

FIGURE 3. Results obtained from different image enhancement techniques.

95.3% because it is most effective when applied to images with high levels of noise instead of enhancing the contrast and texture of the image. On the other hand, received an accuracy of 94% with contrast stretching, which produces good results in contrast enhancement but, in some cases, may introduce noise or other artifacts into the image. Apart from that, CLAHE receives 97% accuracy because CLAHE is useful to avoid the introduction of artifacts and preserve important details in the image. It has been concluded from the above results that CLAHE performs better in terms of enhancing the contrast and texture features of water than other enhancement techniques.

Now we further evaluate the other parameters of WNet in the light of CLAHE, as CLAHE has been proven to improve WNet accuracy compared to other enhancement techniques. So, Table 3 and Fig. 5 show the effect of CLAHE on the

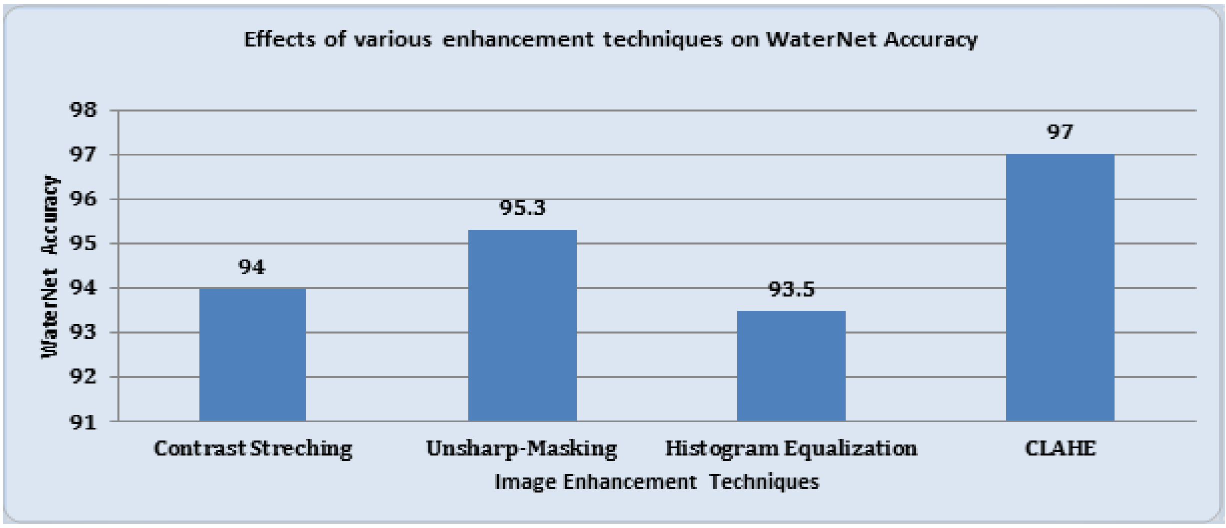

FIGURE 4. Effect of various image enhancement techniques on WaterNet(WNet) accuracy.

