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Analysis of Ice-Ice Disease on Seaweed Using the K-Nearest Neighbor Algorithm in Vision Robot Technology

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Abstract— Abstract: The advancement of remote sensing technology has significantly enhanced marine monitoring, particularly in assessing the quality of seaweed—a vital natural resource for various industries. Traditional seaweed monitoring methods often lack precision in disease detection. This study introduces a refined approach using the K-Nearest Neighbors (KNN) algorithm, tailored for remote imagery and sensor-based seaweed disease identification. Two key aspects are emphasized: first, the classification of seaweed diseases, critical for maintaining growth and quality; and second, detection based on color and size analysis to ensure productivity. By utilizing image analysis of detection vessels, the system effectively identifies diseases, particularly Ice-Ice disease, optimizing treatment strategies for seaweed farmers. The research demonstrated the system's capability through 44 tests, achieving an accuracy rate of 86.67%. This innovation significantly boosts production efficiency and seaweed quality, providing substantial benefits for sustainable seaweed farming practices. This study highlights the potential of integrating IoT and machine learning technologies to support precise, efficient disease detection and monitoring, contributing to the sustainability and economic viability of the seaweed industry.

Keywords— Internet of Things (IoT), Classification of Ice-Ice disease , K-Nearest Neighbors (KNN) Method

I. INTRODUCTION

Indonesia has a vast marine area, reaching 6.4 million km², with a coastline of around 108,000 km. Indonesia's marine and fisheries resources have a potential of around 225 trillion, with superior commodities such as tuna, shrimp, skipjack, grouper and seaweed. One of the high-value commodities is seaweed, especially the Euchema Sp and E-Cottoni types. Trademap data shows that Indonesia is one of the main players in international seaweed trade, with an export volume in 2018 of 213 thousand tons, ranking first with a contribution of 30% of total world exports [1]. The high export data shows that seaweed production can stimulate the community's economy, especially coastal communities. Seaweed production requires economical and affordable operational costs, but can provide significant income for farmers. In general, in conventional care and checking for disease in Mansih seaweed, farmers still check for disease in seaweed by having to go directly into the water to check directly.

Development of Remote Sensing Technology in Ocean Monitoring. Integration of Disease Classification and Seaweed Ice-Ice disease detection to Improve Quality and Productivity. Remote sensing is one technology that has made a significant contribution to the field of marine monitoring. An important aspect of marine monitoring is the identification of seaweed quality. Seaweed is a valuable natural resource and has various applications in the fields of food, pharmaceuticals, cosmetics and other industries [2].

Along with the very advanced development of Internet of Things (IoT) technology, we can now optimize the benefits of an Internet connection for marine monitoring. IoT is a concept that allows devices with internal sensors to collect and transmit data over a network without manual intervention, and this also applies to remote sensing for ocean monitoring.

In developing seaweed monitoring technology using detection vessel imagery, there are two important aspects that need to be considered. Namely, First, the classification of diseases in seaweed is crucial because various diseases can affect the growth and quality of seaweed. By using the K-Nearest Neighbors (KNN) classification method, diseases in seaweed can be identified and classified with high accuracy, enabling precise and efficient treatment. This classification technology will help seaweed farmers recognize diseases that attack their plants so they can provide timely preventive or treatment measures. Detection of seaweed Ice-Ice disease based on color and size analysis is also an important aspect in the development of monitoring technology. Detecting Ice-Ice disease in seaweed is very important to ensure optimal quality and productivity of seaweed [3].

Through color image analysis on detection vessels, a system can be developed that is capable of detecting diseases in seaweed that is optimal for taking action as quickly as possible. By using an algorithm that is able to interpret color and size information, this system will help seaweed farmers determine the right disease, increase production efficiency, and ensure the quality of the seaweed produced remains optimal. Combining Ice-Ice's disease classification and disease detection technology based on color and size into a seaweed quality recognition system using detection vessel images will provide a comprehensive and ustainable solution in monitoring and optimizing seaweed quality and production effectively. With this technology, seaweed monitoring can be carried out more accurately and efficiently, thereby contributing to improving the overall quality and productivity of seaweed. Apart from the benefits for seaweed farmers, the development of remote sensing technology also has a positive impact on the food, pharmaceutical, cosmetics and other sectors that use seaweed as raw materials [4].

