Implementation of Extreme Learning Machine Based on HSV Color Features for Marine Animal Image Classification

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Abstract - Recognizing sea animals is a significant challenge in digital image recognition. This is due to the diverse visual characteristics of marine animals, including morphological shapes, body surface colors, and textures displayed in images. Environmental factors also influence image quality, such as underwater lighting conditions, water turbidity, and other external elements. To address these classification challenges, one proposed approach is the use of the Extreme Learning Machine (ELM) method, which can be implemented by utilizing HSV (Hue, Saturation, Value) color features as the main input. The HSV color space is chosen because it more closely resembles the way humans perceive colors. In this model, color is separated into three main components: hue represents the type of color, saturation indicates the intensity or purity of the color, and value refers to its brightness or darkness. The dataset consists of several classes of marine animals such as clams, squids, and shrimp, collected from high-resolution image datasets. Test results show that the ELM model can classify images with competitive accuracy, achieving up to 83% accuracy in a much shorter training time compared to traditional learning methods. This study demonstrates that combining HSV color features with the ELM algorithm can be an efficient approach for classifying marine animal images.

Keywords - *Shell, Squid, Shrimp, ELM,HSV*

1. INTRODUCTION

The accurate identification and classification of marine animal species play a crucial role across multiple domains. In scientific research, it enables a deeper understanding of species characteristics, behaviors, and ecological roles, which forms the basis for further biological and environmental studies. In fisheries management, species-level identification supports sustainable exploitation strategies, quota determination, and regulation enforcement to prevent overfishing. Furthermore, in marine stock monitoring, accurate classification allows for the systematic tracking of species abundance, distribution patterns, and population trends over time, which are vital for assessing the health of marine ecosystems. Lastly, in biodiversity conservation, it aids in the recognition and protection of endangered or vulnerable species, facilitates habitat preservation efforts, and supports global initiatives aimed at maintaining the ecological balance and resilience of marine environments [1].

To date, the classification of marine animal species is predominantly conducted manually by marine biota experts. While effective to a certain extent, this conventional approach is time-consuming, labor-intensive, and often susceptible to human error or subjectivity—particularly when different species exhibit similar morphological characteristics or color patterns. Such limitations can hinder the accuracy and efficiency required in various critical domains. In scientific research, manual misidentification can compromise the reliability of data and subsequent analyses. In fisheries management, classification errors may lead to incorrect stock assessments or harvesting strategies, potentially resulting in unsustainable practices. Similarly,

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inaccurate species identification during marine stock monitoring can obscure population trends and ecological shifts. Moreover, in biodiversity conservation, failure to distinguish between species accurately may delay necessary protection measures for vulnerable marine organisms. In response to these challenges, the advancement of digital image processing technologies offers a promising and efficient alternative. Automated image-based classification systems not only reduce reliance on expert judgment, but also provide faster, more consistent, and scalable methods for identifying marine species—thereby supporting efforts in scientific research, sustainable fisheries, ecosystem monitoring, and conservation planning [2].

One of the most critical visual features utilized in image processing for object classification is color, as it serves as a distinguishing characteristic across different species. Each type of marine animal typically exhibits unique color patterns that can aid in its identification, making color a valuable feature for automated classification systems. In this context, the HSV (Hue, Saturation, Value) color space is commonly employed because it effectively separates chromatic content (hue and saturation) from intensity (value), offering a more robust and perceptually relevant representation compared to the traditional RGB (Red, Green, Blue) color space. For instance, HSV can better handle variations in lighting conditions, which are common in underwater environments, making it more reliable for consistent color-based analysis. Given these advantages, the use of HSV color features becomes a strong foundation in the preprocessing stage of marine animal image classification before applying machine learning methods such as Extreme Learning Machine (ELM).

