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Shrimp Classification Using Generative Adversarial Network with ResNet

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ABSTRACT

Shrimp species classification continues to be difficult in terms of morphological features, small datasets (in general), and environmental noise associated with image capture. Standard techniques based on handmade shallow features alone have proved very poor on challenging tasks. Recent developments in deep learning have demonstrated great potential; however, this relies heavily on a large and diverse amount of data, which limits its potential to be applied for shrimp studies, as such data resources are scarce. To alleviate the challenge, we propose a unified platform, which integrates shallow and deep Convolutional Neural Networks (CNN) features for improved classification accuracy. Furthermore, to bridge the gap in data availability and balance, Generative Adversarial Networks (GANs) are employed to synthesize realistic shrimp pictures, thereby broadening our training set with a wider range of possible inputs beyond those already used in traditional augmentation methods. Experimental results show the proposed method at 91.66% precision, 89.8% accuracy, and 0.94 F1-score, robustly. These data suggest that GAN-based augmentation and hybrid feature extraction contribute to a significant improvement of shrimp image classification and provide a great contribution for aquaculture monitoring and automatic marine species classification systems.

1. INTRODUCTION

In the past two decades image classification has evolved significantly, simultaneously based on the advancement in computational capacity, large datasets and sophisticated image feature extraction methods. Image classification, at its most basic level, is the process of assigning images to defined classes based on a set of visual representations, a problem widely useful in applications as diverse as those in medical diagnostics, agricultural monitoring, food quality assessment and biometric recognition. Deep learning has gained the greatest success in the computer vision literature but we can still find reasons to pay attention to features in our handcrafted images when the datasets are either small or domain-specific in the way that we have previously studied. In such use cases, hand-designed methods such as morphometric analysis, color histograms, texture descriptors, and shape features have often occupied the central position, on account of their ability to have good sensitivity and generalization in very small data.

