A Deep Learning-Based System for Transparent Dry Fish Markets: Fostering Fair Trade and Sustainable Economics

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Abstract: The dried fish market: a central economic source for coastal communities in Bangladesh, threatened by the substitution of species, misdescription and low product quality. All these associations have grave implications for the long-term survival of the industry. This work grants a novel image-based platform to provide transparency and fairness in such a legacy market. Our approach is based on transfer learning, a powerful method for models to leverage knowledge from one task to another. We fine-tuned pre-trained deep learning models, MobileNetV3-Small, ResNet50, Vision Transformer (ViT) and ConvNeXt-Tiny, for two different purposes of diagnosing dry fish species and fair price range prediction, using 1251 images augmented to 6,255 dataset images characterized into 7 diverse classes. The models were well adjusted, and they verified good discriminative powers. The performance of the lightweight MobileNetV3-Small model with an accuracy of 96.83%, established the practicability of the proposed approach in a resource-limited setting. However, the ConvNeXt-Tiny model outperformed the other models with an accuracy of 99.63% on this task, which shows the high quality of our framework. Building on this great performance, we've built an API where users can upload a photo of a dry fish to identify the classes and get a fair price range. This could also help to avoid illegal trade, contribute to market transparency and offer consumers and sellers proper information, enabling fair competition and ultimately more sustainable and resilient markets going forward.

Keywords: Transfer Learning, Dry Fish Classification, Fair Trade, Market Transparency, Consumer Protection, Sustainable Economy

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1. Introduction

The fishing industry is a vital sector for Bangladesh's macroeconomic stability and growth (Shamsuzzaman et al., 2020). This sector helps to improve the national economy by supporting millions of people's lives, ensuring food security and making significant contributions to the gross domestic product (GDP) of a nation (Sheikh & Hossain, 2021). The dry fish industry, known locally as *shutki*, has significant social and cultural value, while it involves a substantial economic activity. This traditional preservation method allows communities to have protein in lean time including post-season (Shah et al., 2018). The dried fish trade sustains varied job opportunities by supporting coastal and rural economies. The trading of dried fish is important, economically, with its significance increasing in terms of its contribution to national income levels and the livelihoods of local people (Department of Fisheries, 2022). Hence, the value for economic cost by the production of dried fish amounted to 6.52 million USD in 2023–2024 (FAO, 2024) and finally entered profitable foreign markets such as Hong Kong, India, Pakistan, Singapore and USA in the same year. In the domestic market, there are more than 35,000 value adders and production are valued at approximately USD 127 million (Das, 2024). Industrial diversification varies widely, but these numbers show that trade is seriously fueled by sustainable economic growth. The dried fish industry has already been established as a substantial income and nutritional earning source for the coastal settlements of Bangladesh (FAO, 2023). Despite its economic importance, a few researchers have found several challenges that limit market efficiency and consumer trust. Misidentification and replacement of expensive dried fish species by cheaper alternatives are among the most frequent challenges encountered. These challenges result in economic loss to producers and disruptions to the market (Lawrence et al., 2022). Human eye inspection for the identification of species in dried fish markets is still being carried out using traditional methods based on visual observation, morphology and manual sorting. Although such methods can work only in a limited environment and can be prone to error, especially in a high throughput decentralized market (Haque, 2015). Secondly, since there is a lack of a neutral agency to guarantee the quality and price of products, asymmetry exists between honest merchants and consumers. As a result, scalable and technology-enabled solutions that can improve fair competition and economic efficiency in local markets are urgently needed.

