Improvement of Interpolation Performance with Statistical Method in Total Suspended Solid Identification

Hadi Syahputra[1,*], Yuhandri[2], Sumijan[3]

[1,2,3]Department of Information Technology, Universitas Putra Indonesia YPTK, Padang, Indonesia

(Received: October 3, 2025; Revised: December 1, 2025; Accepted: March 10, 2026; Available online: May 3, 2026)

Abstract

Total Suspended Solids (TSS) is one of the key parameters used to determine water quality, which can be observed through the density level of suspended particles. The determination of TSS aims to ensure that river pollution levels can be controlled to maintain good environmental quality. However, the identification of TSS is still performed manually, which requires a relatively long processing time. This condition highlights the need for an effective and efficient identification process. Based on these considerations, this study aims to develop an extraction technique to identify TSS in river water using the Interpolation Mean Square (IMS) algorithm. The development of the extraction technique within the IMS algorithm is crucial for improving the performance of linear interpolation methods. Mean Square is proposed as a parameter in the interpolation process to optimize the extraction algorithm. The segmentation process based on the performance of the IMS algorithm involves exploring and grouping image intensity values. The resulting segmented image clusters are subsequently selected based on the values produced by the Mean Square computation, which are then processed as the final segmentation output. The experimental results show an improvement in the performance evaluation results of the IMS algorithm providing an increase of 7% to 10% over the previous linear interpolation method. The evaluation results produced by the IMS algorithm are 90.19% accuracy, 99.99% sensitivity, and 83.33% specificity. These results indicate that the improved interpolation method presented in the IMS algorithm produces optimal results in determining TSS. Improving the performance of the interpolation method through the development of an IMS-based extraction technique has succeeded in producing optimal identification results. The superiority of the IMS algorithm provides novelty in the development of interpolation techniques for automated segmentation. Furthermore, the findings of this study can effectively support the West Sumatra Environmental Agency in addressing river water pollution issues.

Keywords: Identification, Total Suspended Solids (TSS), Segmentation, Interpolation Mean Square (IMS), Extraction Techniques

1. Introduction

Water has become an important component in human life and is a primary need for all living things [1]. Water sources that have been widely used for the survival of the community can be obtained from river water [2]. Previous research in the study of the problem of determining river water conditions needs to be an important topic of discussion due to the large amount of river water pollution [3]. Determination of the quality due to river water pollution has been carried out by measuring the normative level of the water quality index by determining the TSS object [4]. These measurements ensure that they produce information about particles such as the levels of chemicals that are used as considerations in determining water quality [5]. Based on this, the use of image processing technology is needed to present a flexible water quality measurement process with the TSS object identification process.

Image processing technology has been utilized in various aspects such as the process of analyzing and predicting water quality [6]. Research in the case of water quality has been carried out using the MRSE-Net algorithm on the CNN architecture in segmented TSS analysis [7]. Another study reported that image processing technology has been quite successful in utilizing vision technology to determine water quality based on image acquisition, suspended solids recognition, quantity statistics, size estimation, and other image analysis processes [8]. The same study also explains that image processing technology can measure TSS objects to avoid the impacts that will be produced [9]. A study that is not much different also states that the concept of image processing is adopted in determining clean water which is seen based on the TSS value produced [10]. The development of image processing technology can be seen in extraction techniques that have been able to contribute to solving various problems [11]. Extraction techniques are basic concepts

*Corresponding author: Hadi Syahputra (hadisyahputra@upiyptk.ac.id)
DOI: https://doi.org/10.47738/jads.v7i2.1190

in image processing that can be used in the identification process [12]. Extraction techniques can be explored by presenting knowledge contained in an image [13]. The resulting knowledge can be used as a reason for carrying out the identification process on an image [14]. The development of extraction techniques based on previous research can also be collaborated with interpolation techniques to manipulate images for the interests of the detection process [15]. The contribution of interpolation techniques can improve image quality in describing image objects [16]. Interpolation techniques require modification of geometry by matching the existence of objects that can affect the proportion of image elements as a whole [17].

Previous research reported the performance of interpolation techniques by playing neighboring pixel values providing image output that changes image quality [18]. Research using interpolation techniques combined with the Artificial Neural Network (ANN) method has also provided quite significant results with a matrix coefficient accuracy level of 88% [19]. The same study also presents an image reconstruction process based on image resolution improvements [20]. A parallel study also reports that interpolation techniques have played an active role in modifying changes in improving image pixel values to minimize the effects of noise on an image [21]. The development of interpolation techniques can also be presented in the extraction process by manipulating images using the inserted method to provide fairly good output results in forensic images [22]. Interpolation techniques are also able to provide increased Deep Learning performance in classifying lung cancer [23]. The image extraction process with experiments using interpolation techniques combined with enhancement methods can present image resolution improvement output [24].

