ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

SHRIMP CLASSIFICATION VIA MULTI-VIEW FEATURE EXTRACTION USING PRETRAINED DEEP FEATURES

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ABSTRACT

Shrimp classification is a complex task in computer vision applications. Very few research works have been carried out by researchers because shrimp features are difficult to extract due to their complex shape. The taste of shrimp-based foods depends on whether the same shrimp category is used. The export shrimp business relies on the quality of classification. Manual identification and classification of shrimps is a time-consuming process. In this work, Shrimps are classified based on different angular views, shape, and texture features. Features are extracted using both Zernike and pre-trained deep features. Further, shrimps are classified by regression. The qualitative and quantitative analysis shows that the proposed framework performs better with hand-crafted and deep features. The proposed framework with Zernike moments and VGG-16 features shows robustness with an accuracy of 89% and a precision of 91.7%.

Keywords: *Shrimp classification, multi-feature extraction, Zernike features, VGG-16, multi-view features.*

1. INTRODUCTION

The quality of shrimp-based food depends on the shrimp used for food preparation—identification of defective shrimps and exporting the same category of shrimps while packing is a difficult task. Classification of shrimps is a complex task in computer vision [1]. There are several classes of shrimps in the world based on taxonomy and commercial importance. Some commonly found shrimps are categorized as Penaeidae, Luciferidae, Hippolytidae, and Caridea. The Penaeidae family-based shrimps, such as the monodon shrimp (Black-Tiger), Vannamei shrimp (White-Leg), and Indicus shrimp (Indian-Tiger), are famous due to the high yield of shrimp production. Few researchers have developed shrimp classification with handcrafted features. Due to the complex shape and texture features, many researchers fail to classify the shrimps.

Luo et al. (2015) developed a technique for object recognition using Scale-invariant feature transform (SIFT) [2]. This study introduces a tactile-SIFT descriptor that extracts features from tactile image gradients to describe invariant objects, to object translation and rotation, to handle unknown object movement. Even though this method produces robust results, computational time is very high due to the larger number of clusters used. Hayat, Bennamoun, and An (2015) developed a deep network-based reconstruction model for the classification of image data [3]. The geometric structure of a series of images may be automatically discovered using a deep learning framework, unlike many other methods that assume they lie on a geometric surface. Template Deep network reconstruction model parameters are initialized via a pre-trained Gaussian Restricted Boltzmann Machine by an unsupervised layer-wise. The TDRM learns class-specific DRMs for every image class during initialization. Three classification voting processes are developed using the learned class-specific models' least reconstruction errors. Numerous experiments demonstrate that this framework for face and object recognition from image collections works. The recommended technique consistently outperforms state-of-the-art methods in experiments.

Xiao Bai et al. (2015) developed the technique for remote-sensing image classification [4]. A softmax feature fusion method by regression is employed in this technique to classify data by unique weights learning for various features. The estimation of the conditional probabilities by the fusion method that each object classification and class similarity measures. Ultimately, the marginalized kernel is used to construct a Support Vector Machine (SVM) classifier by incorporating the similarity and fusion

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

information obtained. Qin (2015) developed a shape feature based on mean shift vectors for classifying high-resolution images collected from space [5]. This feature of the method works especially well to tell the difference between houses and roads with similar spectral responses but different two-dimensional shapes. It employs independent component analysis to get the spectral features and an SVM algorithm to sort the spatial and spectral features into groups. It then compares the new feature to state-of-the-art structural and spatial features. This method is utilized for high-resolution image classification. Siddiqui, Mammeri, and Boukerche's (2016) dictionary-building approaches are evaluated: "single dictionary" and "modular dictionary"[6]. Based on the improved dictionaries, the SURF characteristics of vehicle rear- or front-face video frames are integrated into BoSURF histograms, which are then utilized for training multiple classes of support vector machines (SVMs) for categorization. Firuzi et al. (2019) suggested that two "image feature extraction" approaches, the Histogram of Oriented Gradient (HOG) and the Local Binary Pattern (LBP), are used to extract features from grayscale images [7]. In this procedure, several Support Vector Machine (SVM) versions are tuned to ensure optimum categorization of PD sources. The impact of image processing characteristics such as random noise, image resolution, and phase shift on identification accuracy is studied and addressed. Shape analysis plays a major role in classification techniques. Elastic shape analysis (ESA) has lately attracted interest driven by its complete framework for simultaneous registration, deformation, and shape comparison. These approaches attain computing efficiency and enable the use of statistical tools and conventional algorithms by employing particular square-root representations that convert invariant elastic measures into Euclidean metrics. A fundamental need in shape analysis is a technique for inverting solutions (deformations, averages, modes of variation, etc.) derived in SRNF space, returning to the source surface area for visualization and inference purposes [8].