In the HSV color space, each component—Hue, Saturation, and Value—contributes uniquely to capturing an object's visual characteristics, making it highly suitable for image-based classification tasks. Hue represents the basic color type and is measured on a scale from 0° to 360°, distinguishing colors such as red, green, or blue. Saturation measures the intensity or purity of the color, while Value reflects the brightness or luminance level. This separation of color and brightness information allows classification systems to maintain consistency even when lighting conditions vary, a common challenge in underwater imaging. For example, in marine animal classification, shrimp typically exhibit a reddish hue, shells tend to appear pale or beige, and squids are characterized by a gray or silvery white tone. These color distinctions form the foundation for extracting discriminative features using HSV, which are then used as inputs for machine learning algorithms such as ELM.

The significance of HSV features in marine classification is supported by previous research such as that of Rachmat et al. [1], who used HSV in combination with HOG (Histogram of Oriented Gradients) features for classifying marine fish species. Their work employed Support Vector Machine (SVM) as the classifier and achieved good accuracy, demonstrating the relevance of color features in distinguishing marine animals. However, SVM requires careful tuning of hyperparameters and may not scale well with large datasets, which presents a challenge in real-time classification scenarios.

To address the need for faster and more scalable classification, this study employs the Extreme Learning Machine (ELM) algorithm. ELM is a machine learning model derived from single-layer feedforward neural networks (SLFNs) and is known for its rapid training speed and high generalization performance. Unlike conventional neural networks that rely on iterative learning processes such as backpropagation, ELM operates with a different approach: it randomly assigns input weights and biases and calculates output weights analytically in a single step. This enables ELM to achieve fast learning without sacrificing classification accuracy. For example, studies have shown that ELM can outperform traditional neural networks in tasks involving large datasets or real-time processing scenarios due to its minimal computational overhead [3][4].

ELM has been successfully applied in various image classification domains, including hijaiyah letter recognition [2], brain tumor detection via MRI [4][5], coffee quality classification based on HSV features [9], and fruit classification by color and texture [10]. These studies demonstrate the versatility and robustness of ELM in dealing with diverse visual datasets. In

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marine animal image classification, the combination of HSV color feature extraction and ELM classification offers a compelling solution that balances speed, scalability, and accuracy. This integrated approach forms the core methodological framework of this study.

The effectiveness of ELM in diverse classification tasks is further evidenced by several studies summarized in **Table 1**. These works illustrate not only the wide applicability of ELM across various datasets but also highlight the typical challenges or limitations encountered in different scenarios.

Table 1. Review of Studies Using ELM for Image and Data Classification

No	Reference	Method	Dataset	Accuracy	Weakness
1	Rachmat et al. (2021)	SVM + HOG & HSV Features	Marine fish images (25 species)	86.25%	Performance decreases with non-uniform backgrounds
2	Sarifah et al. (2023)	Extreme Learning Machine (ELM)	Hijaiyah letter images	94%	Not mentioned
3	Fikriya et al. (2017)	ELM	General digital image objects	94.44%	Limited to simple images
4	Wahid et al. (2020)	ELM	Brain tumor MRI images	90%	No comparison with other methods
5	Ariyanti et al. (2023)	ELM + PSO	Heart disease dataset (UCI)	86.27%	Sensitive to PSO parameters
6	Harum et al. (2018)	ELM	Harum Bakery sales data	92.11%	Less suitable for highly fluctuating data
7	Pauziah & Herliana (2021)	ELM	Traffic sign images	95%	Dataset details not explained
8	Wardani & Agustin (2020)	ELM	Medicinal leaf images	89.47%	Less robust to image noise
9	Rachmat & Rahmawati (2022)	ELM + HSV	Coffee quality images	88%	Highly dependent on image lighting
10	Permata & Zarlis (2021)	ELM (color & texture features)	Apple fruit images	91.25%	Preprocessing steps not clearly described
11	Hidayat et al. (2021)	ELM	Academic data of students	93.3%	Lacks k-fold validation explanation
12	Candra & Kurniawan (2022)	ELM + Color Features	Organic & inorganic waste images	90.6%	Prone to errors under poor lighting
13	Nugroho et al. (2021)	ELM	COVID-19 spread data	95.3%	Sensitive to outdated data