Based on the research described previously, this study will also experiment with modifying the performance of interpolation techniques using statistical methods to develop image extraction techniques. This development is presented in the Interpolation Mean Square (IMS) algorithm to perform a series of image extraction processes to identify TSS objects. The use of Mean Square is based on generating average values that serve as parameters in interpolation-based segmentation. Mean Square ensures that the resulting values provide accuracy in the detection process. The development of extraction techniques based on the IMS algorithm presents a novelty in image processing techniques, particularly in identification. The proposed IMS algorithm is expected to provide optimal results in determining river water quality. This study also aims to contribute by presenting an alternative solution for the TSS object identification process.

2. Literature Review

The TSS identification process using semantic segmentation techniques based on the performance of the CNN model with CoANet presents the results of river water image segmentation in the identification process. The results of this study indicate that the CNN model with CoANet provides a significant increase in identification accuracy [25]. The same study also confirms that the TSS prediction process by utilizing the performance of the Regression method in Machine Learning (ML) has produced prediction results with a fairly good level of accuracy [26]. ML implementation can also be presented by involving statistical methods and regression models, which can also improve ML learning in predicting and identifying TSS objects [27]. A similar study on the identification process has also been developed based on ML concepts, involving Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Network (ANN) methods, which have produced results with a precision level of 82% in TSS identification [28].

The involvement of ML concepts in the same process can also be seen through the use of the Neighbor Mean Interpolation by Neighboring Pixels method. These two methods contribute significantly to the identification process, resulting in an 8% increase in accuracy in TSS identification [29]. The application of digital image processing concepts in ML also yields improved results in the detection and image manipulation process for determining TSS objects, based on the performance of the interpolation method [30]. Modifications to the performance of the interpolation method can also be presented in the Neighbor Interpolation update, which presents ML performance in TSS object detection [31]. The application and combination of remote sensing with multiple linear methods or concepts in ML performance can improve the accuracy of air quality predictions. This model can be used to integrate TSS variations [32]. Based on this, improvements in ML performance can be made by proposing the development of the IMS method in this research in the study of the identification process.

3. Methodology

The development of extraction techniques by modifying interpolation techniques in the TSS object identification process series presents novelty in the form of the IMS algorithm. The IMS performance algorithm is proposed to provide improvements in image quality that will later be used in the extraction process in TSS object identification. The use of modified interpolation techniques based on the IMS algorithm can provide an overview of the identification process used in detecting TSS objects. The performance of the IMS algorithm can be presented in the research framework in figure 1.

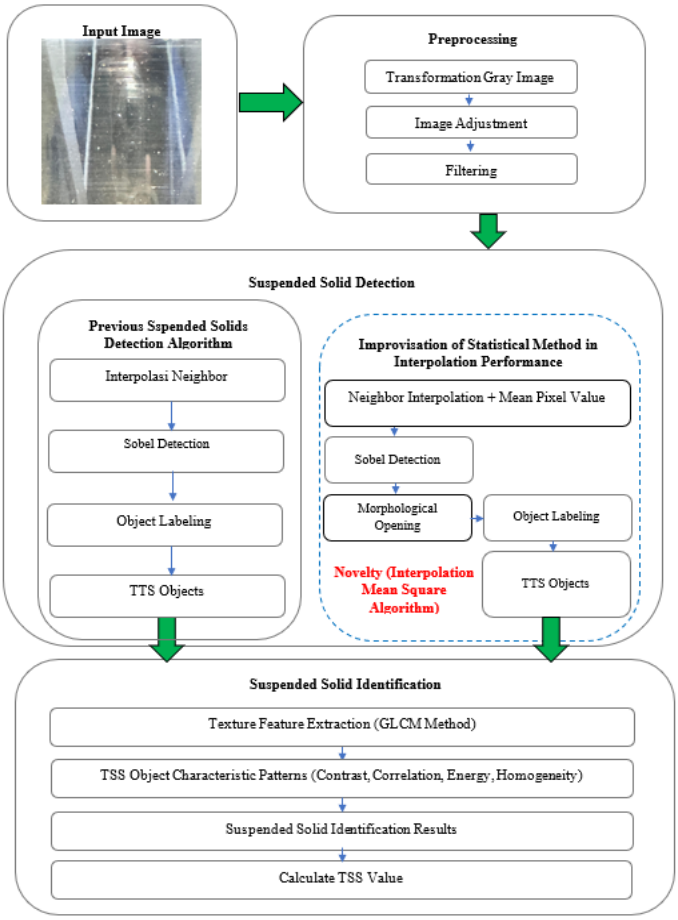


Figure 1. Research Framework

Figure 1 is a describes the TSS object identification process for determining river water quality by developing an extraction technique using the IMS algorithm. The extraction technique presented describes the identification process stages, consisting of pre-processing and identification. The pre-processing stage employs image transformation and filtering to remove noise from the input image. The results of the pre-processing stage are then used in the next stage to perform the identification process using the IMS algorithm developed in the extraction technique. The IMS algorithm's performance is measured using statistical methods to calculate the mean square to generate parameter values used in edge detection. Figure 1 also explains the differences between the classical neighbor interpolation technique and the IMS algorithm's performance in detecting TSS objects. The detection process with the IMS algorithm, developed using the interpolation technique, improves pixel quality compared to the previous process. The IMS output is also refined by feature extraction to improve the TSS object detection process for determining river water quality. The detected TSS objects are then processed by calculating the object area and determining the image object characteristics using the GLCM method for identification.