Shrimp classification yields significant practical implications across diverse sectors notably in fisheries aquaculture and environmental monitoring spheres quite often. Accurate identification of shrimp species bolsters economic benefits greatly while supporting sustainable fishing practices and aiding biodiversity conservation efforts effectively. Key aspects of shrimp classification and its far-reaching implications are outlined in subsequent sections with considerable thoroughness and varying detail. Proper classification optimizes shrimp farming pretty significantly by pinpointing species boasting higher market value, thereby jacking up profitability somewhat.

• Consumer Safety: Accurate species identification helps prevent mislabeling, ensuring consumers receive the correct product, which is crucial for food safety.

Accurate species identification prevents mislabeling, thus ensuring consumers get the correct products, crucial for food safety, obviously.

• Geographical Classification: Techniques like fluorescence fingerprinting can reveal environmental influences on shrimp, aiding in ecological assessments and habitat management.

Taxonomic studies furnish vital information pretty much daily for biodiversity conservation initiatives, helping manage shrimp populations effectively in their often-fragile habitats. Fluorescence fingerprinting techniques reveal subtle environmental influences on shrimp, thereby aiding ecological assessments and effectively informing habitat management strategies very quietly.

Handcrafted feature design often entails striking the correct balance between computing efficiency and precision. For instance, the robust Scale Invariant Feature Transform (SIFT) is widely renowned for being robust to scale changes and object rotation; nevertheless, that durability comes at a significant computing cost [9]. The most popular features often produce a group of variations to address the integrated problems in the speed and accuracy of the original versions. For instance, it has been suggested to employ several fast SIFT variations on low-processing devices and in real-time applications [9]. Further several handcrafted features-based object classifications is developed such as K-Nearest Neighbor (KNN)[10], Random Forest (RF), SVM [11], and Gradient Boosted Decision Trees (GBDT)[12] based on three handcrafted feature extraction techniques: LBP, HOG, Speeded up robust features (SURF) and Gabor

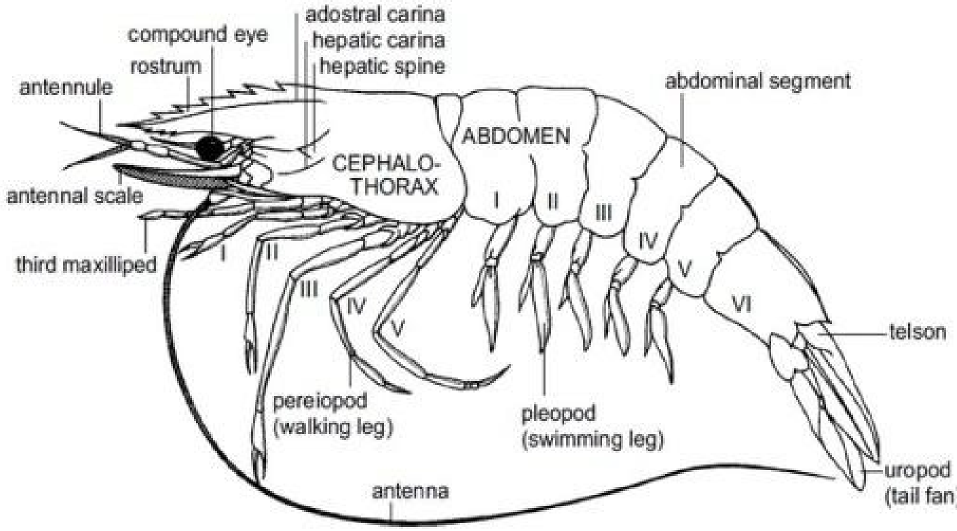

Figure 1: Morphological features of Prawn.

filter [13]. Handcrafted feature-based techniques are applied for shape-based classification [14]. Many classification techniques are complex and time-consuming processes. Shape and texture feature-based classification techniques are robust. Texture feature-based classification is mostly a deep learning-based technique. The deep learning method has been widely implemented in image classification, resulting in excellent classification accuracy. Certain deep learning methodologies are capable of classifying images more accurately than a human. Image classification has a wide range of practical applications.

