Automated Dried Fish Classification Using MobileNetV2 and Transfer Learning

Rajmohan Pardeshi[1], Rajermani Thinakaran[2], Sanjay Kharat[3]
Department of Computer Science, Karnatak Arts, Science and Commerce College, Bidar, Karnataka, India[1]
Faculty of Data Science and Information Technology (FDSIT),
INTI International University, Nilai, Negeri Sembilan, Malaysia[2]
Department of Zoology, Modern College of Arts, Science and Commerce, Ganeshkhind, Pune, India[3]

***Abstract*—India, the second largest fish producer globally, contributes significantly to food security, nutrition, and economic development. Dried fish is a vital component of the fisheries value chain, especially in South Asia, yet current classification methods are manual, inconsistent, and labor-intensive. This study aims to automate dried fish classification using MobileNetV2 through transfer learning, enabling real-time, lightweight deployment on edge devices. We trained and evaluated the model across four diverse publicly available datasets using single, bulk, head, and tail image modalities. Our experiments demonstrated high accuracy (up to 100%) and strong generalization across datasets. The proposed model offers a practical, scalable, and efficient solution to modernize dried fish processing and enhance productivity and traceability in fisheries.**

***Keywords*—Dried fish classification; MobileNetV2; transfer learning; edge deployment; fisheries automation**

I. Introduction

India is the second largest fish producer globally, with an extensive coastline of 8,118 km, making fisheries a crucial sector for food security, nutrition, and economic development. The industry contributes 6.56% to global fish production and over 5.37% to the country's agricultural Gross Value Added (GVA), providing livelihoods to millions [1]. With increasing export earnings and government initiatives such as the Blue Revolution, there is a significant potential for sustainable growth. Integrating advanced technologies such as Artificial Intelligence (AI) and Machine Learning (ML) can enhance productivity, modernize infrastructure, and strengthen the fisheries value chain, ultimately maximizing its economic and nutritional benefits.

Among the various seafood products, dried fish is one of the most well-known and widely consumed fish commodities. It is also recognized as an affordable and rich source of protein [2]. Advances in fish processing technologies, including preservation, waste utilization, and safety assurance, have expanded applications from the food industry to pharmaceuticals [3] [4]. The current methods for dry fish processing are mostly manual, time consuming and labor-intensive. Given the industrial and economic significance of dried fish processing, it is essential to develop technological solutions for automating processing, storage, and sorting. As a step toward this objective, we propose an AI-based solution to optimize these processes, improving efficiency and sustainability in the fisheries sector by introducing the deep learning based dried fish classification system [5].

Despite the growing use of AI in fish classification, prior studies have focused predominantly on fresh or underwater fish species, often employing complex, resource intensive models unsuitable for real-time deployment in rural fish markets. There is limited research addressing dried fish, particularly those species endemic to India and Bangladesh. Furthermore, previous works rarely compare multiple imaging modalities (e.g., head, tail, bulk), which are critical for robust classification under practical conditions. This study fills these gaps by applying MobileNetV2 for cross-dataset evaluation under various scenarios, targeting deployment in constrained environments.

The remainder of this study is organized as follows: Section II presents a review of existing literature related to fish classification techniques. Section III details the proposed methodology, including the transfer learning strategy using MobileNetV2. Section IV discusses the experimental results, including dataset descriptions and performance metrics. It also presents a discussion of key findings and their implications. Section V concludes the study and outlines future research directions.

II. Literature Review

Automatic classification of fish has gained attention for more than four decades and considered image classification and shape analysis as a problem of computer vision. The necessity for automatic sorting of fish by species has been addressed in [6] [7]. These researchers characterized fish shape using length measurements (defined as a horizontal straight line from the tip of the head to the base of the tail) and width measurements (defined as the distance from the top to the bottom of the body) taken at several equidistant points along the length. They discovered that they could sort four fish species with a reliability of 95% and seven species with an accuracy of 90%.

The study presented in [8] is for fish species classification. Authors developed three techniques namely, invariant moments, optimization of the mismatch of shape, and shape descriptors for differentiating between fish species. The discriminant analysis method was used for classification and achieved the classification rate of 73%, 63%, and 90%, respectively. In [9], the authors presented the work based on color and shape features such as aspect ratio and area. Discriminant analysis was applied for classification of 18 fish species achieving 98% of accuracy.

A novel artificial neural network-based technique for autonomously counting fish is introduced in [10]. To count artificial fish populations, a back propagation of error feed-forward neural network has been trained. It is then demonstrated that trained networks generalize effectively to scenes of fish tanks that have never been seen before, with 94% success rate on scenarios with up to 100 fish in a range of overlaps and orientations. Authors presented a classifier combination approach for classification of five species of fishes. They applied moment invariants, Fourier descriptors and shape features with combination of local vector quantization, naïve Bayes and MLP classifier and achieved 70% accuracy [11].

An automatic fish species recognition system [12] was designed using shape recognition methods, comparing test fish contours with a database. A power cepstrum-based matching technique was developed and evaluated alongside other methods. Despite a 60% recognition accuracy, the system significantly reduces manual effort and holds potential for biological research. A study explored the identification of a suitable feature set for fish classification [13]. It utilized four size measurement features, 19 shape measurement features, eight color signature features, and 16 texture measurement features. Using a Bayesian classifier, the study achieved 87% accuracy in classifying six fish species. Trials of a computer vision system, The CatchMeter, for identifying and measuring fish species are described [14]. Fish are transported along a conveyor under a digital camera, where image processing algorithms determine orientation using a moment-invariant method. The system achieves 100% accuracy in distinguishing flatfish from roundfish, measures length with a standard deviation of 1.2 mm, and identifies species with up to 99.8% sorting reliability for seven fish species. This study presents an automatic fish species classification framework using image analysis and artificial immune systems. It integrates Scale-Invariant Feature Transform and Principal Component Analysis for feature extraction, Artificial Immune Network and Adaptive Radius Immune Algorithm for clustering, and a nearest neighbor classifier. Validated on economically significant fish species, the framework achieved 92% accuracy, offering a robust alternative to manual classification methods [15].