Figure 1 also presents innovations in the TSS object identification process using the IMS algorithm. The innovation of the IMS algorithm is evident in the improvement of statistical methods by involving Mean Squared Error in finding the average pixel value to be adopted in the segmentation process using the Neighbor Interpolation method. The performance of the IMS algorithm is expected to improve the segmentation process in the overall identification process. The role of the IMS algorithm can also be used as a model in the development of extraction techniques used in the identification process.

The presentation of the identification process based on the performance of the IMS algorithm in the results presented can be concluded that the algorithm's performance has answered the challenge in optimizing the performance of the

ISSN 2723-6471

Neighbor Interpolation method with the involvement of statistical methods. The results of the Mean Squared value presented provide new parameters in the performance process of the Neighbor Interpolation method to present a more optimal segmentation process. The description of the IMS algorithm can be presented in Algorithm 1.

Algorithm 1. Adaptive Mean-Based Interpolation Filter

```
Input : Img_fill (x,y)
Output : (P) Parameter Value
Initialization : img_label, numObjects, idx, m, n, resolution
Image Input
  Selected_Image = imread(fullfile(direktori,namafile));
Interpolation Mean Square
  % Determine the Row and Column Intensity Matrix of image pixels
  ab1 =    median_filtering_Image;  // filtered image variable
  nrows1 = size (ab1,1); // read the line of intensity values of the filtered image results
  ncols1 = size (ab1,2); // read the intensity value column of the filtered image results
  % Calculate the total number of image pixel matrices
  data=J2(1:nrows,1:ncols); // combine rows and columns of intensity values of the filtered image results
  total_row = nrows; // sum the total value of the intensity rows of the filtered image results
  total_colm = ncols; // sum the total values of the intensity column of the filtered image results
  % Total Image Pixel Row Intensity
  jx = sum(data) // sum of the total intensity values of all images
  % Total Image Pixel Column Intensity
  jy = sum(data') // transformation of intensity values of all images
  % Average Intensity Row Pixel
  xround = jx / nrows; // calculate the average value of all rows
  yround = jy / ncols; // calculate the average value of all columns
  % Average Pixel Column Intensity
  xaksen = sum(xround); // the sum of the average values of all rows.
  yaksen = sum(yround); // the sum of the average values of all columns
  value_MS = (xaksen + yaksen)/ (nrows+ncols) // calculate the mean value
        c = zeros([3 3]);
        c (1, 1) = floor(value_MS (1,1));
        c (1, 2) = floor((value_MS (1,1)*2+ value_MS (1,2)*2);
        c (1, 3) = floor(value_MS (1,2));
        c (3, 1) = floor(value_MS (2,1));
        c (3, 3) = floor(value_MS (2,2));
        c (2, 1) = floor((value_MS (1,1)* 2 + value_MS (2 1)*2);
        c (2, 3) = floor((value_MS (2,2)* 2 + value_MS (1,2)*2);
        c (3, 2) = floor((value_MS (2,2)* 2 + value_MS (2,1)*2);
        c (2, 2) = floor((value_MS (1,1) + value_MS (1,2));
  end
end
```

Algorithm 1 presents the working structure of the IMS algorithm, which represents a novel approach to the object identification process. The performance of IMS proves that there has been an improvement in the performance of the Neighbor Interpolation method by involving the Mean Squared statistical method to find the threshold value adopted by the Neighbor Interpolation method. The threshold value generated through the Mean Square calculation is presented based on the average value of the image pixels.

3.1. Data Collection

The TSS object identification process with the development of extraction techniques on the performance of the IMS algorithm is intended for determining river water quality. Input images in the object identification process can use direct addressing results on river water image capture results. The form of the river water image capture results used as a research dataset can be presented in figure 2.

(a) (b) (c)

Figure 2. Sampel Image River Water Photography; (a) Image 1; (b) Image 2; (c) Image 3

Figure 2 shows an example of the image data used in the TSS identification process. A total of 179 TSS images were collected from river water images taken at the laboratory of the West Sumatra Provincial Environmental Agency. The TSS images are in RGB format with a resolution of 512 x 512. These images will serve as input for the recognition process based on the performance of the developed IMS algorithm. The obtained dataset will later be divided into 150 training images and 29 images as test data. This dataset division aims to test the performance of the IMS algorithm in the TSS object identification process.

3.2. Nearest Neighbor Interpolation

Nearest Neighbor Interpolation is a technique in image processing that only manipulates images by playing with image pixel values [33]. The role of interpolation techniques has basically contributed to the development of image processing techniques to overcome problems in the identification process [34]. The performance of interpolation techniques is able to manipulate new pixel values that refer to image pixel values [35]. The Nearest Neighbor Interpolation interpolation technique can be presented in formula (1) [36].

$$\begin{gathered}(x) = \frac{|x|}{|Sx|} \\ (y) = \frac{|y|}{|Sy|} \\ g(x',y') = f(\text{round}(x),\text{round}(y))\end{gathered} \tag{1}$$

Formula 1 explains that $|x|$ is the distance between the point to be interpolated and the image texture. The interpolation process ensures the use of kernel to obtain the pixel value of the interpolation result [28].