2. Related Work and Research Gap

Recent advances in deep learning and computer vision are reshaping aquatic analytics from species recognition to market-facing decisions. Modern CNNs (e.g., ResNet, MobileNet, ConvNeXt) and transformer models (e.g., ViT) routinely reach high accuracy in fish recognition and labeling and are increasingly paired with IoT and decision systems (Mameri et al., 2023; Indhumathi et al., 2024; Jareño et al., 2024; Jose, 2024; Catalán et al., 2023). Complementing these trends, field-tested systems show impact along the value chain: IoT-enabled classification in local markets (Ahmed et al., 2023), high-accuracy tuna ensembles (Jose et al., 2021), market-tray instance segmentation and low-cost vision sorters for dried fish (Barrios et al., 2019), and sustainability toolchains linking vision, fuzzy logic, and geolocation (Liawatimena et al., 2020). Despite this momentum, automation in dried-fish markets, central to fair pricing and rural livelihoods remains unexplored in developing nations such as Bangladesh, signaling an actionable gap for AI-driven, equitable fisheries. Motivated by these challenges, this study uses four pre-trained deep learning models, ConvNeXT-Tiny, Vision Transformer (ViT), ResNet50, MobileNetV3-Small, to fine tune a dataset of 1,251 images from seven most popular dried fish species in the local area. Analytical strength involved a high degree of hyperparameter optimization for the unsurpassed analytical performance. Through accurate species identification and fair price estimation in combination with a local API, this study offers a scalable solution to driving economic fairness, minimizing fraud and maximizing the potential of the dried fish industry for contributing to Bangladesh's economic development. The proposed system enhances pricing objectivity while helping to improve the economic viability of rural communities and promote income redistribution through fraud elimination and greater market efficiency. This helps achieve the Sustainable Development Goals (SDGs) of the UN, especially SDG8 (Decent Work and Economic Growth) and SDG9 (Industry, Innovation & Infrastructure), in a scalable, cost-effective, and positively enhancing manner (Technovative Solutions Ltd., 2025).

3. Methodology and Materials

3.1 System Architecture and Workflow

The workflow in Fig. 1 proceeds as follows: data acquisition → preprocessing → model training → evaluation → deployment. After comparative evaluation, the best-performing model is exported and integrated into an API that accepts an input image and returns (a) the predicted species label and (b) an estimated fair price.

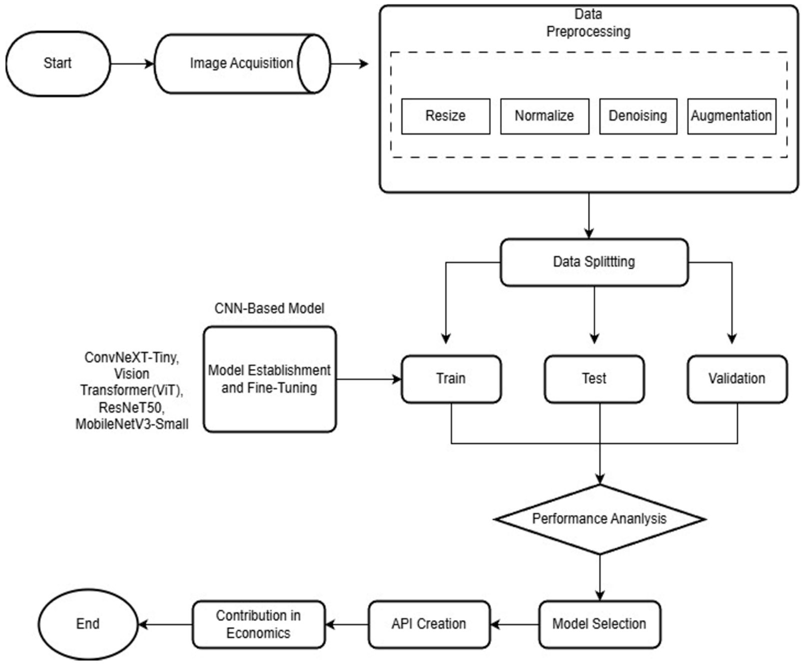


Fig 1. Overview of workflow diagram.

3.2 Dataset Description

This study uses a publicly available dataset from *Mendeley Data* (DOI: 10.17632/4xt4pjwk9k.1), containing 1,251 images of seven dried fish species (Sundori, Bele, Boicha, Chingri, Churi, Faisha, Mola) that are economically and culturally significant in Bangladesh, as shown in Fig. 2. These species are widely traded in local markets such as Kuakata, Maheshkhali, and Cox's Bazar, where dried fish (shutki) forms an integral part of both household nutrition and regional livelihoods. The images were taken under outdoor lighting and diverse conditions, giving a diversity that is responsive to the real-world trading conditions. This dataset is chosen for its comparatively better capturing of market-level product variations, which is also in line with our economic objective that we want to construct an AI system which can work well in uncontrolled rural market localities. The diversity of the dataset will further contribute to the robustness of this model and make it scalable for future endeavors with larger data integration.