A state-of-the-art computer vision method for fine-grained fish species classification using deep learning is presented [16]. The approach employs a cross-layer pooling algorithm with a pre-trained convolutional neural network as a generalized feature extractor, reducing the need for extensive training data. Classification is performed using an SVM on extracted features, achieving 94.3% accuracy on fish species from underwater video imagery captured off the coast of Western Australia. This study introduces a novel approach for automatic remote acoustic identification of fish using pattern recognition techniques [17]. Fish calls are extracted from background noise and parameterized using LFCC, MFCC, Shannon Entropy, and Syllable Length. Three machine learning algorithms—KNN, Random Forest, and SVM—were used for classification, successfully identifying 102 fish species with average accuracies of 95.24%, 93.56%, and 95.58%, respectively. This study proposes a fish species classification method using a 32-layer VGGNet with a deep hierarchical supervision mechanism [18]. Five controlled subnetworks with additional convolutional layers, varied kernels, and hidden layer features were introduced to optimize training and enhance feature extraction. The approach achieved 96% accuracy on the Pak Fish dataset.

An automated real-time deep learning framework was developed using convolutional neural networks and Kalman filters for fish species classification. YOLOv3 and Mask-RCNN achieved mAP scores of 0.73 and 0.62, respectively [19]. The adapted YOLO model successfully detected and classified eight fish species from a high-resolution DIDSON sonar dataset captured in the Ocqueoc River, Michigan, USA. This study presents a dataset of fish tray images [20] from a local wholesale fish market, featuring pixel-wise (mask) labeled specimens, species information, and size measurements. The dataset includes 1,291 labeled images, comprising 7,339 specimens from 59 species across 60 class labels. It is valuable for evaluating fish instance segmentation and size estimation methods, which are crucial for automated stock management systems and can help to sustain fish populations over time. This image dataset is designed for benchmarking automated fish detection and classification algorithms. The dataset contains 69,917 fish tags representing 30 different taxa, with the image content extracted through tagging for accurate identification and analysis [21].

This study highlights the use of artificial intelligence in fish classification and taxonomy, demonstrating its ability to surpass traditional methods in identifying fine-grained morphological features and advancing aquatic biodiversity research [22]. AI's role in conservation, citizen science initiatives, and education is emphasized, showcasing its potential to enhance species protection and environmental preservation. More details about the fish classification can be found in [23]. This study presents a deep learning and convolutional neural network (CNN) model [24] for classifying various types of dried fish, including locally recognized species like Bashpata, Chanda, Ilish, and Tengra. The dataset [29] was augmented and segmented, achieving an accuracy of 97.72%. In the recent study given by authors, the database of Indian dried fishes having 5 common categories and several deep learning models were evaluated for accuracy before and after training. EfficientNetB0 achieved the highest accuracy (95.23%), followed by ResNet50 (94.03%) and Xception (93.89%). InceptionV3 and VGG16 showed relatively lower final accuracies of 89.56% and 87.56%, respectively. These results highlight EfficientNetB0's superior performance in feature extraction and classification.

Despite extensive research on fish classification using image processing and machine learning techniques, most studies primarily focus on fresh fish or underwater species. There is a notable lack of dedicated research on dried fish classification, particularly for regionally significant species found in India and Bangladesh. While deep learning models such as convolutional neural networks (CNNs) have been employed for fish classification, limited studies have explored transfer learning approaches, specifically MobileNetV2, for dried fish classification. Moreover, existing research predominantly relies on full-body fish images, with minimal investigation into classification performance based on different perspectives, such as single images, head, tail, and bulk images. This gap is critical, as considering multiple perspectives could enhance the robustness of classification models in real-world applications, such as wholesale markets and automated sorting systems. Additionally, many studies utilize computationally expensive models like YOLO, Mask-RCNN, and large CNN architectures, which require substantial resources. There is a pressing need for lightweight and efficient models capable of performing real-time dried fish classification on edge devices. Another significant gap lies in dataset availability. While datasets for fresh fish classification exist, comprehensive datasets for dried fish are scarce. The available datasets often lack diversity in terms of species representation, image quality, and environmental variations, which can impact model generalizability. Although our study attempts to address these limitations by evaluating classification performance across multiple perspectives and conducting detailed experiments, further research is needed to develop specialized, transfer-learning-based models that ensure improved accuracy, computational efficiency, and adaptability to real-world deployment.

III. TRANSFER LEARNING USING MOBILENETV2

Transfer learning is a deep learning technique that uses a pre-trained model on a large dataset and fine-tunes it for a specific task with a smaller dataset [25]. This approach is particularly effective in scenarios with limited training data, as it allows the model to use previously learned features to improve performance in new tasks.

Mathematically, if $f(x;\theta)$ represents a deep learning model with parameters θ, transfer learning can be expressed as:

$$\theta^* = \arg\min_{\theta} \sum_{i=1}^{N} \mathcal{L}(y_i, f(x_i;\theta)) \tag{1}$$

where:

- x_i and y_i are input-output pairs in the new dataset,
- $\mathcal{L}$ is the loss function,
- θ^* represents the optimized parameters adapted from the pre-trained model.

MobileNetV2, a lightweight deep convolutional neural network (CNN), is widely used for transfer learning in image classification tasks due to its efficiency in mobile and embedded applications [26]. MobileNetV2 is a convolutional neural network (CNN) architecture designed for efficient performance in resource-constrained environments. It employs inverted residuals and linear bottlenecks, enhancing both accuracy and computational efficiency [27] [36]. The core of MobileNetV2 consists of depthwise separable convolutions, which decompose standard convolutions into two operations: depthwise convolution, where a single filter is applied per input channel, and pointwise convolution, a 1×1 convolution that increases the channel dimension. This approach significantly reduces computational complexity compared to conventional convolutional layers [28]. Additionally, MobileNetV2 introduces inverted residual blocks, where shortcut connections exist between narrow bottleneck layers instead of wide layers, thereby improving feature reuse [26]. Each block follows a sequence: an expansion layer, which scales up the input dimension; a depthwise convolution, which reduces spatial dimensions while maintaining depth; and a projection layer (linear bottleneck), which compresses features into a lower-dimensional space.