3.3. Mean Square Statistical Method

Mean square is one of the statistical methods that has been widely used in analyzing data [37]. Mean square has also been adopted in computational problems that can be presented in an algorithm [38]. Mean Square is used as a process of evaluating a model to measure the effectiveness of machine learning [39]. The mean square equation can be presented in formula (2) [40].

$$\mu = E(X) \int_{-a}^{a} x . f(x) . dx \tag{2}$$

Formula (2) presents the μ (Mean Square) value which is used to measure the distribution or spread of data. f(x) is the frequency of the data and d(x) is the distribution of the data spread [40].

ISSN 2723-6471

3.4. Edge Detection

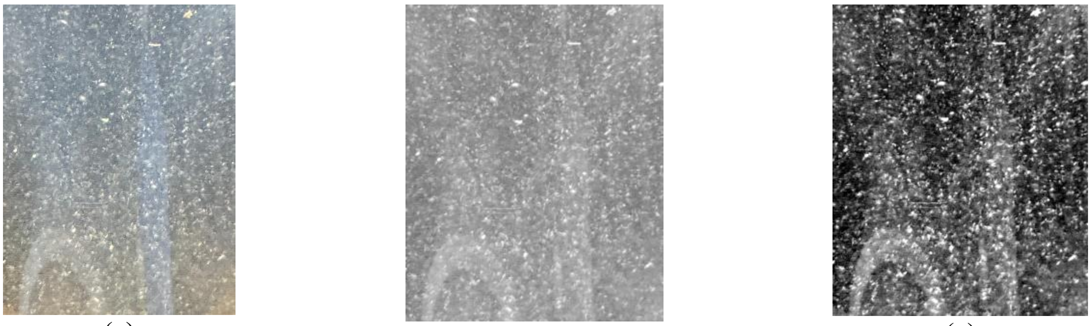
Edge detection in this study is one of the stages of the process in the performance of the IMS algorithm developed in the extraction technique. Edge detection is used to find the edge of an image object by referring to the object area based on the image intensity value [41]. Edge detection using the Sobel operator ensures that the kernel works with horizontal and vertical gradients presented in formula (3) [41]

$$Ix = Gx * I \tag{3}$$

Formula (3) explains that the value of Ix is the value of the horizontal and vertical gradients in describing the edges of the image object. The edge detection process ensures that the image matrix is determined using the kernel (Gx) which can be determined.

4. Results and Discussion

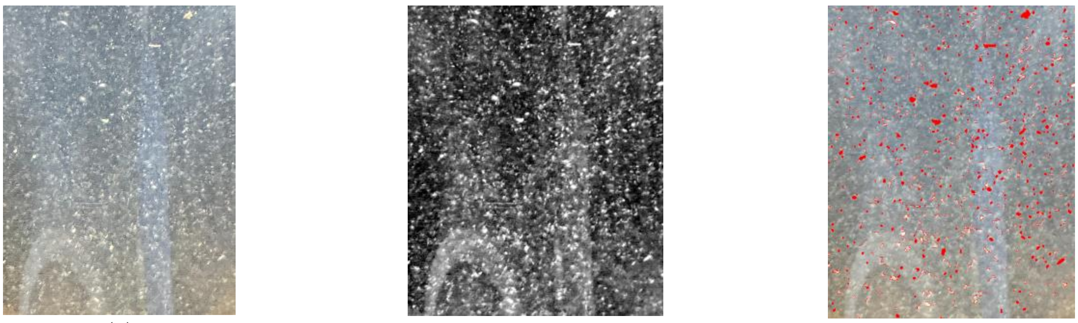
The TSS object identification process using the IMS algorithm is presented in several stages, as shown in figure 1. The initial stage involves preprocessing to improve the previous input image. Preprocessing is also a crucial step, as each image must be free of any noise still present in the input image. The results of the preprocessing stage are presented in figure 3.



(a) (b) (c)

Figure 3. Preprocessing Results; (a) Image Input; (b) Gray Transformation Result 2; (c) Filtering Result

Figure 3 shows the preprocessing results aimed at eliminating noise contained in the previous input image. Figure 3(a) is the input image used in the TSS object identification process in determining river water quality. Figure 3(b) shows the initial preprocessing stage in performing grayscale image transformation. Figure 3(c) shows the continuation of the preprocessing process by using a median filter ring to eliminate previously contained noise objects. The preprocessing results will later become the input image in the TSS object identification process using the IMS algorithm. The performance of the IMS algorithm in improvising the interpolation method based on the mean square method for the TSS object identification process can be presented in figure 4.