Although these studies demonstrate the effectiveness of HSV and ELM in their respective applications, none have specifically explored their integrated use for the classification of diverse marine animal species based on digital imagery. This represents a critical research gap,

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particularly in domains that demand rapid, robust, and scalable classification under underwater imaging conditions. While prior studies have utilized HSV color features [1] or employed ELM in different image classification contexts [2][4][5][9][10], few have explored the specific combination of HSV and ELM for classifying a diverse range of marine animal species. This study addresses that gap by implementing an HSV-based feature extraction method alongside an ELM classifier tailored for marine animal image data. The novelty of this research lies in this integration, which has not been widely investigated in the context of marine biodiversity image analysis. By doing so, the study contributes a fast, reliable, and robust classification framework that can enhance existing efforts in marine ecological research, conservation planning, and digital environmental monitoring systems[12][13].

This study introduces a novel integration of HSV color feature extraction with the Extreme Learning Machine (ELM) algorithm for the classification of marine animal species based on digital images. While previous studies have independently employed HSV features or ELM in various classification contexts, the specific combination of both within the marine biodiversity domain remains underexplored. This research contributes a unique and efficient classification framework that leverages the perceptual robustness of HSV against underwater lighting variability and the computational efficiency of ELM for rapid model training and generalization. As such, this study advances the field by offering a scalable, accurate, and time-efficient approach to automated marine species identification potentially benefiting ecological monitoring systems, marine conservation efforts, and digital biodiversity documentation initiatives.

This study introduces the specific integration of HSV color feature extraction with the Extreme Learning Machine (ELM) algorithm for marine animal image classification. While previous research has employed HSV or ELM independently in various classification contexts, their combined application in the domain of marine biodiversity remains largely unexplored. This integration addresses a clear gap in current literature, particularly in achieving efficient, accurate classification under underwater imaging conditions. Therefore, the proposed approach represents a novel contribution that enhances the capabilities of automated marine species identification systems.

2. RESEARCH METHOD

The research methodology employed in this study is structured as shown in Figure 1.

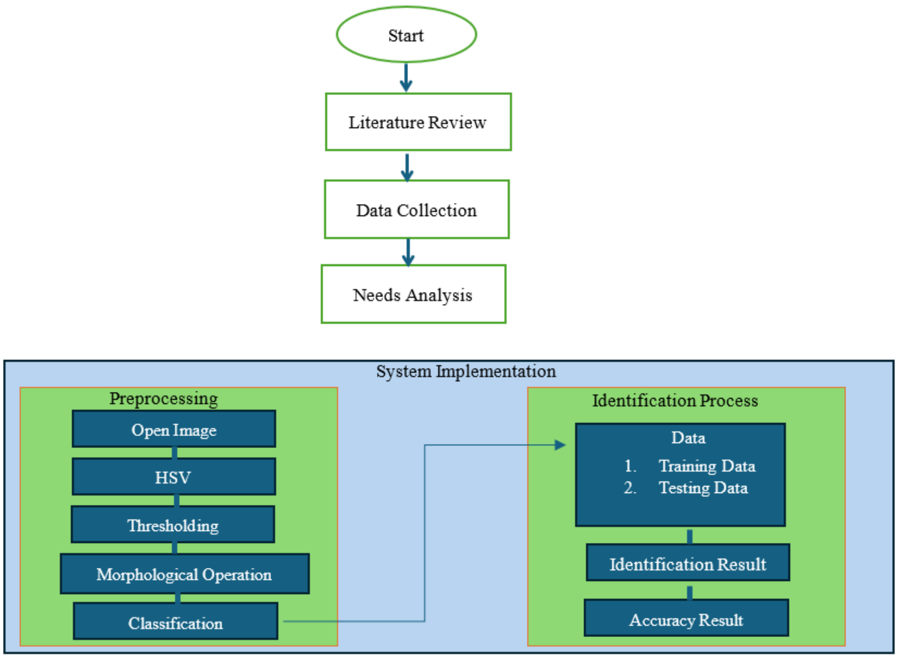

Figure 1. Research Method

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2.1. Image Acquisition and Preprocessing

1. Literature Review

This stage aims to conduct a comprehensive review of relevant theories and previous research studies pertaining to image classification techniques, the HSV (Hue, Saturation, Value) color space model, and the Extreme Learning Machine (ELM) algorithm. The literature review not only serves to provide a theoretical foundation for the proposed methodology but also identifies research gaps, compares existing approaches, and justifies the selection of specific techniques employed in this study. By analyzing prior works in these domains, this section establishes the scientific relevance and contextual framework that supports the development of a robust and efficient classification system for marine animal images.