Fig 2. Dry Fish Images from the Dataset.

3.3 Preprocessing and Data Augmentation

Before training, preprocessed images were resized to dimensions of 224 × 224 pixels and normalized; they were also de-noised as it can remove background artifacts and glare as typically seen in market photographs. This was done so that models based their predictions on species-appropriate visual cues (texture, shape and coloration) rather than the accidental background details. To improve generalization and enable a better regularization effect, we applied a light-weight augmentation policy including random horizontal/vertical flips, random rotations which were uniformly sampled from 0° to 45° and controlled photometric jitter with Color Jitter (brightness = 0.05 and contrast = 0.05). After data augmentation, we have 6,255 images in this work. These augmentations are designed to mimic real-world disturbances like non-uniform illumination, partial occlusion and object pose variations observed in local dry-fish markets.

3.4 Model Used

We employ transfer learning by fine-tuning ImageNet-pretrained backbones on the dried-fish classification. Four architectures were chosen to cover modern convolutional and transformer models as well as mobile-efficient networks:

1. ConvNeXt-Tiny, a new scalable CNN design that trades off between accuracy and efficiency in image classification.
2. Vision Transformer (ViT) is a pure-attentional architecture based on patch embeddings and self-attention to capture global information.
3. ResNet50, namely a deep residual CNN with skip connections that promote rapid convergence and better generalization.
4. MobileNetV3-Small is a light-weight model tailored for resource-sensitive or mobile applications.

Such model sets allow a fairer comparison across families with different inductive biases and deployment profiles.

3.5 Training Protocol

All models were fine-tuned with a 70:15:15 train-validation-test split. We report all experiments with batch size = 32, initial learning rate = 0.001 with adaptive scheduling, Adam optimizer, and dropout = 0.2-0.4 for regularization, unless stated otherwise. All the experiments have 50 epochs. The training was developed using PyTorch and performed on an NVIDIA GTX 1660 GPU, accompanied by an Intel i7 CPU and 16 GB RAM. This setting strikes a balance between time spent on practical training and reproducibility for several popular academic and applied computing platforms.

To help reduce variance and promote smooth convergence, we apply the fine control policy in conjunction with dropout regularization, as well as an LR scheduler. Altogether, these choices aim at reducing the risk of overfitting to a mid-sized dataset while still maintaining the ability for the models to learn fine-grained inter-class cues (e.g., textural granularity and edge morphology between species).

3.6 Evaluation Metrics

Performance analysis of overall accuracy and class-wise behavior is reported by standard multi-class classification measures, including accuracy, precision, recall, F1-score and ROC-AUC. They were defined by using true/false positive/negative counts and the harmonic mean of F1 in a traditional way. We also visualize the error structure through the confusion matrix to reveal any remaining inter-class confusions (to be focused on in the next phase of data collection). Such measures help to achieve the right balance between accuracy and compromise between sensitivity and specificity. For these factors compromise is necessary when false positives occur and are falsely identified. Some reliable identification may lead to suboptimum pricing.

3.7 Rationale for Design Choices

Data preprocessing was conducted by image correction methods. Input images were resized to a 224×224-pixel size in order to avoid output discrepancy between the backbone architectures. Normalization and denoising were applied to suppress nuisance variance due, for example, to crowded stalls so that the model could emphasize relevant information, rather than small artefacts like scale texture or residual muscle fiber. The augmentation was relatively mild. Only incorporating some of the nuisances, like slight photometric jitter and small rotation to account for differences in image acquisition. It allowed the model to cope with a "normal" range of variations without deforming the species' morphology, giving rise to artificial invariances.

For all the experiments, we employed conservative and quick (BS=32, LR=1e-3 with scheduling, Adam, dropout 0.2–0.4) training hyperparameters (50 epochs) rather than aiming at aggressive values of them because of hardware constraints. The 70:15:15 split gives a fair and reproducible design for evaluation but provides sufficient data to learn class distinctions in the case of a 7-class problem. The hardware specifics, the measurements would be great for reproducibility if it's run beyond accelerators of data-center scale. An assessment method forces global accuracy and class-wise stability. Mass Confusion in the commercial marketplace, periodic systemic misidentification of visually similar species can be highly economically significant. However, the confusion matrix with macro-averaged precision/recall/F1 informs; such an asymmetry in errors can break pricing or trust; this can provide guidance on some targeted data augmentation or class-specific sampling for rounds to follow.