By maintaining seaweed quality and optimal production, it will increase the supply of high quality raw materials for various industrial sectors. This will open up opportunities for the development of innovative products and increase industrial competitiveness at the global level. However, the development of seaweed monitoring technology also needs to consider several challenges. One of them is the availability of high quality and up-to-date detection ship image data. In optimizing this technology, accurate and up-to-date image data is needed so that the results of analysis and disease identification as well as Ice-Ice disease detection become more accurate and reliable. Apart from that, it is also necessary to develop and adjust more sophisticated classification and analysis algorithms for the color and size of seaweed. The development of more advanced algorithms will help increase accuracy and efficiency in the process of disease identification and Ice-Ice disease detection. Therefore, investment in research and development of this technology is essential to continue to advance seaweed monitoring systems. Overall, the development of remote sensing technology has brought positive changes in the field of marine monitoring, especially in the recognition of seaweed quality. The integration of Ice-Ice disease classification and disease detection technology based on detection vessel images is a step forward in increasing production efficiency and seaweed quality. By continuing to optimize and develop this technology, it is hoped that it can provide comprehensive and sustainable solutions to support sustainable and environmentally friendly industrial growth [5].

II. SYSTEM PLANNING

The process starts from collecting seaweed image data which is then included in the dataset. This image data goes through a preprocessing stage to prepare the image so that it is ready for further processing. After preprocessing, the image undergoes segmentation to separate important parts of the image that will be used for analysis. The next stage is to carry out KNN classification, where the processed images will be classified based on the KNN algorithm to determine whether seaweed is included in the healthy class or the sick class. The classification results are stored in a database which can then be accessed and displayed via the website, allowing users to monitor the condition of the seaweed efficiently.

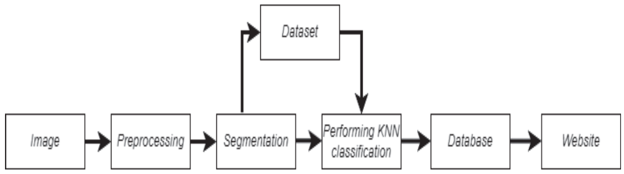

Fig.1. Block diagram

Images are processed through the steps of reading, resizing, improving quality, and calculating features such as average color, standard deviation, skewness, and texture features using the Gray Level Co-occurrence Matrix (GLCM). After feature extraction, predictions are made using the trained KNN model. Prediction results are saved in an existing Excel file or created a new one if one does not already exist. The process ends after all results are saved properly.