For instance, conventional descriptors, like LBP, HOG and GLCM, have been well-accepted for interpretability and computation in the early stage of the image classification research. Their popularity in very specific biological settings such as shrimp classification shows that handiwork not only generated good base rules but also established a basis for further development of deep learning and hybrid methods. While feature extraction has become automated, in some cases handcrafted feature engineering becomes out of sight, it has been maintained as an attractive option for focused classification tasks where sample acquisition is expensive, ethical, or domain specific. It has also been seen in imaging studies that better GLCM descriptors and radiomic features have good performance for MRI and breast lesion detection at the diagnostic level. For instance, Meredith et al. [1] calculated forty radiomic features and fused the automatically learned deep features to enhance tumor image classification. In aquaculture applications, handcrafted descriptors were more prevalent in these early classification models. Sucharita et al. [2] used Gabor filters to extract fine-scale texture patterns in prawns. Their classification performance is about 93%, while Haikal et al. [3] used GLCM-based descriptors to differentiate shrimp quality with ~80% accuracy. Shape descriptors are also promising in discriminative tasks; Poonnoy et al. [4] demonstrated a very high accuracy of 99.8% of RID-based features in ANNs, highlighting the discriminative power of well-defined shape measures. These studies, taken together, indicate that handcrafted features, when used in concert with the fit of classical classifiers like K-Nearest Neighbors (K-NN), Support Vector Machines (SVM), and Random Forests, obtain sufficient baselines, and can be particularly desirable for poor image classification scenarios. There was a definite decline in the extent of work produced by manual feature engineering in terms of issues such as scaling, stability against different light and different directions, generalization to other datasets, and computer vision research moved in the direction of deep learning. Convolutional Neural Networks (CNNs), which provide features in the images of various levels instantiated from their input, significantly changed the classification paradigm, which aims to automate feature extraction by hierarchical convolutional processing. AlexNet, ResNet, and DenseNet were early-mover architectures that would deliver unrivaled performance in wide domains, such as everyday objects and challenging medical images. For instance, strawberry classification reached an accuracy of 99.8% based on CNN models [5], while Residual Networks (ResNet) achieved significant improvements in training efficiency on a complex medical dataset and diminished the vanishing gradient problem [6]. Deep networks were transformative in shrimp classification: Test results for DenseNet121 classification of samples from fresh, frozen, and stale were 98.75% [7], and the same method was applied for InceptionResNetV2 which was able to classify seven shrimp species with 99.4% accuracy, with one to two seconds per sample only [8]. The disease-specific shrimp classification model, the SDNet, which combined unsupervised learning model and deep CNN revealed better adaptation of deep learning and its associated architecture [9]. This development shows the ability of deep learning methods to outperform handcrafted baselines using high dataset size, annotation quality, and computational resources. Techniques of hand or learned feature generation have been investigated for sophisticated image classification schemes which result in hybridization to exploit the combined advantage of both methods. These forms of hybrid feature fusion approaches solve the essential problem of interpretability vs performance, where handcrafted descriptors yield local insights and trained deep learning ensures generalizable feature extraction from high-dimensional data. For instance, Anami and Sagarnal [10] achieved an accuracy of 93.87% for indoor scene classification with multi-level feature fusion, hybrid ones outperforming conventional ones for analysis]. Within the context of aquaculture, Zhang et al. [11] integrated shallow handcrafted descriptors and deeper representations, indicating that shrimp species with low visual variation called for the high discriminative dimensionality of handcrafted forms to be augmented with deep network-dependent abstractions. They acted as an epistemological intermediary between the classical stats feature and representation learning procedures, and were an empirical option that solved empirical problems in domains where isolated applied methods could not be systematically solved. And beyond accuracy, fusion can enhance the confidence to judge classification systems from black-box deep representations as explainable shallow descriptions against opaque and deep representations at a later or stronger level, which translates directly to vital activities like healthcare diagnosis and food quality certification systems. Although deep architectures are still growing and maturing, deep learning methods are data sensitive and there are numerous topics such as shrimp classification and medical diagnosis that have suffered from insufficient structured data, lack of homogeneous representation, poor representation between samples across classes, and ethical dilemmas in training. To overcome these limitations, data augmentation and synthetic sample generation have been applied increasingly, and Generative Adversarial Networks (GANs) is leading the way. GANs produce synthetic realistic samples with the ability to build realistic samples to use within a limited number of training sets, and for problems of large volume of annotated data hard to obtain, these models can help in classification. For dermatology and other sensitive purposes, the introduction of GAN driven synthetic skin images enhanced classification accuracy given the variety representation of input sets [12]. Similarly, some GAN-based methods have recently passed 99.5% accuracy on malware image classification and been successful on industrial forecasting applications [13, 14]. GANs made significant contributions to freshness assessment in aquaculture research: a GAN-augmented APCNN + SVM hypercube approach yielded shrimp freshness classification accuracy of 98.1% [15], while frameworks built with GANs generally improved the freshness assessment accuracy by around 8.68% in shrimp classification experiments with small training datasets [16]. Although GANs are a very robust enhancement, overfitting risks (e.g., mode collapse) and ethical issues are not negligible even when analyzing medical synthetic data, and caution is warranted with the implementation of GAN algorithms. Shrimp classification has evolved over long time series so as to be part of a larger spectrum of overall evolution due to the transition from handcrafted feature engineering methods to hybridization and data heavy deep learning methods. In shrimp classification, we concentrated on handcrafted features from 2014 to 2015, in which shape-based RID classifiers and texture feature shapes processed by Gabor provided significant accuracies. In 2019: A fusion of features — An advancement that marries shallow and deep representation — was born. In case of the year of 2022, disease-based shrimp classification [9] and freshness detection were also improved by GAN enabled CNN architectures [15]. By comparison, the DenseNet, InceptionResNetV2 and other deep learned networks, implemented on such architectures in 2023 and 2024 were widely used, transforming shrimp classification, attaining up to 99% accuracies with less CPU time per sample in comparison time. Also, GAN-based augmentation significantly improved performance under limited training conditions with both stabilization and expansion from these successes [17, 18]. Collectively, this chronological progression is not just about the evolution of technology but an epistemological evolution as well, where well-defined, classical techniques for domain-specific, interpretable handcrafted methods transition towards architecture-agnostic deep learning architectures facilitating high performance, generic feature extraction; where hybrid deep learning methods and GANs are a synergistic bridge to an optimized classification efficacy. This domain of shrimp classification is thus symptomatic of more general evolutionary trends of image classification: it embodies both the lasting tradition of traditional methods as useful for handling current difficulties and revolutionary new possibilities in generative architectures.