Convolutional Neural Networks (CNN) are one of the deep learning techniques that we examined in our research and that are used to develop a range of image categorization techniques [13], Recurrent Neural Networks (RNN) [14], Long short-term memory (LSTM) [15], Generative Adversarial Networks (GAN) [16], Restricted Boltzmann Machine (RBM) [17] and Deep Belief Network (DBN)[18]. Very few shrimp classification techniques have been developed due to the lack of a dataset and the complex shape, as shown in Figure 1.

Due to complex morphological features, it isn't easy to classify shrimp. The head, abdomen, abdominal segment, and telson are the major parts to classify the shrimp. Dasti et al. (2022) developed deep learning-based shrimp classification [12]. Shrimp images in the HSV color space are employed in this approach, which is a lightweight model. A straightforward pipeline illustrates the most critical phases that are implemented to ascertain a pattern that identifies the class to which they belong using their pigmentation. Shrimp-related techniques were developed for the improvement of shrimp production. Gamara, Bandala, and Loresco (2020) developed a technique for the Fuzzy logic-based classification of shrimp feed [19]. Sofwan et al. (2024) utilized a random forest algorithm for the classification of water quality in shrimp ponds [20]. Vembarasi et al. (2024) developed diseased shrimp identification using a neural network model by White Spot Syndrome Virus (WSSV) detection [21]. Numerous researchers have pursued the best traits for shrimp categorization and the most effective approaches requiring little human interaction, as shown by the aforementioned studies. Fortunately, the majority of shrimp classification algorithms are advantageous in some circumstances. Nonetheless, the direct application of these approaches is for multi-class shrimp classification. There are two major issues faced in classification algorithms. The first issue is shrimp classification techniques developed based on tail moment features, turn angle distribution analysis (TADA), tail moment features (TMFs), and area analysis [1]. The techniques produce optimal results and are time-consuming. The second issue, effective algorithms were developed successfully based on shrimp characteristics, but they failed to classify fresh, diseased, and shrimp families due to complex shape analysis.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Shrimp species classification has faced sizable lacunae especially when morphological and genetic identifications are juxtaposed in complex taxonomic contexts. Recent studies underscore complexities inherent in classifying shrimp accurately owing largely to overlapping morphological characteristics and necessity for amalgamating molecular data with traditional taxonomic methods. Several key facets of classification gap in shrimp emerge from this amalgamation of findings rather remarkably. Advancements in molecular techniques and machine learning offer solutions, but reliance on traditional morphological traits still poses significant challenges. Duality highlights need for a comprehensive approach integrating both methodologies effectively for shrimp classification purposes in quite diverse aquatic environments.

In this work, a two-stage feature extraction is developed to extract both the shape and texture features of shrimp. Shape features are extracted using Zernike moments, and texture is extracted using VGG-16 features. The combined feature set is used for classification. For classification, initially prawn image is partitioned into the rostrum, abdomen, and telson. Further, Multiview features such as forward rotation, inverse rotation, scaling, and illumination features are extracted and then classified by the image by average similarity score.

The main contributions of the work are:

1. The developed Multiview feature extraction improves the overall accuracy.

2. The average score of partitioned parts shows that the proposed technique can handle classification challenges such as illumination, scaling, forward rotation, and inverse rotation.

3. The two-stage feature extraction uses Zernike moments for shape, and VGG-16 for texture, and further regression improves the robustness of the proposed classification technique.

The rest of the paper is organized as follows: Section 2 discusses Shrimp classification. Section 3 illustrates the experimental results.