(a) (b) (c)

Figure 4. IMS Algorithm Performance Results; (a) Image Preprocessing Results; (b) IMS Result; (c) TSS Object

Figure 4 illustrates the performance results of the IMS algorithm in identifying TSS objects to determine river water quality. Figure 4(a) is the initial input image used and continued in the preprocessing process, the results of which are presented in figure 4(b). Figure 4(b) shows the results of the IMS algorithm in detecting TSS objects. The detection

ISSN 2723-6471

results produce optimal TSS object accuracy with a clear image of water particles. The final detection results are also clearly presented in figure 4(c), which can describe the TSS objects. The performance of the IMS algorithm in the TSS object identification process can also be simulated in a tool presented in figure 5.

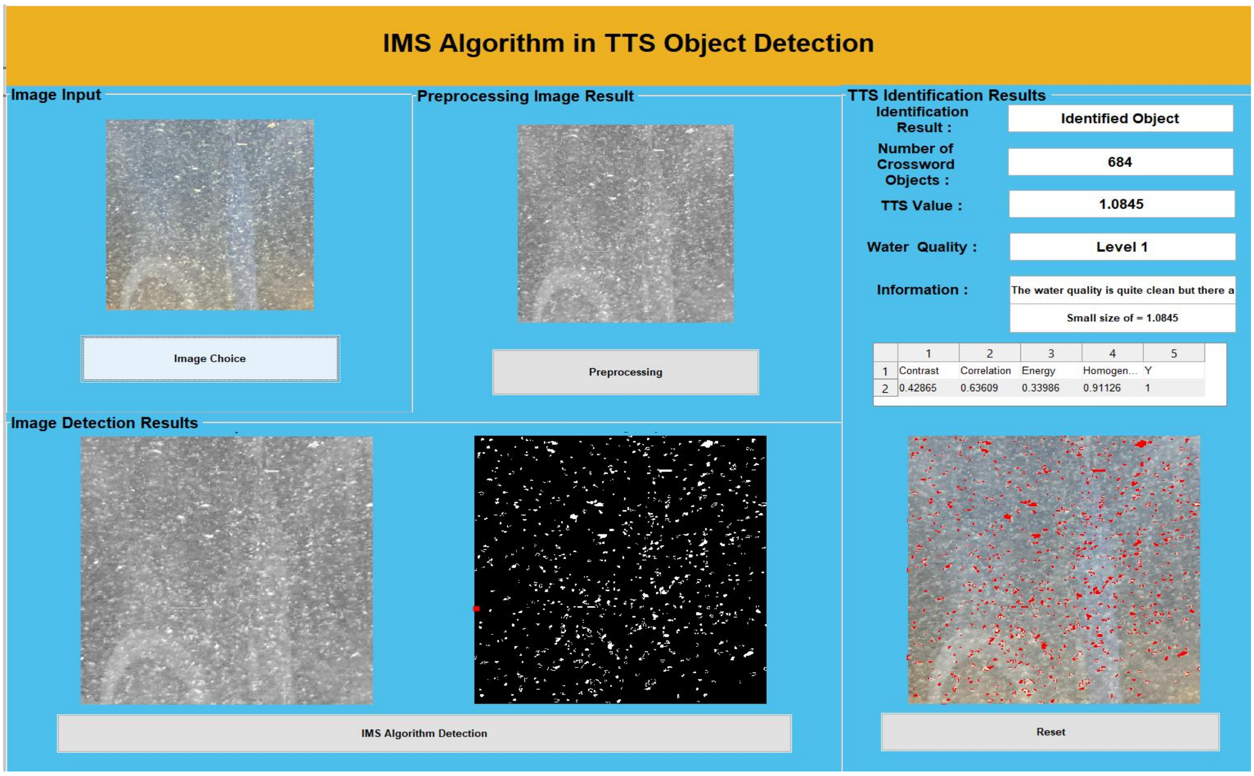


Figure 5. TSS Object Identification Process

Figure 5 shows the performance of the IMS algorithm in a tool designed for the TSS object identification process. The IMS algorithm has been proven capable of displaying TSS object output with visualization of detected objects and providing identification-related information. Based on these results, it can be explained that the IMS algorithm has also provided quite good performance in the object identification process, and can be claimed that the IMS algorithm offers innovation in the identification process. The performance of the IMS algorithm can also be compared with previous research in the use of Neighbour Interpolation and several other methods and concepts in the identification process, presented in table 1.

Table 1. The Significance of The Relationships in The Model

No	Previous Research Results	Performance of IMS Algorithm in TSS Object Identification
1	The development of architectures such as VGG-16, VGG-19, Inception-V3, Xception, DenseNet-121, MobileNet, and NASNet-mobile delivers an accuracy rate of 87% in TSS identification [42]	The development of a semantic segmentation model based on Resnet-18 using an unsupervised model presented an accuracy value of 97.09%, sensitivity of 90.05% and specificity of 97.70%.
2	The combination of interpolation techniques combined with the Artificial Neural Network (ANN) method has also provided quite significant results with a matrix coefficient accuracy level of 88% [19]	
3	The machine learning model successfully predicted SSC with High spatiotemporal resolution analysis 82% [28]	
4	The resulting Deep Learning model successfully detects particles in images with high accuracy (AP50 > 85% and F1 Score > 82%) [43]	

ISSN 2723-6471

Table 1 presents a comparison of the performance results of the IMS algorithm in the identification process based on previous research. The IMS algorithm's performance is superior, with an identification accuracy of 97.09%, a sensitivity of 90.05%, and a specificity of 97.70%. These results indicate that the IMS algorithm is quite successful in providing an identification process that can be claimed as innovative. This innovation is evident in the performance of the IMS algorithm supported by improvements in the Neighbor Interpolation method, which incorporates the Mean Squared statistical method. The results of this study can also provide maximum contribution. in handling problems in determining river water quality effectively and efficiently. This is needed to assist related parties in monitoring and maintaining the environment, especially river water quality.