This paper addresses the following contributions:

1. A robust data augmentation approach employing Generative Adversarial Networks (GAN) for depicting realistic shrimp images was accomplished.

2. The efficacy of augmentation using GANs with a ResNet classifier surpassed the performance achieved with traditional data augmentation methods.

3. The accuracy, F1-score, and precision of the least capable shrimp class were greatly enhanced as a result of using augmentation with GANs to balance the sample size of each class.

2. SHRIMP CLASSIFICATION

The proposed shrimp classification method using GAN-

ResNet is illustrated in Figure 1. The proposed GAN was developed using ResNet in both the generator and the discriminator. Synthetic shrimp images were generated using a generator, and the discriminator classified the shrimp images based on the shrimp and the generated datasets. Penaeidae: A dominant family with 135 species, including commercially important species, such as Fenneropenaeus indicus and Penaeus monodon [8]. Sergestidae include smaller species, such as Acetes spp., which are significant for local consumption. Among the collected shrimp images, five of the most common shrimps were selected for classification: Giant River shrimp, white shrimp, Procambarus clarkii, Marsupenaeus japonicus, and Peacock mantis shrimp. A deep CNN network, ResNet50, was used to classify shrimp images according to the classes. The ResNet50 architecture is shown in Figure 2.

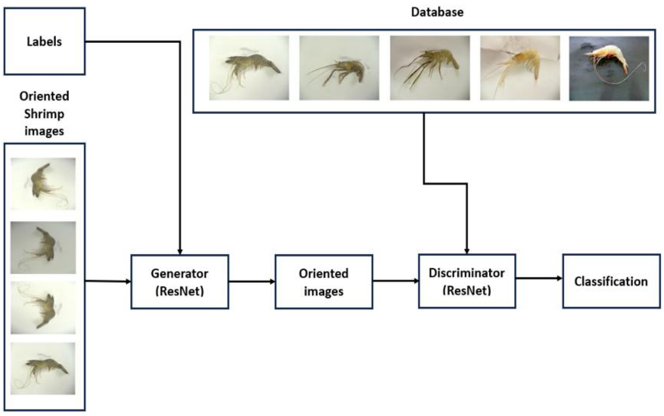

Figure 1. Shrimp classification using GAN-ResNet

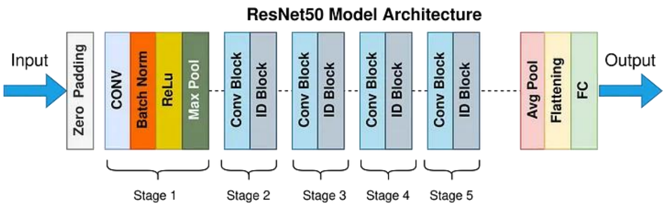

Figure 2. ResNet50 architecture

ResNet-50 is a convolutional neural network design from the ResNet (Residual Networks) family, which addresses deep neural network training issues. ResNet-50, developed by Microsoft Research Asia, excels in image categorisation. Deep ResNet topologies include ResNet-18, ResNet-32, and ResNet-50, a medium-sized version. The 2015 ResNet-50 model continues to improve image categorisation.

ResNet-50 in generator

ResNet-50 is a deep residual network with 50 layers, incorporating skip connections to improve gradient flow and learning capacity. In the GAN context, ResNet-50 can be used in the generator primarily in two ways:

•As a backbone for feature extraction and representation learning within the generator to produce high-quality images.