Algorithm 1 Dried Fish Image Classification Using MobileNetV2 and Transfer Learning

Require: Image dataset $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N}$, where $x_i \in \mathbb{R}^{h\times w\times c}$ and y_i is the label
Ensure: Trained classification model $f_\theta : \mathbb{R}^{h\times w\times c} \rightarrow \mathbb{R}^K$
Step 1: Data Preprocessing
Load dataset $\mathcal{D}$ from directory
Resize images: $x_i \leftarrow \text{resize}(x_i, (224, 224)) \quad \forall x_i \in \mathcal{D}$
Normalize images: $x_i \leftarrow \frac{x_i}{255} \quad \forall x_i \in \mathcal{D}$
Split dataset into training set $\mathcal{D}_{train}$ (80%) and testing set $\mathcal{D}_{test}$ (20%)
Step 2: Model Construction
Initialize pretrained MobileNetV2 backbone $\phi_{\text{MBV2}} : \mathbb{R}^{224\times 224\times 3} \rightarrow \mathbb{R}^d$
Freeze backbone layers: $\phi_{\text{MBV2}} \leftarrow$ frozen
Define classifier head:
  $h_\theta \leftarrow \text{Dense}(128, \text{ReLU})$
  $h_\theta \leftarrow \text{Dense}(128, \text{ReLU})$
  $h_\theta \leftarrow \text{Dense}(K, \text{Softmax})$
Construct final model: $f_\theta = h_\theta \circ \phi_{\text{MBV2}}$
Compile model with Adam optimizer and categorical cross-entropy loss
Step 3: Model Training
for $t = 1$ to T (epochs) **do**
  Train model on $\mathcal{D}_{train}$ using backpropagation
  if Validation loss does not improve for 5 epochs **then**
    Stop Training (Early Stopping)
  end if
end for
Step 4: Model Evaluation
Compute predictions: $\hat{y}_i = f_\theta(x_i) \quad \forall x_i \in \mathcal{D}_{test}$
Compute evaluation metrics:
  Accuracy: $\frac{1}{|\mathcal{D}_{test}|}\sum_i \mathbf{1}(\hat{y}_i = y_i)$
  Precision, Recall, and F1-score from confusion matrix
Generate classification report
End

For dried fish classification, MobileNetV2 is fine-tuned using a dataset containing various species of dried fish images. The preprocessing pipeline includes image resizing, data augmentation (rotation, flipping, normalization), and dataset splitting (80% training, 20% validation) [25]. Transfer learning is applied by leveraging a pre-trained MobileNetV2 model on ImageNet, replacing its fully connected layers with a custom classifier, as given in Fig. 1. The classification function is modeled as a softmax function, where extracted features from the pre-trained layers are fed into a newly trained classification head [26]. The training process involves minimizing cross-entropy loss, optimizing with the Adam optimizer, fine-tuning only the later layers while freezing earlier ones, and evaluating performance using accuracy, precision, recall, and F1-score. This approach ensures efficient and accurate classification of dried fish species while maintaining computational efficiency.

The key parameters used in the model include image size (224×224), learning rate (0.001), batch size (32), and number of dense layers in the classifier head. The choice of MobileNetV2 as a backbone minimizes the number of

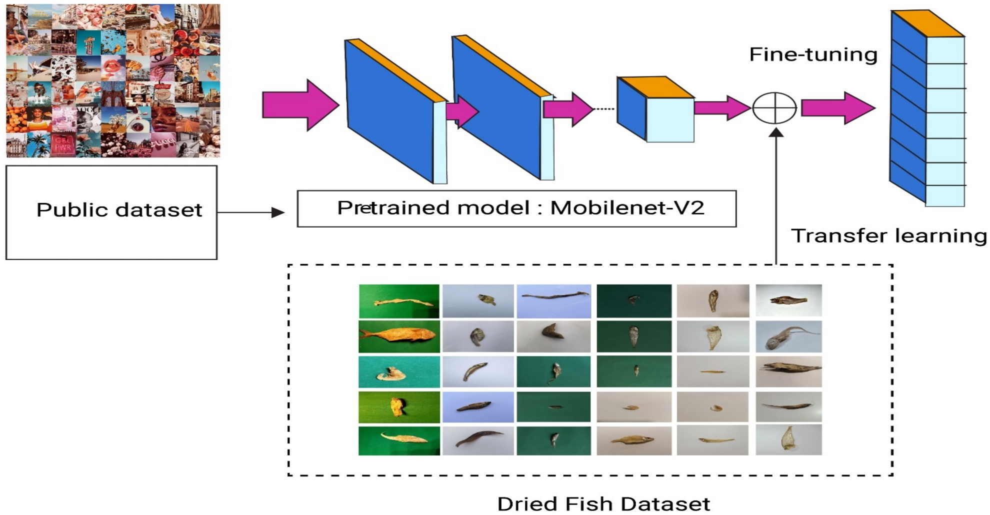

Fig. 1. Transfer learning-based dried fish image classification framework. [35]

trainable parameters (3.4M), supporting fast training. Early stopping was used to prevent overfitting. Sensitivity analysis showed that increasing the number of dense layers beyond two led to overfitting without significant accuracy improvement. Lowering the learning rate increased training time but did not yield significantly better results, justifying the current choice. Algorithm 1 details the dried fish image classification using MobileNetV2 and Transfer learning.

IV. Results and Discussion

A. Dataset Description

The datasets for this research were selected based on their relevance, public availability, and diversity of dried fish species from South Asian regions, especially India and Bangladesh, where dried fish is commercially significant. These datasets—Indian Dried Fish, BDDryFish, DriedFishBD, and SAR-DFD-2025—offer varying image perspectives (single, bulk, head, tail) and environmental conditions, providing a robust testbed for evaluating classification performance.

1) Indian dried fish image dataset [29]: This dataset consists of 8,290 images of dried fish, including both single and bulk images. It covers five fish categories commonly found in India: Prawns (Shrimp), Small Anchovi (Tingle), Golden Anchovi (Mandeli), Mackerel (Bangada), and Bombay Duck (Bombil). The dataset provides 6,784 single images and 1,506 bulk images, making it useful for fish classification and quality assessment studies (see Table I).

2) BDDryFish an image dataset of dry fishes found in Bangladesh [30]: This dataset includes 1,251 images of seven different dried fish species commonly found in Bangladesh. The fish categories include Shundori Shutki Aluva, Bele Fish, Boicha Shutki, Chingri Fish, Churi Shutki, Faisha Shutki, and Mola Fish. The dataset is useful for species identification and classification research in the domain of dried fish processing and trade (see Table II).

3) DriedFishBD a detailed image dataset of common small-sized dried fish varieties in Bangladesh [31]: This dataset contains 3,288 images of eight different small-sized dried fish species. Each fish category is represented through multiple perspectives, including single, bulk, head, and tail images, making it a rich dataset for detailed morphological analysis. The categories include Chanda, Chapila, Chela, Chepa, Guchi, Kachki, Loitta, and Tengra (see Table III).

4) SAR-DFD-2025 a high-quality and diverse dry fish dataset from South Asia [32]: SAR-DFD-2025 is a comprehensive, high-quality dataset designed for dry fish species identification in South Asia. It features a diverse collection of 2,138 images across 11 fish species, captured under varying lighting conditions and angles. The dataset includes species such as Boro Chingri, Chanda, Chela, Kachki, Kocho Chingri, Mola, Tengra, Poti, Shundori, Taki Actual, and Faissa. This dataset serves as a crucial resource for image-based fish species recognition and classification, aiding research in fisheries and related fields (see Table IV).