2. Data Collection

The data utilized in this study were collected in the form of high-resolution images of marine animals, specifically squid, shellfish, and shrimp, obtained directly from real-world specimens. This dataset serves as the foundation for both the training and testing phases of the classification model, enabling the system to learn distinctive visual features and evaluate its performance in identifying different marine species accurately.

3. Needs Analysis

In this study, the needs analysis focuses on determining the quantity and categories of image data required to develop and evaluate a marine animal classification model. The dataset comprises high-resolution images representing three distinct classes of marine animals: squid, shellfish, and shrimp. For each class, a total of 14 images were collected, resulting in an overall dataset of 42 images. To facilitate supervised learning, the dataset is partitioned into training and testing subsets. Specifically, 10 images per class are allocated for training purposes, while the remaining 4 images per class are reserved for testing. This proportional distribution ensures balanced representation across all classes and supports robust model evaluation.

Table 2. Marine Animal Image Dataset Composition

No	Marine Animal	Number of Training Images	Number of Test Images
1	Squid	10	4
2	Shellfish	10	4
3	Shrimp	10	4

4. System Implementation

The implementation of the system is structured into two major components, with the first being the preprocessing stage. Preprocessing is a critical step designed to enhance and transform raw image data into a format that is suitable for subsequent feature extraction and classification tasks. This stage involves several systematic procedures:

a. Preprocessing stage

   Preprocessing aims to prepare images so that they can be processed by classification systems. This process consists of:

   - Image Acquisition (Open Image): The system begins by reading and loading image files from the prepared dataset. This step ensures that input data is accurately retrieved for further processing.
   - HSV Conversion: The color space of the image is converted from RGB (Red, Green, Blue) to HSV (Hue, Saturation, Value). This transformation simplifies the extraction of color-based features, as HSV better separates chromatic content from intensity, which is particularly beneficial in scenarios with varying lighting conditions

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- Thresholding: This segmentation process applies predefined HSV value ranges to isolate the object of interest from the background. By filtering out irrelevant regions, thresholding improves focus on the marine animal subject within the image
- Morphological Operations: To enhance image quality and structure, morphological techniques such as erosion and dilation are applied. These operations are essential for removing noise, closing gaps, and refining the shape of the segmented object, thereby improving the reliability of subsequent feature extraction.
- Feature Extraction and Classification: The final stage of preprocessing involves extracting relevant color features from the processed image, which are then used as inputs for the classification algorithm. In this study, the Extreme Learning Machine (ELM) is employed as the classifier due to its high learning speed and generalization capability. The extracted HSV features enable the model to distinguish between different marine animal species effectively. These features are divided into two datasets: training data and testing data. The training data is utilized to train the ELM model by learning the characteristic patterns of each marine animal class, while the testing data is used to evaluate the model's ability to accurately classify new, unseen images. This separation ensures the model's performance is assessed objectively and provides a basis for measuring classification accuracy and reliability.

b. Identification Process Stage

This stage encompasses two fundamental components that are instrumental in both the development and validation of the classification model's performance:

- Training Data: This component consists of a labeled dataset of marine animal images, including squid, shellfish, and shrimp, which is employed to train the Extreme Learning Machine (ELM) model. The purpose of this phase is to facilitate the model's ability to learn representative patterns and extract salient features that characterize each class. Through supervised learning, the model iteratively adjusts its internal parameters in response to the provided inputs and target outputs, thereby enhancing its capacity to accurately perform classification tasks.
- Testing Data: This component comprises a separate subset of images that were not previously exposed to the model during the training phase. It is specifically utilized to evaluate the model's generalization ability—namely, its performance when applied to new and unseen data. The outcomes obtained from this evaluation serve to validate the effectiveness, robustness, and predictive accuracy of the ELM-based classification system.