2. METHODOLOGY

Figure 2 shows the proposed Shrimp Classification Via Muti-view Feature Extraction using Zernike moments and VGG-16 features. The features of the collected data set are extracted using shape, and texture. Initially, every image in the dataset is converted to an image containing the rostrum, abdomen, and telson. Further, converted to four images with different challenging views such as forward rotation, backward rotation, scaling, and illumination. The dataset images after preprocessing, features are extracted. Shape features are extracted using Zernike moments, and texture features by pre-trained VGG-16 features. The database feature set is trained with a support vector machine (SVM) classifier. Figure 3. Testing methodology of the proposed technique.

2.1 Zernike moments

The shape characteristics derived from Zernike moments exhibit insensitivity to noise, and the values of these moments are usually replicated due to the orthogonal radial polynomial kernel of the Zernike moment. The Zernike moments of lower order contain the overall shape of the image, whereas the Zernike moments of higher order characterize the more complex details. The shape characteristic of the image may be expressed by a collection of Zernike moment values. Let P(r, Θ) be the image pixel intensity of the given image f(x, y). Then the Zernike moments can be computed with variance order using Equation 1.

$$Z_{mn} = \frac{m+1}{\pi} \sum_r \sum_\theta P(r,\theta) V_{mn}^*(r,\theta) \quad r \leq 1 \qquad (1)$$

where $V_{mn}^*(r,\theta)$ is the complex conjugate of the Zernike polynomial $V_{mn}(r,\theta)$ and m is the order of the 2-D Zernike moment with repetition n.

The various Zernike moment values may be computed based on the variance of repetition in instances of invariance order. The findings may be interpreted as the Zernike moments corresponding to the designated image shape characteristic. The Zernike moments set Z of the image's shape feature may be readily obtained by first sorting the Zernike moments values in ascending order for each order, followed by sorting the values of each repetition in ascending order.

The feature vector using Zernike moments is given by Equation 2

$$F = \{f_Z\} \qquad (2)$$

2.2. VGG-16 features

The pre-trained VGG-16 has proved robust in object feature extraction. Several applications, such as image classification and medical diagnosis VGG16 pretrained features. The VGG 16 was created [26] and carries on the ReLU legacy with AlexNet. It has 13 convolution layers and three fully connected layers, shown in Figure 3. The more comprehensive version of VGG16 is called VGG-19. The feature vector using VGG16 is given by Equation 3

$$F = \{f_V\} \qquad (3)$$

The combined feature vector using Zernike moments and pre-trained VGG-16 is given by Equation.4

$$F = \{f_Z, f_V\} \qquad (4)$$

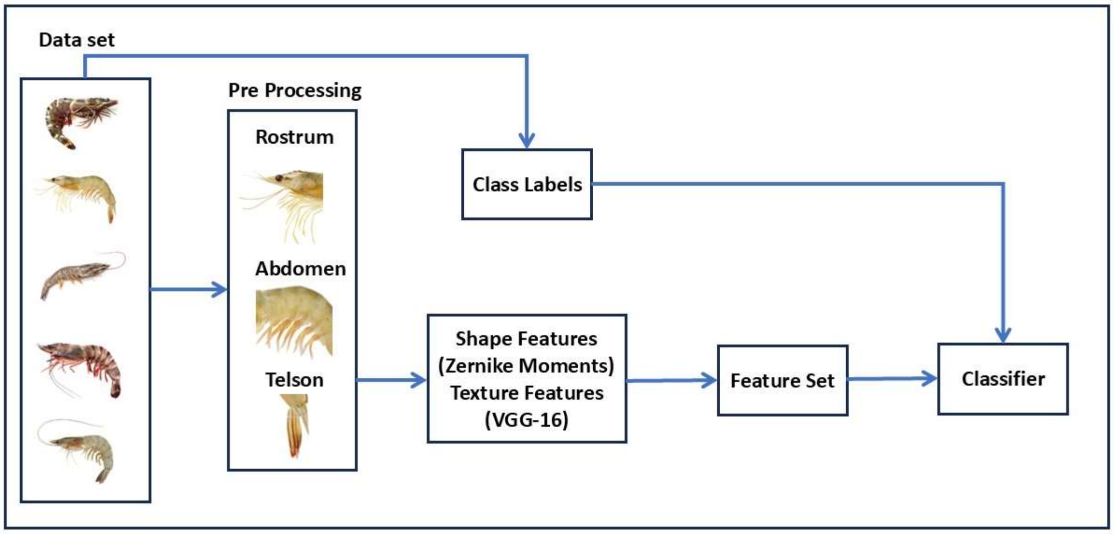

Figure 2. The Proposed Shrimp Classification Via Muti-View Feature Extraction Using Zernike Moments And VGG-16 Features.