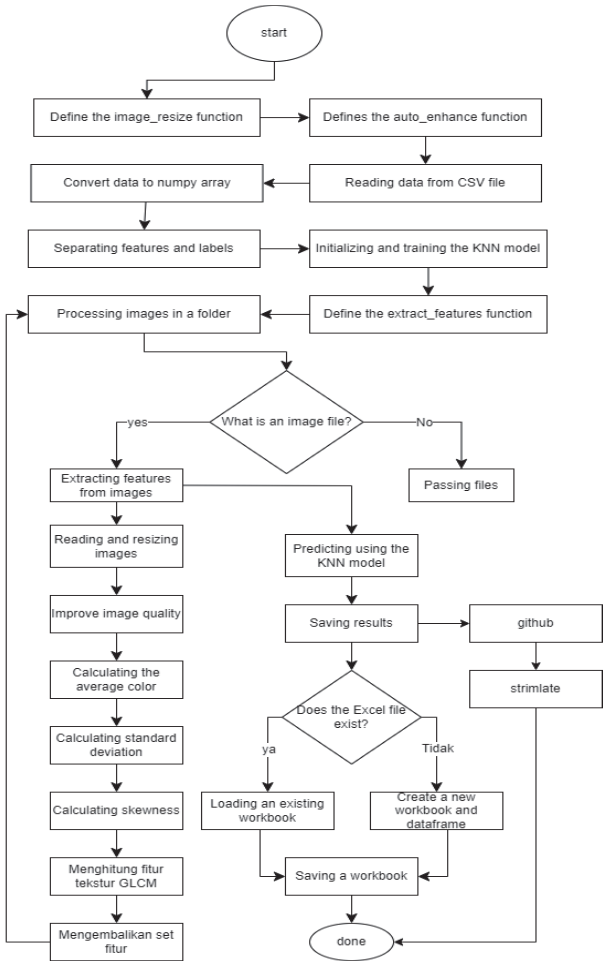

Fig. 2. Flowchart

A. Datasets

Seaweed quality criteria are divided into two classes: Healthy Class and Sick Class. The Healthy Class must be free from disease, while the Sick Class is characterized by ice-ice disease which can be seen from changes in color and texture. Seaweeds are also classified based on their physical condition, with different visual appearances for each class. This comprehensive and representative data collection from a variety of quality criteria and physical conditions allows the KNN model to learn and classify seaweed accurately. The number of images in each class is 200 images for the Healthy Class and 200 images for the Sick Class, for a total of 400 images.

Fig. 3. Image Dataset

Seaweed quality criteria are divided into two classes: Healthy Class and Sick Class. The Healthy Class must be free from disease, while the Sick Class is characterized by ice-ice disease which can be seen from changes in color and texture. Seaweeds are also classified based on their physical condition, with different visual appearances for each class. This comprehensive and representative data collection from a variety of quality criteria and physical conditions allows the KNN model to learn and classify seaweed accurately. The number of images in each class is 200 images for the Healthy Class and 200 images for the Sick Class, for a total of 400 images.

B. Pre-Processing

In this research, image preprocessing is carried out through several stages to prepare data for further analysis and feature extraction. P rocessing includes image resizing, automatic enhancement, and extraction of various statistical and texture features.

C. Resizing

Images were resized using the `image_resize` function so that all images were a consistent size of 400 pixels high, while maintaining the original aspect ratio. For example, if the original image has dimensions of 800x600 pixels, after resizing it, the image will have dimensions of 533x400 pixels.

D. Auto Upgrade

Automatic image enhancement is carried out using the CLAHE (Contrast Limited Adaptive Histogram Equalization) method via the `auto_enhance` function. This process involves converting the image from RGB to LAB color space, applying CLAHE to the L (luminosity) channel, and then recombining the enhanced L channel with the A and B channels before converting back to the BGR color space. This step helps increase image contrast automatically

E. Color Statistics

Color features can be obtained from statistical calculations such as mean and deviation standard. Calculations are carried out on each component R, G and B.

1. Mean RGB

   The average provides a measure of distribution and is calculated by:

$$\text{Mean}_R = \frac{1}{N}\sum_{i=1}^{N} R_i \tag{1}$$

$$\text{Mean}_G = \frac{1}{N}\sum_{i=1}^{N} G_i \tag{2}$$

$$\text{Mean}_G = \frac{1}{N}\sum_{i=1}^{N} G_i \tag{3}$$

2. Standard Deviation

   Standard deviation measures the distribution of pixel data from its average. It shows how much variation or spread the pixel intensity has in the image. Standard Deviation Formula for Channels R, G, and B:

$$StdDev_R = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(R_i - Mean_R)^2} \tag{4}$$

$$StdDev_G = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(G_i - Mean_G)^2} \tag{5}$$

$$StdDev_B = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(B_i - Mean_B)^2} \tag{6}$$