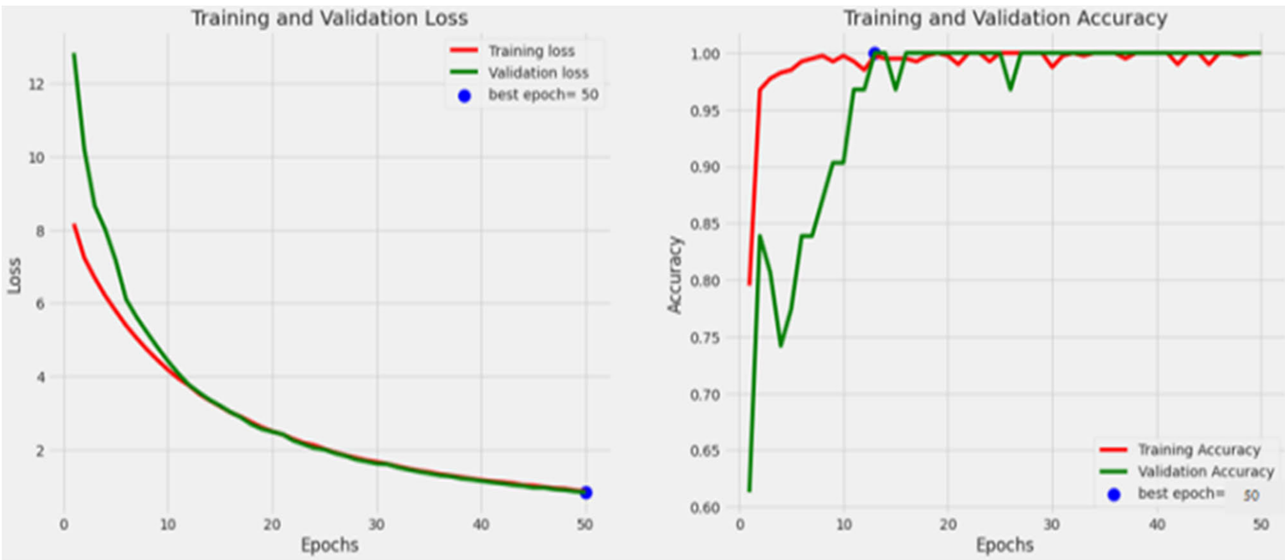

FIGURE 5. Left is the loss and right depicts the accuracy of WaterNet(WNet).

TABLE 3. Results of approach waterNet(WNet).

Samples	Training Accuracy%	Validation Accuracy%	Testing Accuracy%	Training Loss	Validation Loss
308	100	100	97	0.84	0.82

training, validation, and testing accuracy of the proposed WNet.

The WNet successfully classifies the water sources according to their contrast and texture features. Fig. 6 shows the results of the image classification for water sources.

Most unseen test samples have been correctly classified by the WNet, and most of the predicted categories for unseen test samples match the real categories. This shows that the WNet is exceptionally effective at classifying water images. To further analyze the effectiveness of WNet, values of evaluation metrics, i.e., accuracy, sensitivity, and F1-Score, have been calculated using the testing dataset. The calculated value of the evaluation measures for each class is shown in Table 4.

According to the results, the total predicted accuracy for the WNet is 97% on the test data. The WNet's thorough test performance is shown in a confusion matrix. After the training process, the confusion matrix provides precise information on the classification accuracy for each class. Fig. 7 represents the confusion matrix of the WNet for testing data.

The image enhancement approach CLAHE has significantly improved the classification accuracy of WNet. The

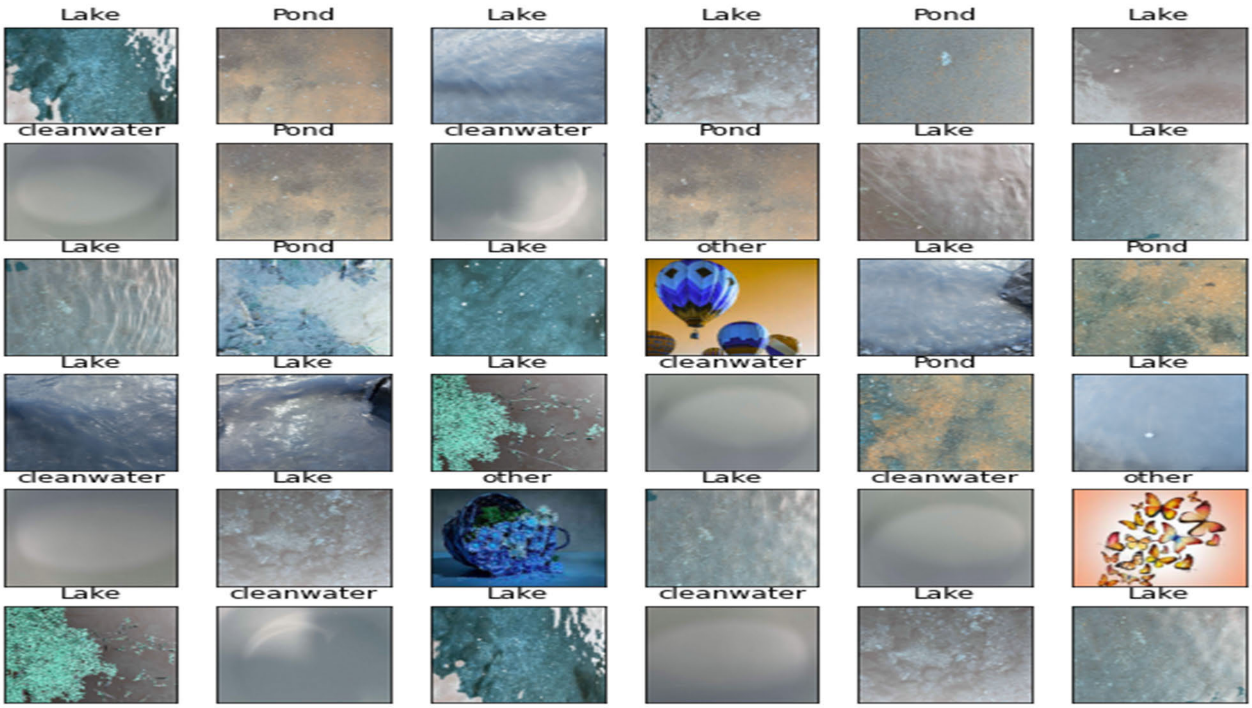

FIGURE 6. Classification results of WaterNet(WNet).