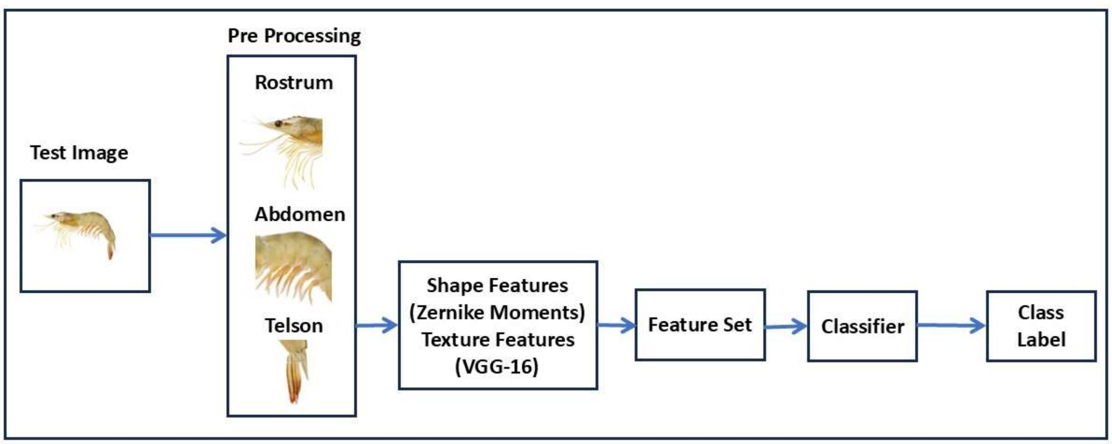

Figure 3. The Proposed Framework Testing Process.

2.2 Support vector machine

While the support vector machine (SVM) is a popular supervised learning algorithm, it is also one of the most extensively utilized approaches for regression and classification problems. However, it is mostly used for addressing categorization issues in machine learning. The SVM approach tries to determine the ideal line or decision boundary that may classify classes by splitting them into n-dimensions. This is done to simplify the process of classifying new data points in the future. A hyperplane is the term that we use to describe this optimum decision boundary. When it comes to the formation of the hyperplane, the SVM is responsible for selecting the extreme vectors and points. Because these extreme circumstances are referred to as support vectors, the technique is considered to be a Support Vector Machine approach. It is possible to classify categories in SVM by using either a decision boundary or a hyperplane.

2.3 Shrimp Classification

Initially, the features are extracted for the collected datasets. Let the collected dataset I be expressed in Equation 5.

$$I = \{I_1, I_2, I_3, \dots\dots\dots\dots I_n\} \quad (5)$$

where $I_1, I_2, I_3, \dots\dots\dots\dots I_n$ represents dataset images.

Each shrimp image is partitioned into rostrum, abdomen, and telson. After preprocessing the dataset, I is expressed as

$$I = \left\{ \begin{matrix} \{I_{1r}, I_{1a}, I_{1t}\}, \{I_{2r}, I_{2a}, I_{2t}\}, \{I_{3r}, I_{3a}, I_{3t}\}, \\ \ldots\ldots\ldots\{I_{nr}, I_{na}, I_{nt}\} \end{matrix} \right\}$$
(6)

where $\{I_{1r}, I_{1a}, I_{1t}\}$ represent labeled image 1 with rostrum, abdomen, and telson, similarly n images.

Feature vectors are extracted using Zernike moments and ResNet18 using Equation 4. The feature vector of the dataset is given by

$$F = \left\{ \begin{matrix} \{f_{1r}, f_{1a}, f_{1t}\}, \{f_{2r}, f_{2a}, f_{2t}\}, \{f_{3r}, f_{3a}, f_{3t}\} \\ ,\ldots\ldots\ldots\{f_{nr}, f_{na}, f_{nt}\} \end{matrix} \right\}$$
(7)

$$F = \{f_1, f_2, f_3, \ldots\ldots\ldots f_n\} \quad (8)$$

Where $f_1 = \{f_{1r}, f_{1a}, f_{1t}\}$ represent feature vector set on labeled image 1 with rostrum, abdomen, and telson features.