•Adapted into the generator with residual blocks to facilitate deeper architectures, allowing better image generation.

Step 1: Input noise vector

Start with a noise vector $z \in \mathbb{R}^d$ sampled from a simple distribution (e.g., $z \sim \mathcal{N}(0, I)$).

Step 2: Project and reshape

z is projected through a fully connected layer to form a low-resolution feature map tensor:

$$f_0 = \phi(W_p z + b_p), f_0 \in \mathbb{R}^{C \times H \times W} \tag{1}$$

where, ϕ is an activation (ReLU), W_p, b_p are weights and biases, and C, H, W are channel, height, and width dimensions for the feature map.

Step 3: ResNet-50 blocks (residual learning)

The feature map f_0 is passed through multiple residual blocks adapted from ResNet-50 architecture. Each residual block mathematically can be expressed as:

$$f_{l+1} = f_l + \mathcal{F}(f_l, W_l) \tag{2}$$

where, f_l is input feature map at layer l, $\mathcal{F}$ is the residual function (a stack of convolutions, batch normalizations, activations), and W_l are the block parameters.

The ResNet-50 generator uses a sequence of these residual blocks to incrementally refine features while preserving gradients via skip connections.

Step 4: Upsampling layers

The output from ResNet blocks is upsampled (e.g., using transpose convolutions or nearest-neighbor upsampling followed by convolution), mathematically: to increase spatial resolution towards the image size while refining features.

Step 5: Output layer

Finally, a convolutional layer maps the feature map to an image with 3 color channels:

$$\hat{x} = \sigma(W_o * f_L + b_o) \tag{3}$$

where, $\hat{x} \in \mathbb{R}^{3 \times H_{img} \times W_{img}}$ is the generated image, σ is an activation (e.g., Tanh for pixel values normalized between -1 and 1), W_o and b_o are weights and bias.

Step 6: Training objective

Generator weights (including the ResNet-50 blocks) are updated to minimize discriminator ability to distinguish $D(\hat{x})$ from real, using adversarial loss such as binary cross-entropy or variants:

$$\mathcal{L}_G = -\mathbb{E}_{z \sim p_z}[\log D(G(z))] \tag{4}$$

For the discriminator, ResNet-50 takes input x (image), passes through layers of convolutions and residual blocks, and outputs

$$D(x) = \sigma(W \cdot f(x) + b) \tag{5}$$

where, *f*(*x*) is the feature vector output by ResNet before the final classification layer, W, b are weights and bias of the final layer, and σ is the sigmoid function.

Step-by-Step Mathematical Flow is given below

1. **Input:** Image *x* (real or fake) with shape (H, W, C)
2. **Initial convolution:** Apply convolution Conv(x), batch normalization BN, and ReLU:

$$x_1 = \mathrm{ReLU}(\mathrm{BN}(\mathrm{Conv}(x))) \tag{6}$$

3. **Residual blocks:** For each Residual block i in [1, 2, ..., N], $x_{i+1} = x_i + F(x_i, W_i)$, where F has convolutions, BN, ReLU.

This residual connection helps gradients flow better during backpropagation.

4. **Feature extraction:** After passing through all residual

blocks, get feature map f(x).

5. **Pooling:** Apply Global Average Pooling GAP(f(x)) to reduce feature map to a vector:

$$v = \text{GAP}(f(x)) \tag{7}$$

6. **Fully connected layer:** Compute output logit

$$l = W \cdot v + b \tag{8}$$

7. **Sigmoid activation:** Calculate probability of being real data:

$$D(x) = \sigma(l) = \frac{1}{1 + e^{-l}} \tag{9}$$

8. **Discriminator loss:** For batch size m,

$$J_D = -\frac{1}{m}\sum_{i=1}^{m} [\log\, D(x_i) + \log\,(1 - D(G(z_i)))] \tag{10}$$

This loss is minimized to improve discrimination.