3. Skewness

   Skewness measures the skewness of the distribution of pixels in an image. Positive skewness values indicate a distribution skewed to the right, while negative values indicate a distribution skewed to the left. Skewness Formula for R, G, and B Channels:

$$\text{Skewness}_R = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{R_i\text{-Mean}_R}{\text{StdDev}_R}\right)^3 \tag{7}$$

$$Skewness_G = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{G_i - Mean_G}{StdDev_G}\right)^3 \tag{8}$$

$$Skewness_B = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{B_i - Mean_B}{StdDev_B}\right)^3 \tag{9}$$

4. Kurtosis

   Kurtosis measures the peak distribution of pixels in an image. High kurtosis values indicate a distribution with sharp peaks, while low values indicate a flatter distribution. Kurtosis Formula for Channels R, G, and B:

$$Kurtosis_R = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{R_i - Mean_R}{StdDev_R}\right)^4 - 3 \tag{10}$$

$$Kurtosis_G = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{G_i - Mean_G}{StdDev_G}\right)^4 - 3 \tag{11}$$

$$Kurtosis_B = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{B_i - Mean_B}{StdDev_B}\right)^4 - 3 \tag{12}$$

III. KNN METHOD

K-Nearest Neighbor (k-NN) is a data-based classification algorithm that uses previous data to categorize objects. In the process, training data is identified, then the k value is generated from the data that is most similar to the test data using Euclidean distance. During classification, the same features are calculated for the test data, either to retest data for which classification is unknown or to verify the accuracy of the classification. This algorithm stores feature vectors during the learning stage and classifies data based on the smallest distance or similarity of the objects. The distance from the new vector to the training data vector is calculated, and some of the closest k values are taken. Classification is determined based on the points that appear most frequently in their nearest neighbors. Euclidean distance is often used to measure closeness, where higher values indicate greater similarity and lower values indicate closer similarity. Even though it is simple and has the disadvantage of having data that is too close together, this method is easy to understand. The KNN algorithm works by categorizing data through related inputs with similar outputs. The two main parameters in developing a KNN model are the number of nearest neighbors (k) and the distance between data points, which can be calculated using Euclidean, Manhattan, or Minkowski distance. To train the model, the training data is placed in a coordinate system that corresponds to the dimensions of the data. KNN requires an integer value k, a training data set, and a metric to measure closeness [15].

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E. Normalized Spatial Moment and Central Moment

The spatial moment equation is:

$$M_{pq} = \sum_{x=0}^{M-1} \sum_{x=0}^{N} x^p y^p i(x,y) \tag{13}$$

The central moment is a spatial moment calculated relative to the center of mass. Equality The central moment is:

$$\mu_{pq} \sum_{X=0}^{M-1} \sum_{Y=0}^{N-1} (x-\bar{y})^p i(x,y) \tag{14}$$

The moments above are *invariant* (not affected) by translation. In this case, x^{-} and y^{-} obtained through:

$$\bar{x} = \frac{M_{10}}{M_{00}}, \bar{y} = \frac{M_{10}}{M_{00}} \tag{15}$$

The central moment is independent of translation, compression and rotation, so the moment needs to be normalized. The normalized moment equation is:

$$n_{pq} = \frac{\mu_{pq}}{\mu_{00}^{y}}, \gamma = \frac{p+q+2}{2} \tag{16}$$

IV. Research Results and Analysis

Images of certain types of seaweed originating from Sumenep Regency taken using a cellphone camera produce images in 2 classes, namely, the healthy class and the sick class. Where each class has 300 seaweed images so that the total for both classes is 600 images. Collecting data for seaweed classification using K-Nearest Neighbors (KNN) is a crucial stage in building an effective model in identifying seaweed quality. The data collected should include a broad representation of the various seaweed quality criteria, including aspects such as the presence of disease and the physical condition of the seaweed.