c. Identification Result Stage

At this stage, the system generates an output in the form of a predicted class label that corresponds to the type of marine animal depicted in the test image. The classification result is derived from the model's interpretation of the extracted features, allowing the system to determine whether the input image belongs to the squid, shellfish, or shrimp category. This output reflects the model's ability to generalize from the training data and accurately identify unseen instances during the testing phase.

d. Accuraty Result

The accuracy result represents the quantitative evaluation of the classification model's performance. It is calculated by comparing the number of correctly classified test images with the total number of test images. This metric provides a clear indication of the system's effectiveness in identifying marine animal species based on the features

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extracted during preprocessing. A high accuracy value reflects the model's strong generalization capability and reliability, while a lower accuracy suggests the need for model refinement or additional training data. In this study, accuracy serves as a key performance indicator to assess how well the Extreme Learning Machine (ELM) classifier distinguishes between squid, shellfish, and shrimp images.

2.2. HSV Feature Extraction

The HSV (Hue, Saturation, Value) color space is frequently utilized in image analysis due to its perceptual relevance and robustness in representing color information under varying lighting conditions. Unlike the RGB color model, which is device-dependent and less intuitive, the HSV model aligns more closely with the way humans perceive and distinguish colors.

- Hue (H) denotes the dominant wavelength of the color and is expressed in degrees ranging from 0° to 360°, enabling clear differentiation between basic color types (e.g., red, green, blue).
- Saturation (S) quantifies the degree of color purity, with higher saturation indicating more vivid and intense colors, whereas lower saturation approaches grayscale tones.
- Value (V) represents the luminance or brightness of the color, with higher values corresponding to lighter appearances.

Upon converting images from RGB to HSV space, a set of statistical features is computed from each of the three channels. These features typically include the mean, standard deviation, and skewness, which capture essential color distribution characteristics within the image. These numerical descriptors form a compact and discriminative feature vector that serves as input to the classification model. The extraction of such statistical metrics from HSV components enhances the system's ability to identify patterns and discriminate between different classes of marine animal species with greater accuracy.

2.3. Classification Using Extreme Learning Machine (ELM)

The ELM is employed as the classifier due to its high learning speed and effective generalization with minimal training time. The ELM structure comprises three layers:

- Input Layer: Receives the HSV feature vector.
- Hidden Layer: Contains a fixed number of neurons. The weights between the input and hidden layers are randomly initialized and not updated.
- Activation Function: A nonlinear function (e.g., sigmoid) is applied to the hidden neurons.
- Output Layer: The output weights are computed analytically using the Moore-Penrose pseudoinverse.

$$H = \ g\,(XW) + b$$
$$\beta = H + T$$

Where H is the hidden layer output matrix, X is the input feature matrix, W is the random weight matrix, b is the bias vector, β is the output weight matrix, T is the target output, and H + T denotes the pseudoinverse of *H.*

The dataset is split into two subsets:

- Training Data: Used to train the ELM model by mapping input features to class labels.
- Test Data: Used to evaluate the model's generalization on unseen data.

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2.4. Justification for Using Extreme Learning Machine (ELM)

The Extreme Learning Machine (ELM) was selected as the classification method in this study due to its notable advantages in terms of computational efficiency and generalization performance. Unlike traditional neural networks that rely on iterative gradient-based optimization, ELM employs a single-pass, non-iterative learning mechanism, wherein the input weights and biases of the hidden layer are randomly assigned and remain fixed, while the output weights are analytically determined using a least-squares solution. This results in significantly faster training times, making ELM highly suitable for real-time or resource-constrained applications.

Moreover, despite its relatively simple architecture, ELM has been empirically shown to exhibit robust generalization ability across various classification tasks. This characteristic is particularly beneficial when working with small to medium-sized datasets, as is the case in this study, where overfitting can pose a significant challenge.