The training and evaluation components were provided. The generator and discriminator networks have their weights assigned randomly at the start. While the generator's goal is to create fake data that is as realistic as possible, the discriminator aims to correctly identify real data and define authentic data from fake data. The generator starts with random noise that serves as input to create fake data. That fake data will then be combined with real data, if available, to create a training batch. The discriminator receives the generator's output, and a loss is calculated, which stems from the level of fooling the discriminator experiences. The generator's loss is reduced by adjusting its weights through gradient descent, leading to improved data output realism. The output data can either be real or fake, and the discriminator will classify them as real or fake. The loss the discriminator has is based on how accurately it can tell real data apart from fake data. To reduce this loss, the discriminator's weights are adjusted so that the ability to tell genuine data apart from synthetic data is enhanced. The core principle of GANs is the adversarial training process, in which the generator and discriminator improve simultaneously through competition.

The generator's ability to produce realistic data improves as training continues, while the discriminator improves in its ability to tell real data apart from fake data. Training continues for several epochs or until a convergence criterion is met. A generator tried to make data that was close to real, and a discriminator tried to tell if the data was real or fake. The generator continuously fails to obtain the data from the discriminator repeatedly. When training is finished, the generator attempts to create fake data for the discriminator to evaluate.

3. RESULTS AND DISCUSSION

This section evaluates the performance of the proposed shrimp classification using GAN-ResNet with the collected dataset. The collected dataset includes shrimp categories such as Giant River shrimp, White shrimp, Procambarus clarkii, Marsupenaeus japonicus, and Peacock mantis shrimp. Table 1 presents the shrimp classes dataset with the number of images for training and testing. The training and testing were done in a Windows 10 environment, using an Intel Core i7-7700 central processing unit (CPU) and an Nvidia RTX 2080 graphics processing unit (GPU). TensorFlow v1.13.0 and Keras are two deep-learning frameworks that were used in the process of developing and training the models.

Table 1. Shrimp data set collected for training and testing

Category	White Shrimp	Giant River	Marsupenaeus Japonicus	Procambarus Clarkii	Peacock Mantis	Total
Training	562	511	506	532	525	2636
Testing	541	492	498	431	419	2381
Total	1103	1003	1004	963	944	5017

Before training the classifier models, the AC-GAN's produced synthetic pictures were tuned. The AC-GAN was trained with varying numbers of training images of each class. This was done to determine the lowest number of images required to make synthetic images that closely resemble genuine ones. Figure 3 shows the collected shrimp dataset, and Figure 4 shows the generated synthetic shrimp images for each class using ResNet.

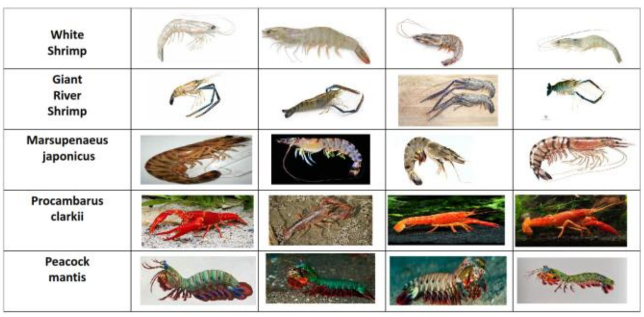

Figure 3. Collected shrimp data set

Figure 4. Synthetic images generated per class using various AC-GAN training sample sizes

The GAN component was employed for synthetic data augmentation, enhancing dataset diversity and reducing overfitting, while ResNet-50 acted as the deep feature extractor and classifier. Training was conducted over 50 epochs, allowing the model to iteratively optimize both generator and discriminator objectives in tandem with ResNet-50's classification loss. Throughout testing, the model achieved an overall accuracy of 89.8%, precision of 91.6%, and F1-score of 94.1%, with per-class precision consistently ranging from 0.89 to 0.93.