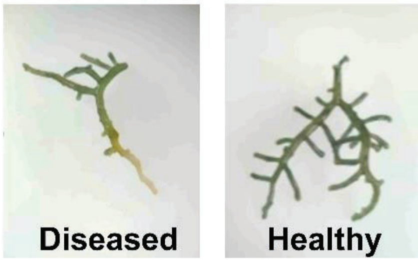


Fig. 4. Healthy and Sick Seaweed

Fig. 4 shows samples of diseased and healthy seaweed. The dataset contains 200 samples of diseased seaweed and 200 samples of healthy seaweed, totaling 400 samples. The diseased samples exhibit typical visual symptoms of Ice-Ice disease, such as discoloration to a paler or yellowish hue, as well as a decrease in quality, with a weaker or damaged texture. In contrast, the healthy samples display a stronger green color, with an intact and robust structure, showing no signs of damage or discoloration caused by disease.

Separate color channels, and calculate the mean, standard deviation, skewness, and kurtosis for each color channel. The results provide a statistical and textural description of the analyzed image.

Feature	Red (R)	Green (G)	Blue (B)
Mean Color	211.0853095684803	220.84691369606003	215.8636163227017
Standard Deviation	37.68488845628084	27.685679100352786	26.77435218898575
Skewness	-2.898262884720996	-2.354997336691239	-2.572900671089337
Kurtosis	8.145021836768125	5.8269360285632	6.96206938255l645

Fig. 5. Statistical and Texture features

Gray Level Co-occurrence Matrix (GLCM) is a method used to extract texture features from images. This method measures how pairs of pixels with certain gray values (gray levels) appear in the image with certain spatial relationships. GLCM is calculated by creating a matrix that stores the frequency of occurrence of pairs of pixels with certain intensity values at a certain distance and direction.

Some texture properties that can be calculated from GLCM are:

a. Contrast: Measures the difference in intensity between a pixel and its neighbors over the entire image. A high contrast value indicates a large difference in intensity.

b. Correlation: Measures the degree to which pixels at a given distance correlate with each other. A high correlation value indicates a linear relationship between pixels.

c. Homogeneity: Measures the closeness of the distribution of elements in a GLCM to the GLCM diagonal. A high homogeneity value indicates a smooth texture.

d. Energy: Measures texture compactness by calculating the sum of squares of GLCM elements. A high energy value indicates a uniform texture.

e. Entropy: Quantifying chaos in textures. High entropy values indicate complex and irregular textures.

f. Variance: Measures the spread of intensity values around the mean value. High variance indicates a texture with a lot of variation in intensity.

Tests were carried out to determine whether the K-Nearest Neighbors (KNN) method was suitable for the task of analyzing ice-ice disease from seaweed. The results obtained from this test provide a deeper understanding of whether the developed model can be relied upon for use in a wider application context, such as in the seaweed processing industry. Thus, the results of this test become an important basis for decision making regarding the application of technology in automatic processing and sorting of seaweed. The following are the results of the analysis of ice-ice disease in seaweed using the KNN method.