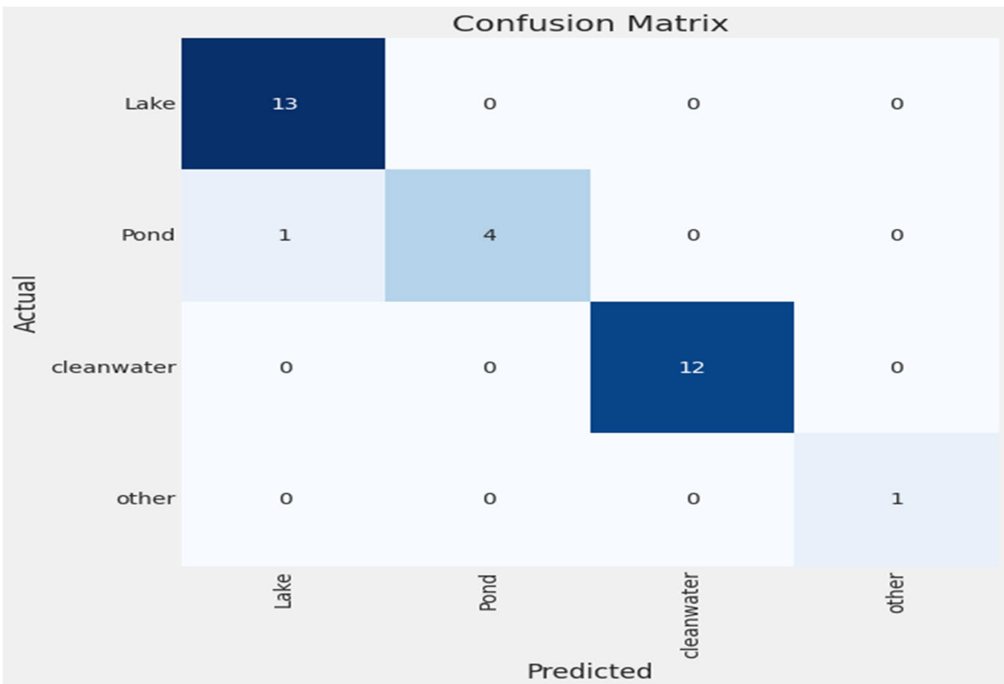

FIGURE 7. Confusion matrix.

CLAHE improved the image quality by enhancing the contrast and texture features of water. This helps the CNN's ability to extract and learn the essential features, resulting in better classification accuracy.

C. EFFECTS OF VARIOUS EPOCHS ON WNET ACCURACY

The WNet outcomes after the 10, 20, 30, 40, and 50 epochs are shown in Fig. 8. To choose the best epoch for the