2.5. Performa Evaluation

To assess the effectiveness of the proposed classification model, several evaluation metrics were utilized, each providing insights into different aspects of classification performance. These metrics were computed based on the predictions generated from the test dataset and are defined as follows:

- **Accuracy**

Accuracy measures the proportion of correctly predicted instances (both positive and negative) over the total number of predictions. It is formulated as:

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

TP: True Positives
TN: True Negatives
FP: False Positives
FN: False Negative

- **Precision**

Precision indicates the proportion of correctly predicted positive observations to the total predicted positive observations. It is calculated as:

$$Precision = \frac{TP}{TP + FP}$$

- **Recall**

Recall measures the ability of the model to correctly identify all relevant instances of the positive class. It is given by:

$$Recall = \frac{TP}{TP + FN}$$

- **F1-Score**

The F1-score represents the harmonic mean of precision and recall, providing a single metric that balances both concerns, especially in cases of class imbalance:

$$F1 - Score = 2x\frac{Precision\ x\ Recall}{Precision\ x\ Recall}$$

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3. RESULTS AND DISCUSSION

This section presents the experimental results and an analytical discussion of the performance of the proposed classification model, which integrates HSV color features and the Extreme Learning Machine (ELM) algorithm for the identification of marine animal species. The dataset comprised 90 RGB images categorized into three classes: shrimp, shellfish, and squid, with 30 samples per class. The images were converted into the HSV color space, and relevant features were extracted prior to classification. A stratified partitioning strategy was adopted, allocating 70% of the dataset for training and 30% for testing.

In its implementation, users input images through the GUI (Graphical User Interface) interface by utilizing the uigetfile function in MATLAB. Once the image is selected, the system will automatically convert the image from RGB format to HSV format using the rgb2hsv function. This conversion process aims to extract the main color components which are then used as input features in the classification stage of marine animal imagery.

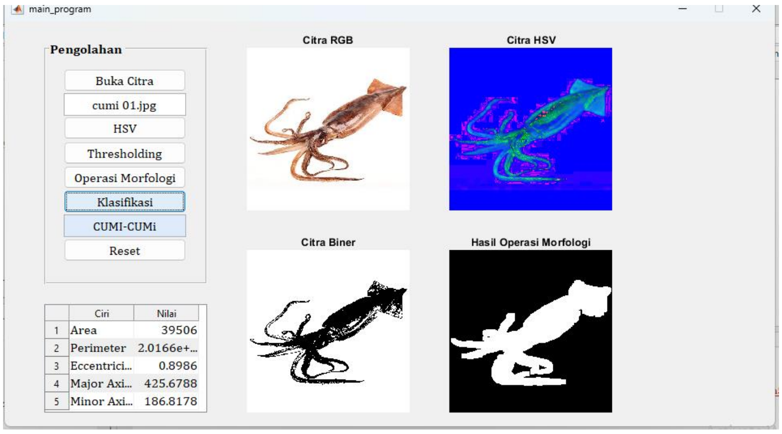

Figure 2. Image classification process with HSV for Squid

The MATLAB GUI displays the processing workflow for a squid image. The RGB image is converted into the HSV color space to extract its color components. Binary conversion and morphological operations are then applied to separate the object from the background. Feature values such as area, perimeter, eccentricity, major axis, and minor axis are shown in the left panel. These values, combined with HSV color features, are fed into the ELM classifier for species classification.