TABLE I. SEAWEED TEST RESULTS

No	Image Name	KNN results	Probability of Health	Probability of Illness
1	1695323379334.jpg	Healthy	100	0
2	1695323382012.jpg	Sick	33.33333333	66.66666667
3	1695323384758.jpg	Healthy	66.66666667	33.33333333
4	1695323387430.jpg	Healthy	66.66666667	33.33333333
5	1695323390109.jpg	Healthy	100	0
6	1695323392831.jpg	Healthy	100	0
7	1695323395592.jpg	Healthy	66.66666667	33.33333333
8	1695323398168.jpg	Healthy	66.66666667	33.33333333
9	1695323400251.jpg	Healthy	100	0
10	1695323402563.jpg	Healthy	100	0
11	1695323404579.jpg	Healthy	66.66666667	33.33333333
12	1695323406619.jpg	Healthy	100	0
13	1695323408732.jpg	Healthy	100	0
14	1695323410858.jpg	Healthy	100	0
15	1695323413073.jpg	Healthy	100	0
16	1695323415209.jpg	Healthy	66.66666667	33.33333333
17	1695323417407.jpg	Healthy	100	0
18	1695323419611.jpg	Healthy	100	0
19	1695323421630.jpg	Healthy	66.66666667	33.33333333
20	1695323423693.jpg	Healthy	100	0
21	1695323425912.jpg	Healthy	100	0
22	1695323428062.jpg	Healthy	100	0
23	1695323430123.jpg	Healthy	100	0
24	BP5AE3SENP0019.jpg	Healthy	100	0
25	BP5AE3SENP0020.jpg	Healthy	100	0
26	BP5AE3SENP0021.jpg	Healthy	100	0
27	BP5AE3SENP0022.jpg	Healthy	100	0
28	BP5AE3SENP0023.jpg	Healthy	100	0
29	BP5AE3SENP0024.jpg	Healthy	100	0
30	BP5AE3SENP0025.jpg	Healthy	100	0
31	BP5AE3SENP0026.jpg	Healthy	100	0
32	BP5AE3SENP0027.jpg	Healthy	100	0
33	BP5AE3SENP0028.jpg	Healthy	100	0
34	BP5AE3SENP0029.jpg	Healthy	100	0
35	BP5AE3SENP0030.jpg	Healthy	100	0
36	BP5AE3SENP0031.jpg	Healthy	100	0
37	BP5AE3SENP0032.jpg	Healthy	100	0
38	BP5AE3SENP0033.jpg	Healthy	100	0
39	BP5AE3SENP0034.jpg	Healthy	100	0
40	BP5AE3SENP0035.jpg	Healthy	100	0
41	BP5AE3SENP0036.jpg	Healthy	66.66666667	33.33333333
42	BP5AE3SENP0037.jpg	Healthy	100	0
43	BP5AE3SENP0038.jpg	Healthy	100	0
44	BP5AE3SENP0039.jpg	Healthy	100	0

To find out the percentage success rate for the KNN algorithm, use the following equation:

$$Akurasi\% = \frac{\text{Jumlah Data Sesuai Target}}{\text{Jumlah Data}} \times 100 \quad (17)$$

1. Image of training results

$$Akurasi\% = \frac{200}{200} \times 100 = 100\% \quad (18)$$

2. Image of test results
   a. Image of seaweed with Ice-Ice disease

$$Akurasi\% = \frac{19}{24} \times 100 = 79.17\% \quad (19)$$

   b. Image of healthy seaweed

$$Akurasi\% = \frac{20}{20} \times 100 = 95.24\% \quad (20)$$

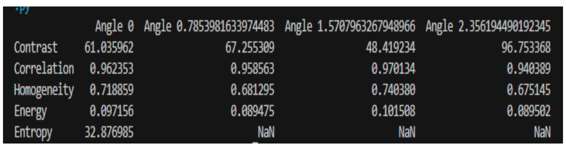
3. Overall image of seaweed

$$Akurasi\% = \frac{39}{44} \times 100 = 86.67\% \quad (21)$$

4. Failure accuracy value

$$Akurasi\% = \frac{6}{44} \times 100 = 13{,}33\% \quad (22)$$

In testing, images of seaweed affected by Ice-Ice disease had an accuracy of 79.17%, while images of healthy seaweed achieved higher accuracy, namely 95.24%. Overall, the KNN method produces an accuracy of 86.67% for all types of seaweed images tested. However, there was a failure accuracy value of 13.33%, indicating that some data was not classified correctly.



	Angle 0	Angle 0.7853981633974483	Angle 1.5707963267948966	Angle 2.356194490192345
Contrast	61.035962	67.255309	48.419234	96.753368
Correlation	0.962353	0.958563	0.970134	0.940389
Homogeneity	0.718859	0.681295	0.740380	0.675145
Energy	0.097156	0.089475	0.101508	0.089502
Entropy	32.876985	NaN	NaN	NaN

Fig. 6. GLCM feature results

Web page that displays the results of seaweed disease analysis using the K-Nearest Neighbors (KNN) algorithm. This page is hosted on Firebase and presents data in interactive tables organized with the jQuery DataTables plugin. Important visible elements include:

1. Page Title: "Dataset Table" indicates the page for displaying the dataset in a table.
2. Page Description : Describes the display of data in interactive tables to efficiently manage and analyze information.
3. Dataset Table: Columns include sequence number, seaweed image, health status (such as "sick" for ice-ice disease), image features (Homogeneity, Energy, Entropy, Variance), KNN classification results (such as "Diseased" or "Healthy"), and the level of classification accuracy.
4. Interactive Features: Tables are equipped with search, sorting, and pagination for easy navigation and searching of data.