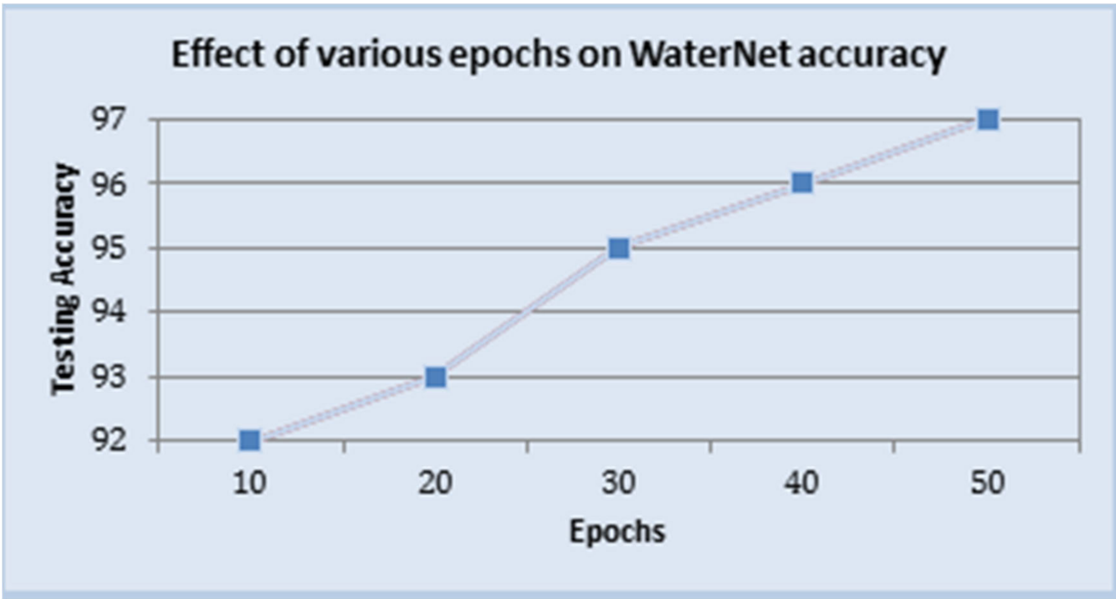

FIGURE 8. WaterNet(WNet) accuracy at various epochs.

TABLE 4. Calculated values of evaluation measures.

Classes	Precision	Re-Call	F1-Score
Lake	0.93	1.00	0.96
Pond	1.00	0.80	0.89
Clean-Water	1.00	1.00	1.00
Other	1.00	1.00	1.00

TABLE 5. WaterNet(Net) comparison with state-of-the-art models.

Models	Training Accuracy%	Validation Accuracy%	Testing Accuracy%	Training Loss	Validation Loss
Mobile-Net	99	100	100	0.03	4.12
Inception_v3	90	77	78	0.46	2.95
DenseNet-201	100	92	92	0.00	0.72
Inception_ResNet_v3	98	100	100	0.04	2.31
WaterNet	**100**	**100**	**97**	**0.84**	**0.82**

suggested model, an analysis has been performed. Other parameters remained static as epochs were increased. The accuracy of the suggested WNet increased steadily over 50 epochs. As a result, 50 epochs were selected for the WNet. The results indicate that epoch change is necessary to improve the model's accuracy.

D. COMPARISON WITH STATE-OF-THE-ART

Moreover, to further evaluate performance of the WNet, various CNN approaches, such as Inception_v3 [26], Mobile-Net [27], DenseNet-20 [28], and Inception_ ResNet_v2 [29], are selected for the comparative experiments with the proposed model. These CNN models have been trained and validated, and they achieve 100 percent accuracy on the testing set. Training, validation, and testing accuracy and loss for each CNN and the proposed model WNet are shown in Table 5 and Fig. 9, respectively.

The findings indicate that the proposed methodology attains higher accuracy when compared to the existing state-of-the-art models. WNet shows excellent outcomes across a range of benchmarks and metrics as compared to state-of-the-art models. Furthermore, WNet architectural design incorporates deep convolutional layers and powerful feature extraction methods, allowing it to detect complicated and complex patterns easily. Also the