Applying for training feature set F using SVM classifier.

$$FSVM = SVM(F) \quad (9)$$

During the testing process, the test image I_T is partitioned to the rostrum, abdomen, and telson.

$$I_T = \{I_r, I_a, I_t\} \quad (10)$$

where I_r represented for rostrum, I_a represented for the abdomen, and I_a represented for the telson.

Extraction of features using equation.4 for $I_r, I_a, and\ I_t$ images. The feature vector set F_T is given by Equation 11.

$$F_T = \{f_{tr}, f_{ta}, f_{tt}\} \quad (11)$$

Applying the feature set to the classifier using Equation 9 identifies the shrimp category.

3. Experimental Results

This section provides a comprehensive assessment of the performance of the two-stage feature extraction shrimp classification approach utilizing the collected dataset, since no public datasets are available for the shrimp dataset. Procedural pre-processing steps were applied in the experiments, including Multiview shrimp feature extraction using Zernike moments and VGG-16 features, combined feature set feature matching, and classification. The collected dataset consists of 765 images from various sources and public sharing websites. Fig. 4 demonstrates the collected dataset with banana shrimp, Indian shrimp, giant shrimp, white shrimp, and green tiger shrimp images. The experiments are performed on 765 total images from the rostrum, abdomen, and telson. The training of 528 images is carried out and 237 images are chosen for the testing of the proposed two-stage feature extraction classifier. Figure 5 displays the qualitative results of the proposed shrimp classification on the collected database. In each shrimp-classified image, the proposed classification technique successfully classified the shrimp with a precision above 95%. Furthermore, the shrimp classification may be enhanced with multi-feature extraction to increase detection performance and minimize computation complexity.

Classification of shrimp particularly within Penaeus genus faces significant thorny challenges owing largely to fervent debates surrounding phylogenetic relationships. Challenges underscore necessity for stringent critique standards ensuring reliability of various classifications quite thoroughly nowadays. Penaeus s.l. was split into six genera but molecular analyses suggest original classification might better reflect evolutionary relationships somewhat accurately. Genus Neocaridina faces intense scrutiny owing largely to considerable morphological variability that muddles species validation necessitating rather complex integrative approaches. Reliance on morphological traits often precipitates misclassification starkly evident in glaring discrepancies between genetic data and traditional classifications. Classification of parasitic crustaceans and treatment of larval characters further complicates phylogenetic assessments indicating need for radically updated methodologies. Critique criteria need revamping and should probably incorporate molecular data alongside certain morphological characteristics addressing limitations inherent in existing classifications. Integration of molecular data advances crustacean classification significantly but reliance on traditional morphological criteria remains a pretty big barrier somehow.

The performance of the proposed object detection approach with the estimate was quantitatively assessed using a confusion matrix. Precision, recall, average precision, and detection speed are the performance measures used for qualitative evaluation. The performance of two-stage shrimp classification results in Tables 1, 2, and 3 demonstrates that compared with Zernike moments and VGG-16 features, the proposed technique results in a robust precision score of 77.47%, accuracy of 67.59%, and F1 score of 0.8. The proposed approach meets the most recent visual classification standards regarding overall performance metrics.

Various object detection techniques, including InceptionResNetV2 [23], SDNET [24], Multi-layer Fusion [25], and GLCM [26] were used to evaluate and compare the overall performance results. The proposed technique effectively classifies shrimp images with improved precision compared to the classification techniques InceptionResNetV2, SDNET, Multi-layer Fusion, and GLCM. The average precision of each technique on the collected

Fig.4. The Collected Shrimp (Prawn) Dataset.