This web page provides a clear and interactive visualization of KNN analysis results, useful for research or seaweed disease detection applications. Data is stored and retrieved from Firebase, ensuring availability and reliability.

Fig. 7. KNN results page

The results of accuracy analysis using the K-Nearest Neighbors (KNN) method to detect seaweed disease show that this method is able to provide an average accuracy of around 86.67%. This shows that KNN is quite effective in recognizing and distinguishing between healthy seaweed and those affected by Ice-Ice disease. However, there is significant variation in accuracy between tests which can be caused by dataset quality, model parameter tuning, and test conditions such as lighting and seaweed cleanliness.

Trials were carried out 45 times on each image, and the best data from each trial was taken for final testing. The results show that KNN is quite effective in identifying the condition of seaweed, although there are challenges in detecting certain cases of disease. In conclusion, the KNN method can be a useful tool in monitoring seaweed health, but needs further improvement to reduce the classification failure rate. This research provides a strong basis for further exploration and refinement of the KNN model to make it more sensitive to variations in seaweed conditions, increasing productivity and product quality in related industries.

V. CONCLUSION

The KNN algorithm has proven to be quite effective in identifying the condition of seaweed, both healthy and affected by ice-ice disease. The accuracy of the model on the training data was considered effective , in 44 tests the overall accuracy on the test data reached 86.67%. This shows that the KNN algorithm has high potential to be applied in seaweed disease detection. This study also highlights the potential of vision robotics in sustainable aquaculture practices by automating the detection of Ice-Ice disease, reducing the need for manual labor and minimizing the use of chemical treatments. The findings demonstrate how a KNN-based vision system could be deployed on farms to monitor seaweed health efficiently, thus contributing to sustainable practices in seaweed farming. The KNN method sensitive to irrelevant features and dimensionality: Features that don't contribute much to the image content can mislead KNN. Also, KNN works best with low-dimensional data. For high dimensional image data (e.g., many pixels), it can perform poorly.

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VII. REFERENCES

[1] J. Huang et al., "A New High-Resolution Remote Sensing Monitoring Method for Nutrients in Coastal Waters," in IEEE Transactions on Geoscience and Remote Sensing, vol. 61, pp. 1-15, 2023, Art no. 4206315, doi: 10.1109/TGRS.2023.3294436.

[2] Á. Chavarín, E. Cuevas, O. Avalos, J. Gálvez and M. Pérez-Cisneros, "Contrast Enhancement in Images by Homomorphic Filtering and Cluster-Chaotic Optimization," in IEEE Access, vol. 11, pp. 73803-73822, 2023, doi: 10.1109/ACCESS.2023.3287559.

[3] Adi Kurniawan Saputro, Kunto Aji Wibisono and Faiddhatus Puji Pratiwi “Identification Of Disease Types On Tea–Plant Varieties Based Image Processing With K-Nearest Neighbor Method” Journal of Physics: Conference Series, 2020

[4] S. Garg, D. Dixit and S. S. Yadav, "Disease Detection in Plants Using KNN Algorithm," 2022 4th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N), Greater Noida, India, 2022, pp. 938-943, doi: 10.1109/ICAC3N56670.2022.10074491.

[5] M. Sesio Dhia Ramadhan, L. C. Munggaran, and E. Syahrul, “Remote Sensing Image Enhancement Using Filtering Method in Seaweed Cultivation Area,” Jurnal Ilmiah MATRIK, vol. 21, no. 3, 2019.