TABLE I. Dataset1 : Indian Dried Fish Image Dataset [29]

Sr. No	Category	No. of Single Images	No. of Bulk Images
1	Prawns (Shrimp)	1021	245
2	Small Anchovi (Tingle)	1051	408
3	Golden Anchovi (Mandeli)	977	499
4	Mackerel (Bangada)	2633	114
5	Bombay Duck (Bombil)	1102	240
Total		**6784**	**1506**

B. Experimental Results

The experimental results for the classification of dried fish species using deep learning models are presented in this section. The classification was conducted on multiple datasets, including Indian Dried Fish, BDDryfish, DriedFishBD, and

TABLE II. BDDryFish: An Image Dataset of Dry Fishes Found in Bangladesh [30]

Sr. No	Category	Total Images
1	Shundori Shutki Aluva	208
2	Bele Fish	202
3	Boicha Shutki	209
4	Chingri Fish	219
5	Churi Shutki	101
6	Faisha Shutki	104
7	Mola Fish	208

TABLE III. Dataset 3: DriedFishBD - A Detailed Image Dataset of Common Small-Sized Dried Fish Varieties in Bangladesh [31]

Sr. No	Category	Single	Bulk	Head	Tail	Total
1	Chanda	100	100	100	100	400
2	Chapila	120	100	102	100	422
3	Chela	100	100	100	100	400
4	Chepa	100	100	100	100	400
5	Guchi	105	108	103	111	427
6	Kachki	121	107	103	104	435
7	Loitta	100	100	100	100	400
8	Tengra	100	100	100	104	404

SARDFD2025. The models were evaluated based on precision, recall, and F1-score, which measure the effectiveness of the classification. Accuracy is also reported to provide an overall performance assessment.

Each dataset was tested using different imaging approaches, including single images, bulk images, head-only images, tail-only images, and full-body images. The following subsections provide a detailed breakdown of the classification results for each dataset.

Table V presents the classification results for Indian dried fish species using a single image per sample. The model achieved high precision, recall, and F1-score across all classes, with an overall accuracy of 100%. This indicates that the model correctly identified the species without any misclassification.

The slight variation in recall for Mandeli and precision for Tingali suggests that the model had minor confusion when classifying these species. However, the F1-score remained nearly perfect, demonstrating robust performance.

In the bulk image classification setting Table VI, multiple fish were present in a single image for classification. The overall accuracy remained high at 99%, with some minor variations in precision and recall. Here, Bombayduck showed a slight drop in precision (0.95), suggesting some misclassification in bulk image scenarios. However, the model still maintained strong performance across all classes.

The classification results for BDDryfish, another dried fish dataset, are shown in Table VII. The model achieved an overall accuracy of 99%, with minor variations in precision and recall across some classes. Here, Alua and Chingri fish had slight variations in recall (0.98 and 0.96, respectively), suggesting some misclassification. However, the overall accuracy remained strong, indicating that the model performed well across different fish species.

TABLE IV. SAR-DFD-2025: A High-Quality and Diverse Dry Fish Dataset from South Asia [32]

Sr. No	Fish Category	No. of Images
1	Boro Chingri	214
2	Chanda	240
3	Chela	252
4	Kachki	282
5	Kocho Chingri	257
6	Mola	241
7	Tengra	230
8	Poti	156
9	Shundori	120
10	Taki Actual	84
11	Faissa	62

TABLE V. Classification Results for Indian Dried Fish Species using Single Images

Class	Precision	Recall	F1-score
Bombayduck	1.00	1.00	1.00
Mackeral	1.00	1.00	1.00
Mandeli	1.00	0.99	1.00
Prawns	0.99	0.99	0.99
Tingali	0.98	1.00	0.99
Accuracy	1.00 (Overall)		

TABLE VI. Classification Results for Indian Dried Fish Species (Bulk Images)

Class	Precision	Recall	F1-score
Mandeli	1.00	1.00	1.00
Prawn	1.00	1.00	1.00
Tingali	0.99	0.98	0.98
Bombayduck	0.95	0.98	0.97
Mackeral	1.00	1.00	1.00
Accuracy	0.99 (Overall)		

TABLE VII. Classification Results for BDDryfish Dataset

Class	Precision	Recall	F1-score
Alua	1.00	0.98	0.99
Bele fish	1.00	1.00	1.00
Boicha shutki	1.00	1.00	1.00
Chingri fish	1.00	0.96	0.98
Churi shutki	1.00	1.00	1.00
Faisha shutki	0.96	1.00	0.98
Mola fish	0.95	1.00	0.97
Accuracy	0.99 (Overall)		

The classification results for the DriedFishBD dataset are evaluated under four different settings: Full Image, Head Only, Tail Only, and Bulk. Each setting analyzes how well the model classifies various dried fish species based on different input

TABLE VIII. CLASSIFICATION RESULTS FOR DRIEDFISHBD DATASET

Class	Precision	Recall	F1-score
Chanda	1.00	1.00	1.00
Chapila	0.96	1.00	0.98
Chela	1.00	1.00	1.00
Chepa	1.00	1.00	1.00
Guchi	0.91	0.95	0.93
Kachki	1.00	1.00	1.00
Loitta	1.00	1.00	1.00
Tengra	1.00	0.89	0.94
Accuracy	0.98 (Overall)		

TABLE IX. CLASSIFICATION RESULTS FOR DRIEDFISHBD (HEAD ONLY)

Class	Precision	Recall	F1-score
Chanda	1.00	1.00	1.00
Chapila	1.00	1.00	1.00
Chela	1.00	1.00	1.00
Chepa	0.95	1.00	0.98
Guchi	1.00	1.00	1.00
Kachki	1.00	0.95	0.97
Loitta	1.00	1.00	1.00
Tengra	1.00	1.00	1.00
Accuracy	0.99		

TABLE X. CLASSIFICATION RESULTS FOR DRIEDFISHBD (TAIL ONLY)

Class	Precision	Recall	F1-score
Chanda	1.00	1.00	1.00
Chapila	1.00	1.00	1.00
Chela	1.00	1.00	1.00
Chepa	1.00	1.00	1.00
Guchi	0.90	1.00	0.95
Kachki	1.00	1.00	1.00
Loitta	1.00	0.95	0.97
Tengra	1.00	0.88	0.94
Accuracy	0.98		

TABLE XI. CLASSIFICATION RESULTS FOR DRIEDFISHBD (BULK)

Class	Precision	Recall	F1-score
Chanda	1.00	1.00	1.00
Chapila	1.00	1.00	1.00
Chela	1.00	1.00	1.00
Chepa	1.00	1.00	1.00
Guchi	1.00	1.00	1.00
Kachki	1.00	1.00	1.00
Loitta	1.00	1.00	1.00
Tengra	1.00	1.00	1.00
Accuracy	1.00		

conditions.