5. Conclusion

The improved performance of the interpolation method, developed by developing an extraction technique based on the performance of the IMS algorithm, has been able to provide optimal identification results. This shows that the mean square method can provide accurate parameter values in the identification process, thus providing optimal results. These results can be seen based on the evaluation process with an accuracy of 97.09%, a sensitivity of 90.05%, and a specificity of 97.70%. The presentation of the identification results obtained has become a claim of this study, which states that the IMS algorithm provides a new identification process in determining river water quality. The novelty presented in the IMS algorithm also has limitations in low image resolution which results in poor IMS performance. Based on this, further research is expected to further develop the IMS algorithm by incorporating specific parameters for automatic identification, such as standard deviation, and allowing for comparisons using other statistical methods.

6. Declarations

6.1 Author Contributions

Conceptualization FA and SA.; Methodology: FA and SA.; Software: FA.; Validation: TA.; Formal Analysis: FA and SA.; Investigation: SA.; Resources: FA.; Data Curation: TA.; Writing Original Draft Preparation: FA and TA; Writing Review and Editing: FA.; Visualization: F.A.; All authors have read and agreed to the published version of the manuscript.

6.2 Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3 Funding

The author would like to thank Assoc. Prof. Dr. H. Muhammad Ridwan, SE, MM, as the Rector of Universitas Putra Indonesia YPTK Padang who has provided the opportunity to study in the doctoral program with a study permit letter number: 12/UPI-YPTK/R.KL/IX/2023.

5.4. Institutional Review Board Statement

Not applicable.

5.5. Informed Consent Statement

Not applicable.

5.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] M. Zhu, "A review of the application of machine learning in water quality evaluation," *Eco-Environ. Heal.*, vol. 1, no. 2, pp. 107–116, 2022, doi: 10.1016/j.eehl.2022.06.001.

[2] C. T. Son, N. T. H. Giang, T. P. Thao, N. H. Nui, N. T. Lam, and V. H. Cong, “Assessment of Cau River water quality assessment using a combination of water quality and pollution indices,” *J. Water Supply Res. Technol.*, vol. 69, no. 2, pp. 160–172, 2020, doi: 10.2166/aqua.2020.122.

[3] E. Novita, H. A. Pradana, B. H. Purnomo, and A. I. Puspitasari, “River water quality assessment in East Java, Indonesia,” *J. Water Land Dev.*, vol. 2020, no. 47, pp. 1–12, 2020, doi: 10.24425/jwld.2020.135040.

[4] N. H. Judran and A. Kumar, “Evaluation of water quality of Al-Gharraf River using the water quality index (WQI),” *Model. Earth Syst. Environ.*, vol. 6, no. 3, pp. 1581–1588, 2020, doi: 10.1007/s40808-020-00775-0.

[5] S. Bi, “A comprehensive method for water environment assessment considering trends of water quality,” *Adv. Civ. Eng.*, vol. 2021, no. Jan., pp. 1–12, 2021, doi: 10.1155/2021/5548113.

[6] P. Che, “Water conservancy automation monitoring system based on VR image video and internet of things,” *Mob. Inf. Syst.*, vol. 2022, no. Jan., pp. 1–12, 2022, doi: 10.1155/2022/2008733.

[7] X. Zhang, J. Li, and Z. Hua, “MRSE-Net: multiscale residuals and SE-attention network for water body segmentation from satellite images,” *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, vol. 15, no. Jan., pp. 5049–5064, 2022, doi: 10.1109/JSTARS.2022.3185245.

[8] Z. Sheng and Y. Zhang, “Vision-based automatic detection of suspended solids in bottled mineral water,” *IEEE Access*, vol. 2019, no. Jan., pp. 464–468, 2019, doi: 10.1109/ICICSP48821.2019.8958545.

[9] S. Khullar and N. Singh, “Water quality assessment of a river using deep learning Bi-LSTM methodology: forecasting and validation,” *Environ. Sci. Pollut. Res.*, vol. 29, no. 9, pp. 12875–12889, 2022, doi: 10.1007/s11356-021-13875-w.

[10] D. G. Ebsa and W. F. Kabeta, “Assessment of river water quality and pollution status using physicochemical and biometrics, Awetu River, Ethiopia,” *Geofluids*, vol. 2022, no. Jan., pp. 1–12, 2022, doi: 10.1155/2022/1727739.