[6] Nilay Ganatra and Atul Patel, “A Multiclass Plant Leaf Disease Detection using Image Processing and Machine Learning Techniques,” International Journal on Emerging Technologies, vol. 11, no. 2, 2020.

[7] H. P. Hadi and H. Rachmawanto, “Feature Analysis of Feature Extraction and Color in the Process of Rambutan Fruit Ripeness

Classification Based on K-Nearest Neighbor," SKANIKA: Computer Systems and Informatics Engineering, vol. 5, no. 2, pp. 177–189, 2022.

[8] A. Kurniawati and D. Harto, "Design and Construction of Ice-Ice Disease Identification System on Seaweed Images Using Backpropagation Artificial Neural Network," Jurnal: Elektrika Borneo (JEB), vol. 6, no. 2, pp. 54–59, 2020.

[9] C. Joy, G. N. Sundar and D. Narmadha, "AI Driven Automatic Detection of Bacterial Contamination in Water : A Review," 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2021, pp. 1281-1285, doi: 10.1109/ICICCS51141.2021.9432171.

[10] G. S. Ruchitha, V. Karthick and I. Nasim, "A Novel Approach to Find Accuracy in Credit Card Fraud Detection Using Improved K-Nearest Neighbor Classifier Method Comparing with Logistic Regression Algorithm," 2022 14th International Conference on Mathematics, Actuarial Science, Computer Science and Statistics (MACS), Karachi, Pakistan, 2022, pp. 1-8, doi: 10.1109/MACS56771.2022.10022680.

[11] Febrianto Hadi Kusuma, Achmad Ubaidillah Ms, Achmad Fiqhi Ibadillah, Rosida Vivin Nahari, Koko Joni, Adi Kurniawan Saputro, "Fish Freshness and Type Identification System Using the K-Nearest Neighbor Method Based on Fish Eye Images and Shapes," FORTECH Journal, vol. 1, no. 2, 2023.

[12] D. M. Madkour, M. I. Shapiai, S. E. Mohamad, H. H. Aly, Z. H. Ismail and M. Z. Ibrahim, "A Systematic Review of Deep Learning Microalgae Classification and Detection," in IEEE Access, vol. 11, pp. 57529-57555, 2023, doi: 10.1109/ACCESS.2023.3280410.

[13] H. P. Hadi and H. Rachmawanto, "Feature Analysis of Feature Extraction and Color in the Process of Rambutan Fruit Ripeness Classification Based on K-Nearest Neighbor," SKANIKA: Computer Systems and Informatics Engineering, vol. 5, no. 2, pp. 177–189, 2022.

[14] A. A. Bharate and M. S. Shirdhonkar, "Classification of Grape Leaves using KNN and SVM Classifiers," 2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 2020, pp. 745-749, doi: 10.1109/ICCMC48092.2020.ICCMC-000139. keywords:

[15] J. E. Miranda-Vega, M. Rivas-López and W. F. Fuentes, "k-Nearest Neighbor Classification for Pattern Recognition of a Reference Source Light for Machine Vision System," in IEEE Sensors Journal, vol. 21, no. 10, pp. 11514-11521, 15 May15, 2021, doi: 10.1109/JSEN.2020.3024094.

[16] K. N. V. Satyanarayana, V. Tejasri, Y. S. N. Srujitha, K. N. S. Mounisha, S. T. Yerramsetti and G. D. Darapu, "Human Emotion Classification using KNN Classifier and Recurrent Neural Networks with Seed Dataset," 2022 6th International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 2022, pp. 1717-1722, doi: 10.1109/ICCMC53470.2022.9754091.

[17] Weijun Tan, Hongwei Guo, Rushuai Liu "A Fast Partial Video Copy Detection Using KNN and Global Feature Database" IEEE exlore, 2022

[18] Kunpeng Wang, Jingmei Li "An Intrusion Detection Method Integrating KNN and Transfer Extreme Learning Machine" Date Added to IEEE Xplore: 18 July 2022.