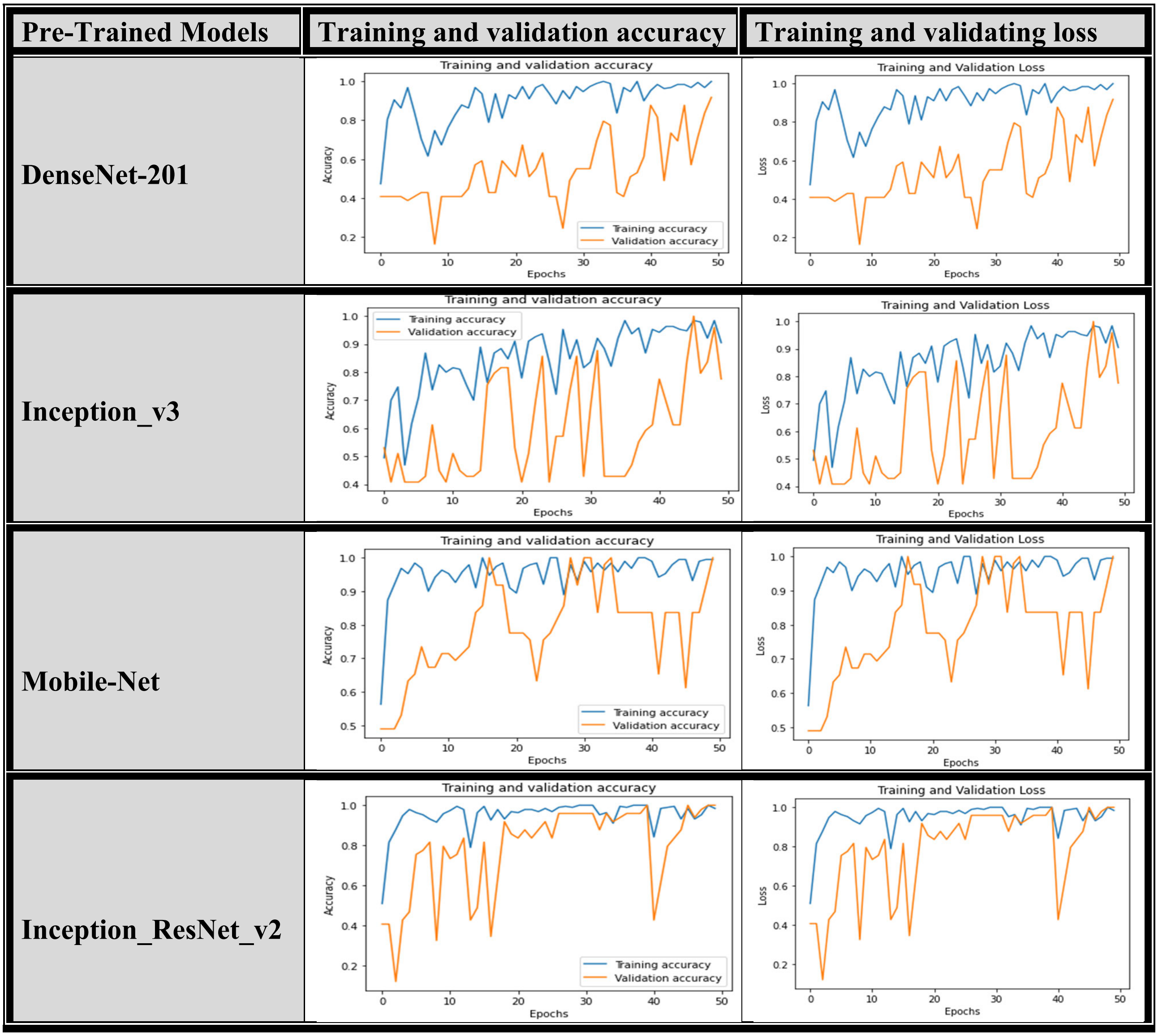

FIGURE 9. Accuracy and loss of state-of-the-art models.

WNet have training and validation loss compare to other models.

VI. CONCLUSION AND FUTURE WORK

Water sources are vital for human beings and the environment. This research has proposed CNN model WNet for classification of various water sources. Different image enhancement techniques help in improving the visual quality of the water image as well as highlighting the contrast and texture features. The proposed model achieves better classification accuracy with CLAHE than other enhancement techniques. However CLAHE is computationally expensive algorithm. This means that it can take a long time to process a large size of image. Other pre-trained models, i.e., DenseNet-201, Inception_ResNet_v2, Inception_v3, and Mobile-Net, are also used for comparison purposes. The future work of this research is to calculate the total amount of nutrients (calcium, chloride, fluoride, magnesium, potassium, and sodium) in water through computer vision.

AUTHOR CONTRIBUTION

Conceptualization: Ghulam Gilanie and Mubbashar Saddique; methodology: Ghulam Gilanie, Mubbashar Saddique, and Saira Asghar; validation: Irshad Ahmed Abbasi and Mohamed Abbas; formal analysis: Heba G. Mohamed; investigation: Heba G. Mohamed and Saira Asghar; Data Curation: Heba G. Mohamed; resources: Saira Asghar, Irshad Ahmed Abbasi, Mohamed Abbas, and Heba G. Mohamed; writing—Saira Asghar; writing—review and editing: Irshad Ahmed Abbasi and Mohamed Abbas; visualization: Saira Asghar; funding acquisition: Mohamed Abbas; and project administration: Ghulam Gilanie and Mubbashar Saddique. All authors have read and agreed to the published version of the manuscript.

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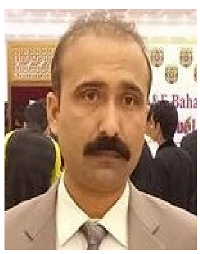

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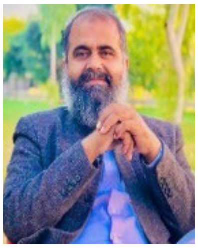

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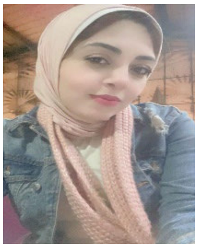

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