[11] J. Wang, H. Zhu, S. H. Wang, and Y. D. Zhang, “A review of deep learning on medical image analysis,” *Mob. Netw. Appl.*, vol. 26, no. 1, pp. 351–380, 2021, doi: 10.1007/s11036-020-01672-7.

[12] A. I. Kadhim, “An evaluation of preprocessing techniques for text classification,” *Int. J. Comput. Sci. Inf. Secur.*, vol. 16, no. 6, pp. 22–32, 2018.

[13] M. Sarrouti and S. O. El Alaoui, “SemBioNLQA: a semantic biomedical question answering system for retrieving exact and ideal answers to natural language questions,” *Artif. Intell. Med.*, vol. 102, no. Jan., pp. 1–12, 2020, doi: 10.1016/j.artmed.2019.101767.

[14] M. Koklu, M. F. Unlersen, I. A. Ozkan, M. F. Aslan, and K. Sabanci, “A CNN-SVM study based on selected deep features for grapevine leaves classification,” *Measurement*, vol. 188, no. Jan., pp. 1–12, 2022, doi: 10.1016/j.measurement.2021.110425.

[15] C. Jittawiriyanukoon and V. Srisarkun, “Evaluation of color image interpolation based on incompressible Navier Stokes technique,” *Bull. Electr. Eng. Inform.*, vol. 10, no. 3, pp. 1634–1639, 2021, doi: 10.11591/eei.v10i3.1820.

[16] X. Li, L. Zhang, P. Wang, and X. He, “A high-precision interpolation method for data transfer in fluid-structure interaction analysis,” *Int. J. Aerosp. Eng.*, vol. 2022, no. Jan., pp. 1–12, 2022, doi: 10.1155/2022/2047796.

[17] X. Li, J. Ma, X. Wang, J. Wu, and Z. Li, “An improved local mean decomposition method based on improved composite interpolation envelope and its application in bearing fault feature extraction,” *ISA Trans.*, vol. 97, no. 1, pp. 365–383, 2020, doi: 10.1016/j.isatra.2019.07.027.

[18] R. Aly, N. A. El-Hag, W. El-Shafai, T. E. Taha, F. E. A. El-Samie, and F. G. Hashad, “Efficient implementation of image fusion and interpolation for brain tumor diagnosis,” *J. Opt.*, vol. 53, no. 1, pp. 30–48, 2024, doi: 10.1007/s12596-023-01159-0.

[19] F. Ahmad, “Deep image retrieval using artificial neural network interpolation and indexing based on similarity measurement,” *CAAI Trans. Intell. Technol.*, vol. 7, no. 2, pp. 200–218, 2022, doi: 10.1049/cit2.12083.

[20] Z. Huang and L. Cao, “Bicubic interpolation and extrapolation iteration method for high resolution digital holographic reconstruction,” *Opt. Lasers Eng.*, vol. 130, no.1, pp. 1–10, 2020, doi: 10.1016/j.optlaseng.2020.106090.

[21] A. Hassani, G. S. Santos, P. Schneider, and N. Castell, "Interpolation, satellite-based machine learning, or meteorological simulation? A comparison analysis for spatio-temporal mapping of mesoscale urban air temperature," *Environ. Model. Assess*., vol. 29, no. 2, pp. 291–306, 2024, doi: 10.1007/s10666-023-09943-9.

[22] D. Kumar, R. C. Pandey, and A. K. Mishra, "A review of image features extraction techniques and their applications in image forensic," *Multimed. Tools Appl*., vol. 2024, no. Jan., pp. 1–102, 2024, doi: 10.1007/s11042-023-17950-x.

[23] U. Prasad, S. Chakravarty, and G. Mahto, "Lung cancer detection and classification using deep neural network based on hybrid metaheuristic algorithm," *Soft Comput.*, vol. 28, no. 15, pp. 8579–8602, 2024, doi: 10.1007/s00500-023-08845-y.

[24] K. L. Reddy and G. B. Mohan, "Enhancing medical imaging: noise reduction and super resolution with transfer learning," *Int. J. Intell. Data Commun. Technol. Internet Things,* vol. 2024, no. Jan., pp. 1430–1435, 2024, doi: 10.1109/IDCIoT59759.2024.10467434.

[25] Z. Fan, J. Hou, Q. Zang, Y. Chen, and F. Yan, "River segmentation of remote sensing images based on composite attention network," *Complexity*, vol. 2022, no. Jan., pp. 1–12, 2022, doi: 10.1155/2022/7750281.

[26] I. L. S. Brandao, J. van der Molen, and D. van der Wal, "Effects of offshore wind farms on suspended particulate matter derived from satellite remote sensing," *Sci. Total Environ*., vol. 866, no.1, pp. 1–12, 2023, doi: 10.1016/j.scitotenv.2022.161114.

[27] M. A. Torres-Vera, "Mapping of total suspended solids using Landsat imagery and machine learning," *Int. J. Environ. Sci. Technol*., vol. 20, no. 11, pp. 11877–11890, 2023, doi: 10.1007/s13762-023-04787-y.