Table VIII presents the classification performance when using the full image of the dried fish. The model achieved a high accuracy of 98%, indicating strong performance in distinguishing the eight fish species. Several species, such as Chanda, Chela, Chepa, Kachki, and Loitta, were classified with perfect precision, recall, and F1-score values of 1.00. However, minor classification errors were observed for Chapila (F1-score = 0.98), Guchi (F1-score = 0.93), and Tengra (F1-score = 0.94), suggesting that these species may have overlapping visual characteristics.

Table IX illustrates the classification results when using only the head portion of the dried fish. The overall accuracy slightly improved to 99%. Most species achieved an F1-score of 1.00, except Kachki (F1-score = 0.97). The improved performance compared to full image classification suggests that the head region contains distinctive features that aid in species identification.

Table X reports the classification performance when using only the tail portion of the fish. The overall accuracy remained at 98%, similar to full image classification. While most species were classified perfectly, slight performance drops were observed for Guchi (F1-score = 0.95), extitLoitta (F1-score = 0.97), and Tengra (F1-score = 0.94). This suggests that the tail alone may not be as distinctive as the head for classification purposes.

Table XI presents the classification results when using bulk images, where multiple fish appear in a single image. The model achieved perfect accuracy (100%) across all classes, indicating that it successfully identified every species without error. This suggests that bulk classification benefits from multiple views of the fish, allowing the model to generalize effectively.

The experimental results indicate that the model performs best on bulk images (100% accuracy), followed by head-only images (99%), full images (98%), and tail-only images (98%).

The head region provides more distinguishing features than the tail, leading to better classification performance.

The species Guchi and Tengra exhibit slightly lower F1-scores, indicating potential visual similarity with other species.

The consistently high accuracy ($\geq 98\%$) across all settings validates the robustness of the classification model for the DriedFishBD dataset.

These results confirm that the proposed classification model is highly effective in distinguishing dried fish species under different conditions.

Table XII presents the classification results obtained for the SARDFD2025 dataset. Precision measures the proportion of correctly identified instances for a given class among all instances predicted as that class. Recall quantifies the proportion of correctly identified instances among all actual instances of that class. The F1-score, which is the harmonic mean of precision and recall, provides a balanced measure of classification performance. The model achieves an overall accuracy of 97%, indicating a high level of classification performance across all classes. The individual class-wise results reveal strong performance across various categories.

The model demonstrates excellent classification performance for multiple fish species, including Faissa and Taki

TABLE XII. CLASSIFICATION RESULTS FOR SARDFD2025

Class	Precision	Recall	F1-score
Boro Chingri	0.95	0.95	0.95
Chanda	0.97	1.00	0.99
Chela	0.92	0.98	0.95
Faissa	1.00	1.00	1.00
Kachki	0.98	0.97	0.97
Kocho Chingri	0.98	0.98	0.98
Mola	0.98	0.92	0.95
Poti	1.00	0.97	0.99
Shondori	0.96	0.96	0.96
Taki Actual	1.00	1.00	1.00
Tengra	0.98	1.00	0.99
Accuracy	0.97		

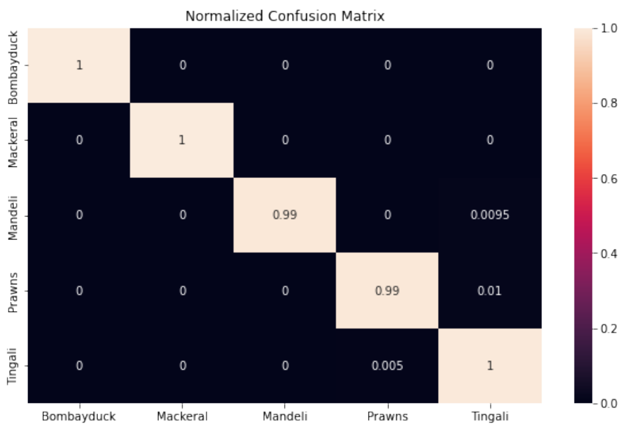

Fig. 2. Confusion matrix for Indian dried fish species using single images.

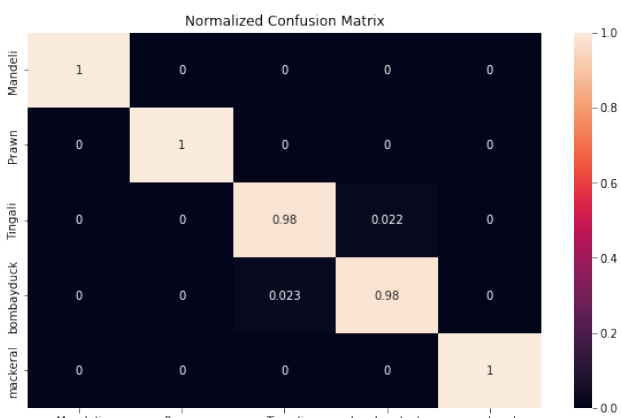

Fig. 3. Confusion matrix for Indian dried fish species (bulk images).

Actual, where both precision and recall reach 1.00, implying perfect classification. The majority of fish classes, such as Boro Chingri, Chela, Kocho Chingri, Mola, and Tengra, achieve F1-scores above 0.95, highlighting the reliability of the model in distinguishing between different species. A few classes exhibit minor differences between precision and recall values. For instance, Mola has a slightly lower recall (0.92) compared to its precision (0.98), suggesting some instances were not correctly identified.

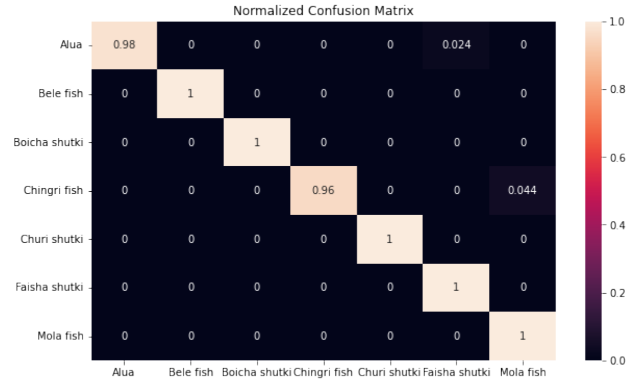

Fig. 4. Confusion matrix for BDDryfish dataset.