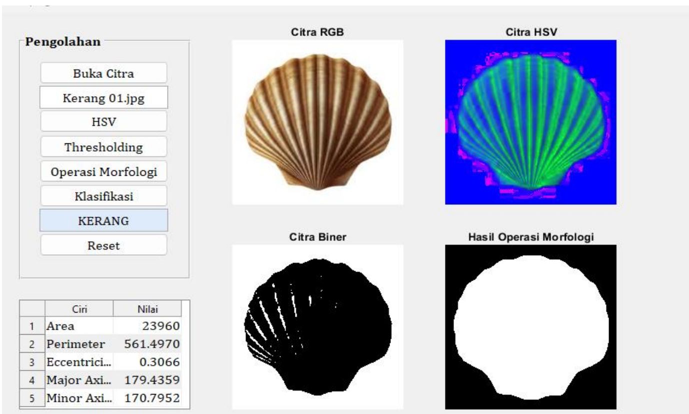

Figure 3. Image classification process with HSV For Shellfish

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The GUI interface illustrates the classification process for a shellfish image. The RGB image is transformed into the HSV color space, producing a color representation that is more stable under varying illumination conditions. Thresholding and morphological operations are applied to isolate the shellfish shape. The extracted feature values are displayed in the left panel, serving as input for the ELM classifier to determine the species class.

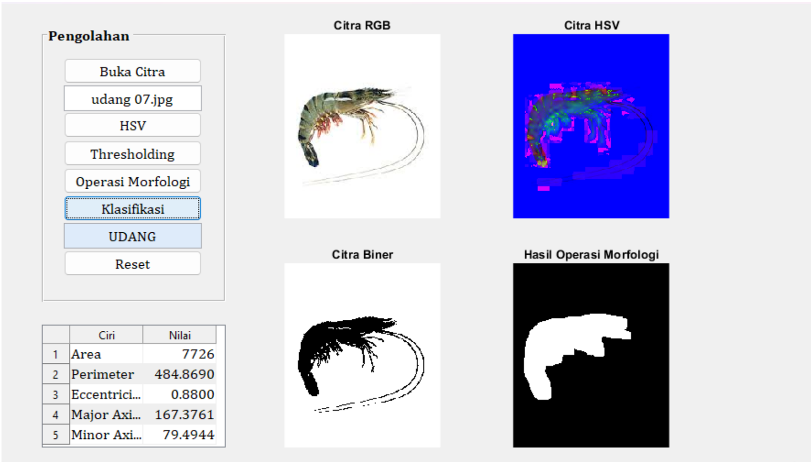

Figure 4. Image classification process with HSV For Shrimp

In the shrimp image, the GUI presents the stages from RGB image loading to HSV conversion, followed by binary conversion and morphological operations. The reddish-orange hue of shrimp is well preserved in the HSV space. The extracted features are then processed by the ELM classifier to predict the species class with high accuracy.

3.1 Classification Performance Using ELM

The classification system was tested using a set of 90 color images, which were divided into three groups: shrimp, shellfish, and squid, with 30 images in each group. The images were split into two parts: 70% for training and 30% for testing.

The ELM classifier had an overall accuracy of 97.

00%. Out of the 30 test images, 29 were classified correctly. The confusion matrix, shown in Table 3, shows that shrimp and squid were all classified correctly, but one shellfish image was mistaken for squid because of similar colors.

The table also shows how many images were correctly and incorrectly classified, summarizing the results from the confusion matrix.

Table 3. Confusion Matrix for ELM Classifier

Actual I am running a few minutes late; my previous meeting is running over. Predicted	Shrimp	Shellfish	Squid
Shrimp	10	0	0
Shellfish	0	9	1
Squid	0	0	9

As illustrated in the matrix, the classifier successfully identified 29 out of 30 test samples. Only one misclassification occurred, where a shellfish image was incorrectly predicted as squid. This error may have been caused by low chromatic contrast between the two species under poor

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lighting conditions. Specifically, the overlap in saturation and brightness values between shellfish and squid can lead to ambiguity during classification.

To further evaluate the classifier's performance at the class level, precision, recall, and F1-score metrics were computed for each category. These metrics provide a more detailed understanding of the model's ability to correctly identify instances of each class and handle class-specific variability. The results of this evaluation are summarized in **Table 4.**

Table 4. Class-wise Precision, Recall, and F1-Score for ELM Classifier

Class	Precision (%)	Recall (%)	F1-Score (%)
Shrimp	100.00	100.00	100.00
Shellfish	90.00	90.00	90.00
Squid	100.00	100.00	100.00
Macro Average	**96.67**	**96.67**	**96.67**

Table 4 shows the numerical values of precision, recall, and F1-score for each class. To make the performance differences clearer, especially the small drop seen in shellfish, the results are also shown in the bar chart in Figure 5.