Figures 3 and 4 demonstrate that, in the case of shrimp images, the appearance of the developed synthetic images was not comparable to that of the real ones. On the other hand, the number of samples collected includes detailed images that seem to be the exact classification of the shrimps. To evaluate the effectiveness of a CNN classifier, a ResNet model consisting of 2636 samples from different categories of shrimps was used for training. For testing, 541 white shrimp images, 492 giant river shrimp images, 498 Marsupenaeus japonicus shrimp images, 431 Procambarus clarkii shrimp images, and 419 peacock mantis shrimp images are used.

Table 2. Overall qualitative evaluation results of the proposed technique

Performance Measure	White Shrimp	Giant River	Marsupenaeus Japonicus	Procambarus Clarkii	Peacock Mantis	Overall
Number of shrimps	541	492	498	431	419	2381
True Positive	443	402	390	371	339	1945
True Negative	39	50	44	24	37	194
False Positive	45	31	47	25	29	177
False Negative	14	9	17	11	14	65
Precision	0.9078	0.9285	0.8925	0.9369	0.9212	0.9166
Accuracy	0.891	0.9187	0.8715	0.9165	0.8974	0.8984
F-1 Score	0.9376	0.9527	0.9242	0.9538	0.9404	0.9415

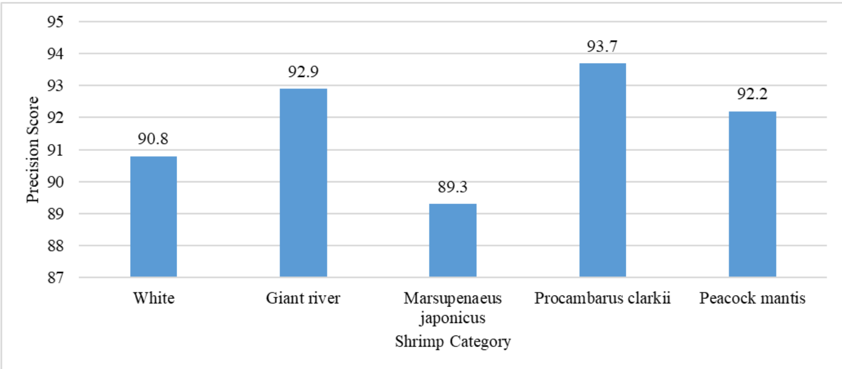

Figure 5. The proposed method of precision score analysis

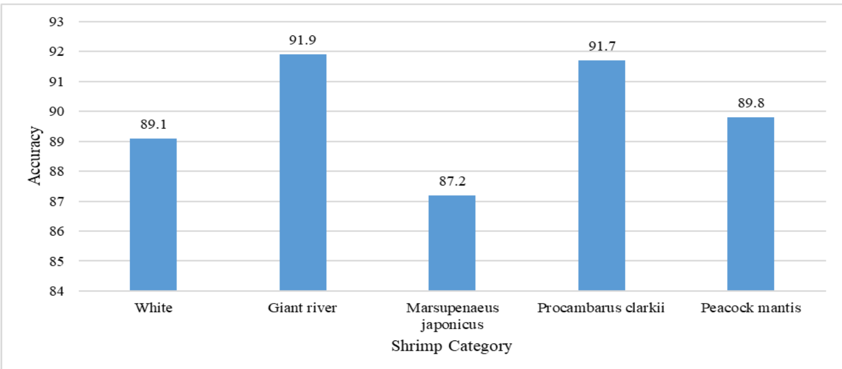

Figure 6. The proposed method of accuracy analysis

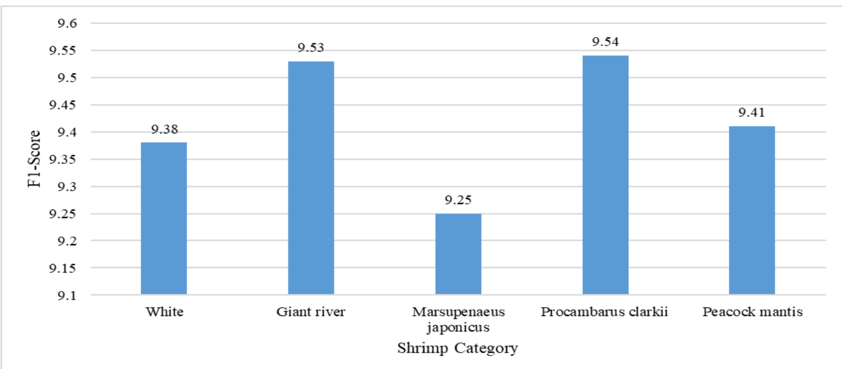

Figure 7. The proposed method of F1-score analysis

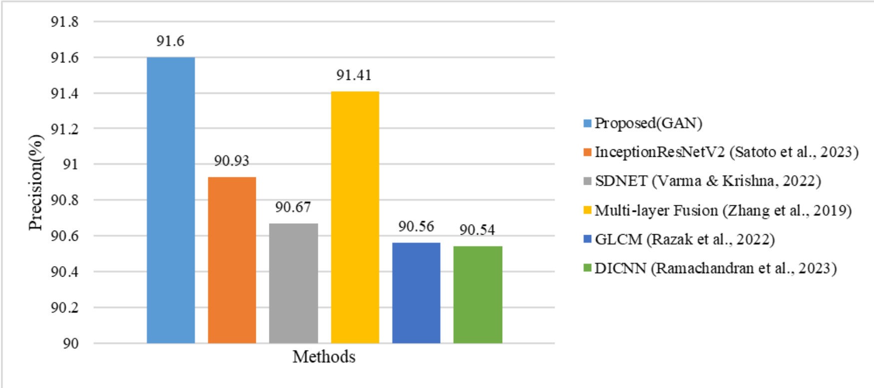

Figure 8. Proposed method performance comparison with state-of-the-art techniques

The proposed technique was qualitatively evaluated using a confusion matrix, as in Table 2. The precision scores achieved 90.78% for White shrimp, 92.8% for Giant river, 89.25% for Marsupenaeus Japonicus, 93.69% for Procambarus clarkii, and 92.12% for Peacock mantis. The precision, accuracy, and F-1 Score of white shrimp, and Marsupenaeus japonicus, are quite low compared to other category shrimps, as shown in Figures 5, 6, and 7, due to their complex shape. The overall precision