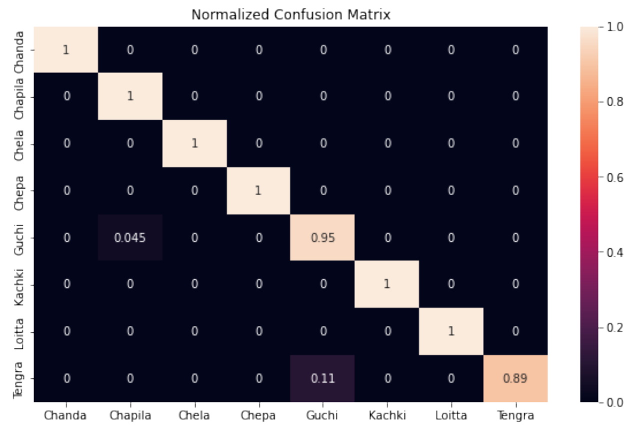

Fig. 5. Confusion matrix for DriedFishBD dataset.

To evaluate the classification performance of the proposed model, we computed the accuracy and its 95% confidence interval (CI) [33] [34] for different dried fish image datasets. The confidence intervals were derived using the standard binomial proportion method to assess the statistical reliability of the classification results.

The model achieved high classification accuracy across all datasets, indicating its robustness in distinguishing dried fish categories. The Indian Dried Fish (single images) dataset recorded the highest accuracy of 100%, with a 95% CI of (0.9994, 1.0000), confirming the model's near-perfect performance.

For the Indian Dried Fish (bulk images) dataset, the accuracy was 99%, with a 95% CI of (0.9863, 0.9951). Similarly, the BDDryfish dataset achieved 99% accuracy, with a 95% CI of (0.9847, 0.9971). The DriedFishBD dataset showed an accuracy of 98%, with a 95% CI of (0.9721, 0.9903), demonstrating slightly lower but still highly reliable classification performance. We have also given the confusion matrices for all datasets in Fig. 2 to Fig. 9 and a comparison between the predicted and actual labels for a sample from the DriedFishBD (Single Images) dataset [31] in Fig. 10 for better understanding of the results.

These results suggest that the model maintains high generalizability across different datasets, ensuring effective clas-

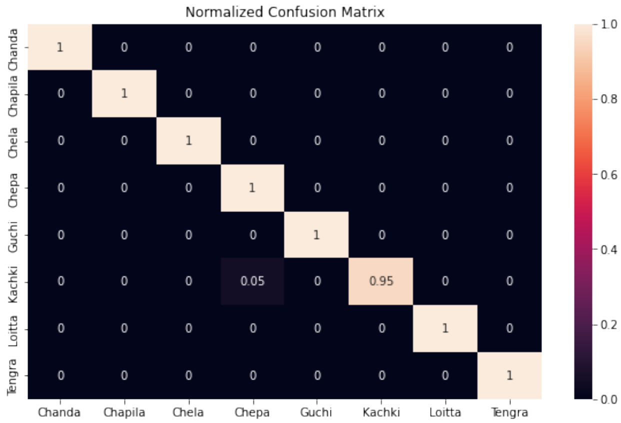

Fig. 6. Confusion matrix for DriedFishBD (head only).

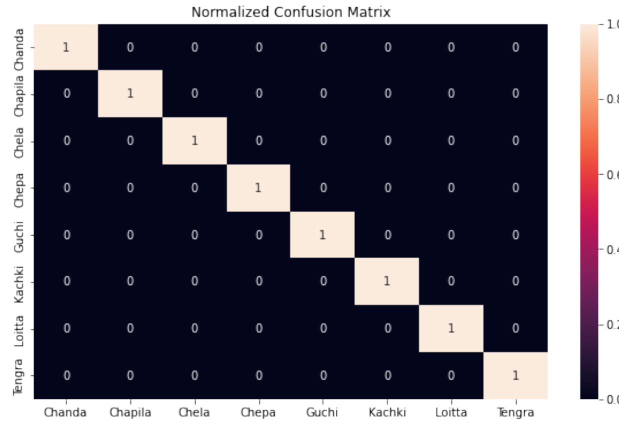

Fig. 8. Confusion matrix for DriedFishBD (bulk).

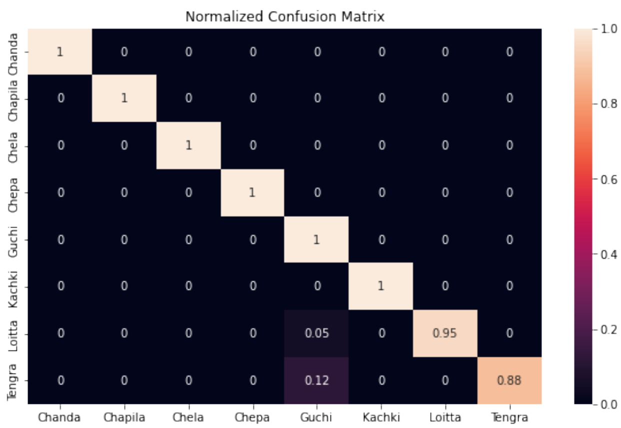

Fig. 7. Confusion matrix for DriedFishBD (tail only).

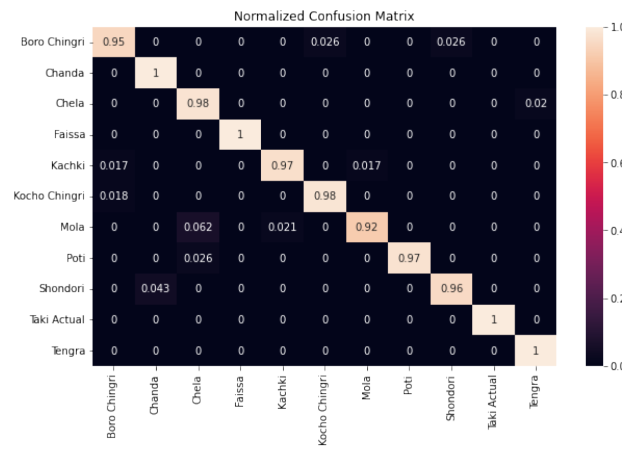

Fig. 9. Confusion matrix for SARDFD2025.

sification regardless of variations in dried fish images. The marginal differences in accuracy across datasets may be attributed to variations in image quality, lighting conditions, and dataset-specific characteristics.