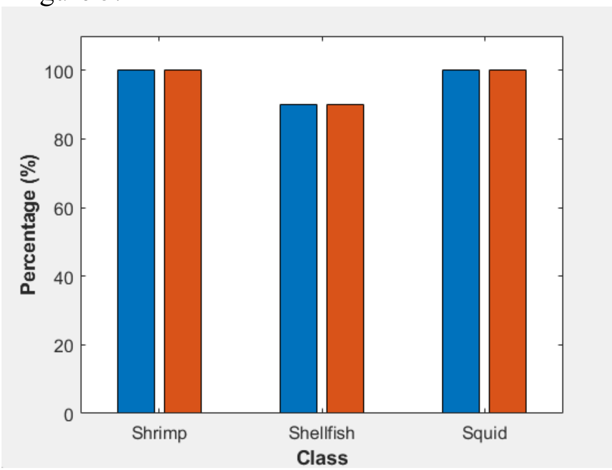

Figure 5. Bar Chart of Class-wise Precision and Recall for ELM Classifier

Figure 5 shows a bar chart that compares the precision and recall scores for each class—shrimp, shellfish, and squid—using the ELM classifier. The chart shows that both shrimp and squid had perfect results with 100% precision and recall, which means the model is very good at telling these species apart based on their HSV color features. However, shellfish had slightly lower scores at 90% for both precision and recall. This is probably because the HSV color features of shellfish can be similar to those of squid, especially when the lighting isn't consistent. This chart gives a clear and easy-to-understand view of how well the model performed in classifying all three species.

3.2 Feature Relevance and Analytical Insight

The superior classification results achieved by the proposed method are closely linked to the discriminative power of the HSV color space. In particular, the Hue component plays a central role in distinguishing marine species, as shrimp generally exhibit reddish tones, shellfish appear beige or yellowish, and squid are characterized by gray hues with low saturation. The Saturation and Value components complement the hue by enhancing visibility under variable lighting conditions, which is a critical factor in underwater image acquisition.

The integration of HSV features with the ELM classifier proved effective, as evidenced by the minimal misclassification rate. Nonetheless, the reduced recall for the shellfish class suggests

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potential for further improvement through the inclusion of additional feature sets such as shape descriptors or texture features, which may help address ambiguities in borderline cases.

4. CONCLUSION

Based on the results of the research conducted, several key conclusions can be drawn. First, the classification system employing the Extreme Learning Machine (ELM) algorithm in conjunction with HSV color space features demonstrated a high level of performance in identifying marine animal species, achieving an overall accuracy of **97.00%** on the testing dataset. The precision and recall values for shrimp and squid reached **100%**, while shellfish achieved slightly lower scores due to overlapping chromatic characteristics. These findings indicate that HSV-based color features, particularly the hue component, are highly effective in capturing species-specific color distinctions, and the ELM classifier offers a fast and accurate learning process with minimal computational overhead.

The key strength of this research lies in its combination of perceptually robust color representation with the computational simplicity of ELM, enabling fast training, real-time inference, and minimal computational requirements. This makes the proposed method highly suitable for practical applications such as real-time marine biodiversity monitoring, automated aquaculture systems, and embedded vision-based devices. Furthermore, the MATLAB GUI-based implementation enhances usability by providing intuitive interaction and real-time visualization, which can be beneficial for researchers, field practitioners, and domain experts without extensive programming expertise.

For future development, incorporating additional feature descriptors such as texture and shape could further improve classification robustness, particularly for species with subtle visual similarities. Expanding the dataset to cover a broader range of species, environmental conditions, and variations in imaging parameters—such as illumination, angle of capture, and underwater background—would further increase the model's generalization capability. Such advancements would strengthen the system's reliability and adaptability for deployment in real-world marine environments.

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