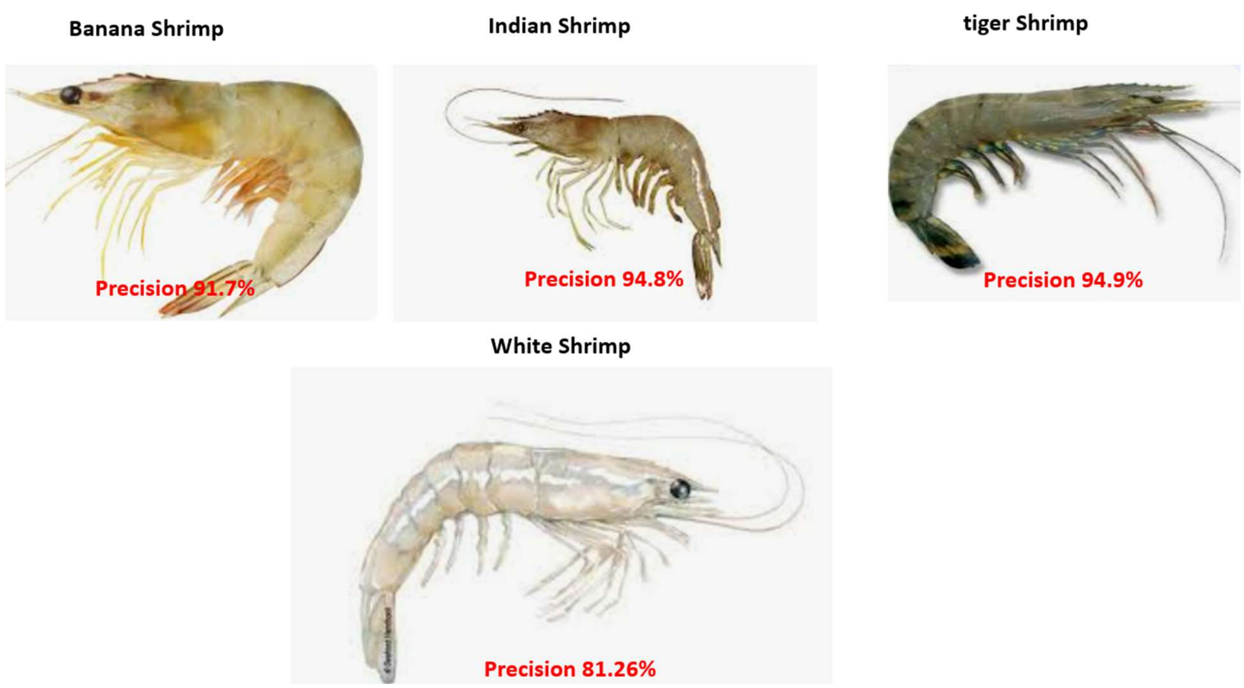

Fig.5. Proposed shrimp classification technique results.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 1: Performance Of Proposed Shrimp Classification Using Zernike Moments.

Performance measure	Zernike moments				
	Banana Shrimp	**Indian Shrimp**	**Tiger shrimp**	**White Shrimp**	**Overall**
Number of shrimps	57	65	46	69	237
True Positive	38	34	29	36	137
True Negative	3	8	7	6	24
False Positive	10	12	4	11	37
False Negative	6	11	6	16	39
Precision	0.79	0.74	0.88	0.77	0.79
Accuracy	0.72	0.65	0.78	0.61	0.68
F-1 Score	0.83	0.75	0.85	0.73	0.78

Table 2 Performance Of Proposed Shrimp Classification Using VGG-16 Features.

Performance measure	VGG-16				
	Banana Shrimp	**Indian Shrimp**	**Tiger shrimp**	**White Shrimp**	**Overall**
Number of shrimps	57	65	46	69	237
True Positive	34	43	34	29	140
True Negative	6	11	6	13	36
False Positive	6	3	2	14	25
False Negative	11	8	4	13	36
Precision	0.85	0.93	0.94	0.67	0.84
Accuracy	0.70	0.83	0.87	0.60	0.74
F-1 Score	0.8	0.89	0.92	0.68	0.82

Table 3 Performance Of Proposed Using Zernike Moments And VGG-16 Features.