The narrow confidence intervals further validate the consistency and reliability of the proposed model. The findings indicate that the model can be effectively used in real-world applications, such as automated fish species identification in fisheries and quality control processes.

While the proposed approach achieves high accuracy across diverse datasets, there are some limitations. First, the datasets used have relatively small sample sizes for certain classes, potentially affecting model generalization in highly imbalanced real-world settings. Second, despite using transfer learning, the model requires moderate GPU resources during training, which may limit its applicability for institutions with limited infrastructure. Third, classification errors occurred in species with similar morphological features, especially under varying lighting conditions. These factors suggest opportunities for further refinement through dataset augmentation and hybrid models.

V. Conclusion and Future Work

This study demonstrates the effectiveness of a MobileNetV2-based transfer learning framework for automated dried fish classification across diverse South Asian datasets. Theoretically, the results validate the feasibility of using lightweight CNNs for species-level classification in low-data domains. Practically, the model supports real-time classification on mobile and edge devices, enabling scalable deployment in local markets and fisheries. The research contributes a novel evaluation of dried fish classification using different image modalities and introduces benchmarks on unexplored dried fish datasets from India and Bangladesh. The proposed method reduces manual labor, increases classification consistency, and supports digitization and traceability in fisheries processing. Its low computational cost suits resource limited environments. However, class imbalance and morphological similarity between species limit precision in specific cases. Performance under real-time video streams and environmental variability also needs validation.

Future studies should focus on integrating Vision Transformers or hybrid CNN-transformer architectures for improved feature extraction, developing a larger, balanced dataset of dried fish species across regions, and implementing explainable AI techniques for model transparency in commercial settings.

Acknowledgment

The authors would like to thank INTI International University Persiaran Perdana BBN, Putra Nilai 71800 Nilai, Negeri

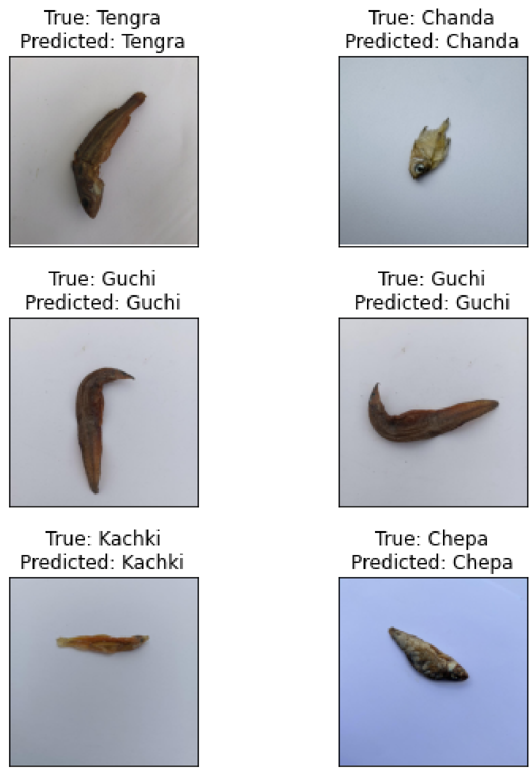

Fig. 10. Few examples of predicted and actual labels for DriedFishBD [31] (single images).

Sembilan for supporting this work.

REFERENCES

[1] Marine Products Export Development Authority. 2018. *Annual Report 2017–18.* Ministry of Commerce and Industry, Government of India. Accessed March 20, 2025. https://mpeda.gov.in/wp-content/uploads/2020/11/1550120514MPEDAAR201718.pdf.

[2] Kallon, A., A. Lebbie, B. Sturm, T. Garnett, and R. Wadsworth. 2017. "Comparative Studies of Fish Smoking and Solar Drying in the Sierra Leone Artisanal Fishing Industry." *Journal of Stored Products and Postharvest Research* 8 (3): 40–48. https://doi.org/10.5897/JSPPR2016.0217.

[3] Majumder, Ranendra K., and Amjad K. Balange, eds. 2023. *Advances in Fish Processing Technologies: Preservation, Waste Utilization, and Safety Assurance.* CRC Press.

[4] Madan, M. S., Radhakrishnan Kalidoss, L. Ranjith, R. Narayanakumar, N. Aswathy, and K. P. Kanthan. 2018. "Economics and Marketing of Dry Fish Production in Thoothukudi District, Tamil Nadu, India." *Indian Journal of Fisheries* 65 (4): 135–141.

[5] Subash, Abhirami, Hareesh N. Ramanathan, and Marko Šostar. 2024. "Market-Driven Mapping of Technological Advancements in the Seafood Industry: A Country-Level Analysis." *Economies* 12 (11): 313. https://doi.org/10.3390/economies12110313.

[6] Tayama, I., Shimdate, M., Kubuta, N., and Nomura, Y., "Application of optical sensor for fish sorting," *Reito (Tokyo) Refrigeration*, vol. 57, no. 661, pp. 1146-1150, 1982.

[7] Shimdate, M., "Automatic fish species and fish size sorting equipment using pattern recognition," *Mitsubishi Denki Hiko (Tokyo)*, vol. 56, no. 3, pp. 44-48, 1982.

[8] Strachan, N. J. C., Nesvadba, P., and Allen, A. R., "Fish species recognition by shape analysis of images," *Pattern Recognition*, vol. 23, no. 5, pp. 539-544, 1990.

[9] Strachan, N. J. C., "Recognition of fish species by colour and shape," *Image and Vision Computing*, vol. 11, no. 1, pp. 2-10, 1993.

[10] Newbury, P. F., Culverhouse, P. F., and Pilgrim, D. A., "Automatic fish population counting by artificial neural network," *Aquaculture*, vol. 133, no. 1, pp. 45-55, 1995.

[11] Cadieux, S., Michaud, F., and Lalonde, F., "Intelligent system for automated fish sorting and counting," in *Proc. IEEE/RSJ Int. Conf. Intelligent Robots and Systems (IROS)*, vol. 2, pp. 1279-1284, 2000.

[12] Lee, D. J., Schoenberger, R. B., Shiozawa, D., Xu, X., and Zhan, P., "Contour matching for a fish recognition and migration-monitoring system," in *Proc. SPIE Two-and Three-Dimensional Vision Systems for Inspection, Control, and Metrology II*, vol. 5606, pp. 37-48, 2004.