[28] A. Mohsen, A. Balla, and T. Kiss, "High spatiotemporal resolution analysis on suspended sediment and microplastic transport of a lowland river," *Sci. Total Environ.*, vol. 902, pp. 1–12, 2023, doi: 10.1016/j.scitotenv.2023.166188.

[29] C. T. Huang, C. Y. Lin, and C. Y. Weng, "Dynamic information-hiding method with high capacity based on image interpolating and bit flipping," *Entropy,* vol. 25, no. 5, pp. 1–12, 2023, doi: 10.3390/e25050744.

[30] C. Lin, R. Chen, W. Tai, and C. Lin, "RADH-A reversible and authenticable data hiding scheme in encrypted domain based on image interpolation and substitution," *Appl. Sci.*, vol. 2024, no. Jan., pp. 1–12, 2024, doi: 10.3390/app142311083.

[31] R. P. Sharma, A. Malik, S. Singh, S. Agarwal, and R. Kumar, "High payload lossless steganography using image interpolation," *Secur. Commun. Netw.*, vol. 2023, no. 1, pp. 1–14, 2023, doi: 10.1155/2023/2068813.

[32] F. Setiawan, "Developing algorithms for estimating total suspended solids (TSS) using unmanned aerial vehicle: a case study in the Upper Citarum River, Indonesia," *J. Degrad. Min. Lands Manag*., vol. 12, no. 2, pp. 7379–7388, 2025, doi: 10.15243/jdmlm.2025.122.7379.

[33] F. S. Hassan and A. Gutub, "Efficient image reversible data hiding technique based on interpolation optimization," *Arab. J. Sci. Eng.*, vol. 46, no. 9, pp. 8441–8456, 2021, doi: 10.1007/s13369-021-05529-3.

[34] D. J. Suroso, A. S. H. Rudianto, M. Arifin, and S. Hawibowo, "Random forest and interpolation techniques for fingerprint-based indoor positioning system in un-ideal environment," *Int. J. Comput. Digit. Syst*., vol. 10, no. 1, pp. 1–12, 2021, doi: 10.12785/ijcds/100166.

[35] L. Lin, J. Zhang, X. Gao, J. Shi, C. Chen, and N. Huang, "Power fingerprint identification based on the improved VI trajectory with color encoding and transferred CBAM-ResNet," *PLoS One,* vol. 18, no. 2, pp. 1–12, 2023, doi: 10.1371/journal.pone.0281482.

[36] I. B. Santoso and S. N. Utama, "The best texture image for Gaussian naïve Bayes with nearest neighbor interpolation," *J. Nas. Tek. Elektro Teknol. Inf*., vol. 13, no. 1, pp. 68–75, 2024, doi: 10.22146/jnteti.v13i1.873.

[37] M. Zheng and J. Yu, "Probabilistic approach for robust design with orthogonal experimental methodology in case of target the best," *J. Umm Al-Qura Univ. Eng. Archit.*, vol. 15, no. 1, pp. 55–59, 2024, doi: 10.1007/s43995-023-00040-2.

[38] A. Mazraeh, M. Bagherifar, S. Shabanlou, and R. Ekhlasmand, "A novel committee-based framework for modeling groundwater level fluctuations: a combination of mathematical and machine learning models using the weighted multi-model ensemble mean algorithm," *Groundw. Sustain. Dev*., vol. 24, no.1, pp. 1–12, 2024, doi: 10.1016/j.gsd.2023.101062.

[39] A. Gogineni, M. K. D. Rout, and K. Shubham, "Evaluating machine learning algorithms for predicting compressive strength of concrete with mineral admixture using long short-term memory (LSTM) technique," *Asian J. Civ. Eng*., vol. 25, no. 2, pp. 1921–1933, 2024, doi: 10.1007/s42107-023-00885-x.

[40] F. Mariani, F. De Santis, and S. Gubbiotti, “The distribution of power-related random variables (and their use in clinical trials),” *Stat. Pap*., vol. 65, no. 9, pp. 5555–5574, 2024, doi: 10.1007/s00362-024-01599-1.

[41] J. N. Archana, P. Aishwarya, and H. Joseph, “Enhancement of digital chest images using a modified Sobel edge detection algorithm,” Indones. J. Electr. Eng. Comput. Sci., vol. 24, no. 3, pp. 1718–1726, 2021, doi: 10.11591/ijeecs.v24.i3.pp1718-1726.

[42] K. Hacıefendioğlu, O. T. Baki, H. B. Başağa, and B. Mete, “Deep learning-based total suspended solids concentration classification of stream water surface images captured by mobile phone,” Environ. Monit. Assess., vol. 195, no. 12, pp. 1–12, 2023, doi: 10.1007/s10661-023-12110-y.

[43] N. Saito, T. W. Washburn, S. Yano, and A. Suzuki, “Using deep learning to assess temporal changes of suspended particles in the deep sea,” *Front. Mar. Sci*., vol. 10, no. 1, pp. 1–12, 2023, doi: 10.3389/fmars.2023.1132500.