score of 91.66%, accuracy of 89.8%, and F-1 Score of 0.94 show the robustness of the proposed technique. Figure 8 shows the overall performance in terms of precision score compared with state-of-the-art techniques. For fair comparison with the proposed technique, state-of-the-art techniques are selected, such as InceptionResNetV2 [19], SDNET [9], Multi-layer Fusion [11], GLCM [3], and DICNN [20]. InceptionResNetV2 architecture achieved an impressive average precision of 90.93%, SDNET precision score of 90.67%, Multi-layer Fusion method precision score of 91.41%, GLCM precision score of 90.56%, DICNN precision score of 90.54%, and the proposed GAN achieved a precision score of 91.6% by utilising the collected dataset [21, 22].

4. CONCLUSION

The proposed GAN-based shrimp classification method successfully utilized the generative network to create high-quality synthetic shrimp images, enriching the training dataset and reducing data scarcity. Experimental analysis confirmed that the synthetic images closely resembled genuine ones, and when used for GAN-based augmentation, the ResNet-50 model consistently outperformed standard approaches in terms of precision, accuracy, and F1-score. The achieved precision of 91.66%, accuracy of 89.8%, and F1-score of 0.94 demonstrate the effectiveness of the proposed technique compared to state-of-the-art methods, particularly for objects with complex shapes.

However, the study did not explore the method's robustness under scenarios with very limited samples or highly complex and cluttered backgrounds, which may pose challenges for accurate classification. As a direction for future work, the model can be extended to handle such challenging conditions by incorporating advanced pre-processing, transfer learning strategies, or attention-based mechanisms. Additionally, applying the proposed framework to broader object categories in agriculture, aquaculture, or food quality inspection could validate its generalizability and scalability.

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