[13] Nery, M. S., Machado, A. M., Montenegro Campos, M. F., Pádua, F. L. C., Carceroni, R., and Queiroz-Neto, J. P., "Determining the appropriate feature set for fish classification tasks," in *Proc. XVIII Brazilian Symposium on Computer Graphics and Image Processing (SIBGRAPI)*, pp. 173-180, 2005.

[14] White, D. J., Svellingen, C., and Strachan, N. J. C., "Automated measurement of species and length of fish by computer vision," *Fisheries Research*, vol. 80, no. 2-3, pp. 203-210, 2006.

[15] Rodrigues, M. T. A., Pádua, F. L. C., Gomes, R. M., and Soares, G. E., "Automatic fish species classification based on robust feature extraction techniques and artificial immune systems," in *Proc. IEEE Fifth Int. Conf. Bio-Inspired Computing: Theories and Applications (BIC-TA)*, pp. 1518-1525, 2010.

[16] Siddiqui, S. A., Salman, A., Malik, M. I., Shafait, F., Mian, A., Shortis, M. R., and Harvey, E. S., "Automatic fish species classification in underwater videos: exploiting pre-trained deep neural network models to compensate for limited labelled data," *ICES Journal of Marine Science*, vol. 75, no. 1, pp. 374-389, 2018.

[17] Noda, J. J., Travieso, C. M., and Sánchez-Rodríguez, D., "Automatic taxonomic classification of fish based on their acoustic signals," *Applied Sciences*, vol. 6, no. 12, p. 443, 2016. DOI: https://doi.org/10.3390/app6120443.

[18] Rauf, H. T., Lali, M. I. U., Zahoor, S., Shah, S. Z. H., Rehman, A. U., and Bukhari, S. A. C., "Visual features-based automated identification of fish species using deep convolutional neural networks," *Computers and Electronics in Agriculture*, vol. 167, p. 105075, 2019.

[19] Kandimalla, V., Richard, M., Smith, F., Quirion, J., Torgo, L., and Whidden, C., "Automated detection, classification and counting of fish in fish passages with deep learning," *Frontiers in Marine Science*, vol. 8, p. 823173, 2022.

[20] Garcia-d'Urso, N., Galan-Cuenca, A., Pérez-Sánchez, P., Climent-Pérez, P., Fuster-Guillo, A., Azorin-Lopez, J., Saval-Calvo, M., Guillén-Nieto, J. E., and Soler-Capdepón, G., "The DeepFish computer vision dataset for fish instance segmentation, classification, and size estimation," *Scientific Data*, vol. 9, no. 1, p. 287, 2022.

[21] Francescangeli, M., Marini, S., Martínez, E., Del Río, J., Toma, D. M., Nogueras, M., and Aguzzi, J., "Image dataset for benchmarking automated fish detection and classification algorithms," *Scientific Data*, vol. 10, no. 1, p. 5, 2023.

[22] Wasik, S., and Pattinson, R., "Artificial intelligence applications in fish classification and taxonomy: Advancing our understanding of aquatic biodiversity," *FishTaxa-Journal of Fish Taxonomy*, vol. 31, 2024.

[23] Saleh, A., Sheaves, M., and Azghadi, M. R., "Computer vision and deep learning for fish classification in underwater habitats: A survey," *Fish and Fisheries*, vol. 23, no. 4, pp. 977-999, 2022.

[24] Laboni, M. A., Rimi, I. F., Deb, S., Afrin, F., and Hena, M. H., "Dried Fish Classification Using Deep Learning," in *Proc. Second Int. Conf. Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT)*, pp. 1-6, IEEE, 2022.

[25] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. MIT Press, 2016.

[26] M. Sandler et al., "MobileNetV2: Inverted Residuals and Linear Bottlenecks," in *CVPR*, 2018.

[27] A. Howard et al., "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications," *arXiv preprint arXiv:1704.04861*, 2017.

[28] F. Chollet, "Xception: Deep Learning with Depthwise Separable Convolutions," in *CVPR*, 2017.

[29] Paygude, Priyanka, Milind Gayakwad, Dhanashri Wategaonkar, Rajendra Pawar, Ramchandra Pujeri, and Rahul Joshi. "Dried fish dataset for Indian seafood: A machine learning application." Data in Brief 55 (2024): 110563. Accessed in January 2025 from PAYGUDE, PRIYANKA (2024), "Dry Fish Dataset", Mendeley Data, V1, doi: 10.17632/b35yrbh762.1

[30] Islam, Mohammad Manzurul; Akash, Md. Anik Khan ; Suhita, Sabira Musfirat (2025), "BDDryFish: An image dataset of dry fishes found in Bangladesh", Mendeley Data, V1, doi:10.17632/4xt4pjwk9k.1 Accessed on February 2025

[31] Ferdaus, Md Hasanul; Prito, Rizvee Hassan; Ahmed, Masud; Haider, Lamia; Hossain, Shajia; Nuzhat, Subah; Shifa, Sadia Tasnim; Islam, Mohammad Manzurul; Ali, Sawkat; Islam, Maheen; Rasel, Ahmed Abdal Shafi; Rahoman, Md Mizanur (2024), "DriedFishBD: A Detailed Image Dataset of Common Small-sized Dried Fish Varieties in Bangladesh for Identification and Classification.", Mendeley Data, V2, doi:10.17632/vz4xgybxr2.2 Accessed on February 2025

[32] Sarower, Afjal (2025), "SAR-DFD-2025: A High-Quality & Diverse Dry Fish Dataset from South Asia", Mendeley Data, V1, doi:10.17632/9ktwk5yh5r.1 Accessed in March 2025

[33] Dietterich, T. G. (1998). Approximate statistical tests for comparing supervised classification learning algorithms. *Neural Computation*, *10*(7), 1895–1923.

[34] Bouckaert, R. R. (2004). Estimating replicability of classifier learning experiments. In *Proceedings of the 21st International Conference on Machine Learning (ICML)*, 15–22.

[35] Wu, Xiaoxin & He, Yigang & Duan, Jiajun. (2020). A Deep Parallel Diagnostic Method for Transformer Dissolved Gas Analysis. Applied Sciences. 10. 1329. 10.3390/app10041329.

[36] Diana, D., Kurniawan, T. B., Dewi, D. A., Alqudah, M. K., Alqudah, M. K., Zakari, M. Z., and Fuad, E. F. B. E. (2025). *Convolutional Neural Network Based Deep Learning Model for Accurate Classification of Durian Types*. Journal of Applied Data Sciences, 6(1), 101–114.