Performance measure	VGG-16 + Zernike moments				
	Banana Shrimp	**Indian Shrimp**	**Tiger shrimp**	**White Shrimp**	**Overall**
Number of shrimps	57	65	46	69	237
True Positive	44	54	37	39	174
True Negative	3	6	4	7	20
False Positive	4	3	2	9	18
False Negative	6	2	3	12	23
Precision	0.92	0.94	0.95	0.8125	0.91
Accuracy	0.83	0.92	0.89	0.69	0.83
F-1 Score	0.89	0.95	0.94	0.79	0.89

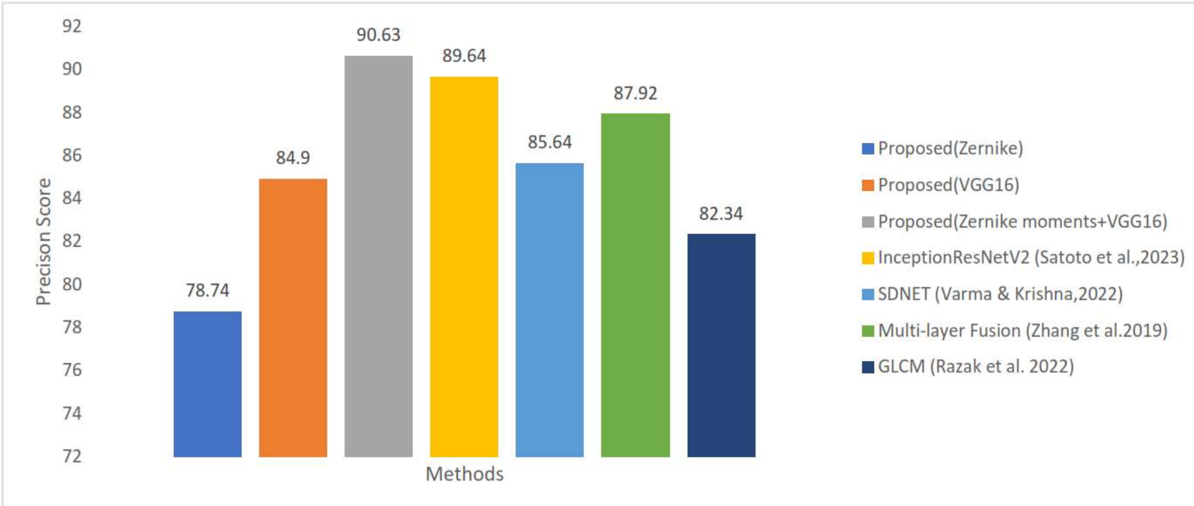

Fig. 6. The Overall Performance Of The Proposed Technique Compared With The State-Of-The-Art Methods.

the dataset is evaluated using a confusion matrix. These results demonstrate the robustness and effectiveness of the proposed technique.

Figure 6 illustrates the proposed technique's overall performance compared to the state-of-the-art methods. The average precision score of the proposed technique of 90.63% shows robust performance compared with the techniques' average precision scores: InceptionResNetV2 of 89.64%, SDNET of 85.64%, Multi-layer Fusion of 87.92%, and GLCM of 82.24%. Furthermore, combined handcrafted and deep feature extraction techniques may enhance the proposed classification approach's performance and classification speed.

4. CONCLUSION

This paper presents a shrimp classification framework with Zernike moments and Pre-Trained VGG-16 features. The process consists of three steps: interest region extraction, feature extraction, and classification. The framework proposed in this study classifies the shrimps through region-based features. Classification is performed using Zernike moments in the initial stage, while pre-trained VGG-16 features are employed in the subsequent stage. The shrimp class is determined by selecting the rostrum, abdomen, and telson region features. The experimental results indicate that the proposed technique has achieved a precision score of 90.63%. This demonstrates the effectiveness and robustness of the shrimp classification technique being proposed. However, the experiment results indicate that multiple irregular shapes of shrimp impact shrimp classification. Hence, it is imperative to consider these aspects in future research. The suggested classification can be adapted to classify multiple shrimps by utilizing distinctive features. The classification of shrimp has seen significant advancements through innovative methodologies that enhance accuracy and efficiency in aquaculture. Recent studies have introduced hybrid models combining deep learning techniques with optimization algorithms, leading to remarkable classification performance. These advancements not only improve shrimp identification but also have broader implications for the aquaculture industry.

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ISSN: **1992-8645** www.jatit.org E-ISSN: **1817-3195**

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