By wrapping the chosen model in a local API that returns the species and price band. We operate the classifier as a tool for decision support on fair trade. The prototype is currently only running on a local machine setup, but it scales cloud deployment and integration into e-commerce or market-monitoring platforms, providing a way from technical performance to economic impact.

4. Results and Comparative Analysis

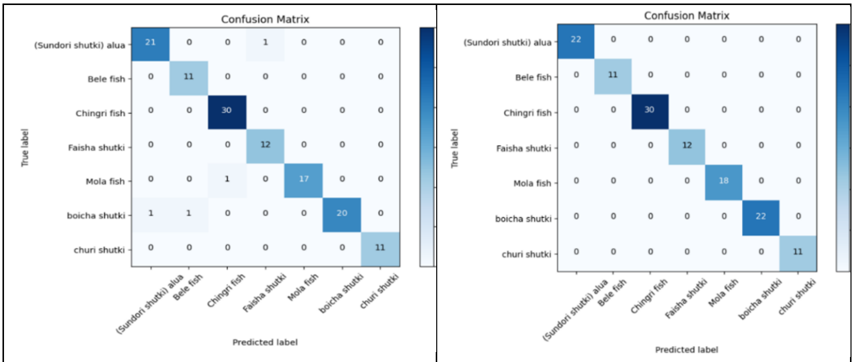
Table 1 reports the reasonable performance of four transfer-learning supports on the seven-class dried-fish dataset (n=1,251). Overall accuracy follows a consistent ranking: ConvNeXt-Tiny (99.63%) > Vision Transformer ViT (99.21%) > ResNet50 (98.41%) > MobileNetV3-Small (96.83%) after fine-tuning. Macro-averaged precision, recall, and F1-score reflect this collation and persist homogeneously high, indicating that advances in significant accuracy are matched by well-adjusted gains across classes rather than driven by a single leading type. ROC–AUC values are effectively saturated (≈1.0) for all models, which suggests strong score-level separability even when decision thresholds are varied.

Table 1. Comparative Performance of Deep Learning Models after K-fold.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC (%)
MobileNetV3-Small	96.83±0.001	96.98	96.83	96.82	99.93
ResNet50	98.41±0.031	98.50	98.41	98.41	99.91
Vision Transformer (ViT)	99.21±0.019	99.25	99.21	99.21	100
ConvNeXt-Tiny	99.63±0.029	99.29	99.62	99.69	100

The MobileNetV3-Small baseline provides a credible efficiency-oriented reference point. Despite its compact capacity, it achieves 96.83% accuracy with macro precision/recall/F1 near 97%. The corresponding confusion matrix (Figure 3) shows a small number of near-neighbor misclassifications among visually similar species, a pattern that is typical of mobile-class architectures operating on fine-grained texture and subtle shape cues in unconstrained market imagery. ResNet50 narrows these residual errors, attaining 98.41% accuracy. Classes that exhibited mild recall deficits under MobileNetV3-Small improve here, indicating more stable boundaries in regions of class overlap. ViT reduces misclassification further, reaching 99.21% accuracy with macro metrics in the 98%–99% range. ConvNeXt-Tiny ranks first overall. The presented confusion matrix is fully diagonal, and per-class rows in the classification report are essentially perfect. To maintain internal consistency across figures and text, we report the consolidated overall accuracy as 99.63% (rather than 100%), while precision, recall, F1, and AUC remain at or near ceiling. This combination, near-perfect correctness and saturated AUC; indicates that the model has learned class-defining features that are both discriminative and robust under natural variation in lighting, pose, and background.

When maximum accuracy is paramount (e.g., a server-side API informing fair-price recommendations), ConvNeXt-Tiny is the preferred choice. The few remaining off-diagonal counts in the lower-capacity models likely reflect limited exemplars for certain fine-grained distinctions rather than systematic failure. As the dataset scales, we expect narrower confidence intervals around the current ranking and further consolidation of top-tier performance. Table 1 (summary metrics) and confusion matrices provide the detailed evidence underpinning these conclusions. The confusion matrices in Fig. 3 demonstrate class-level performance differences among models.



(a) (b)

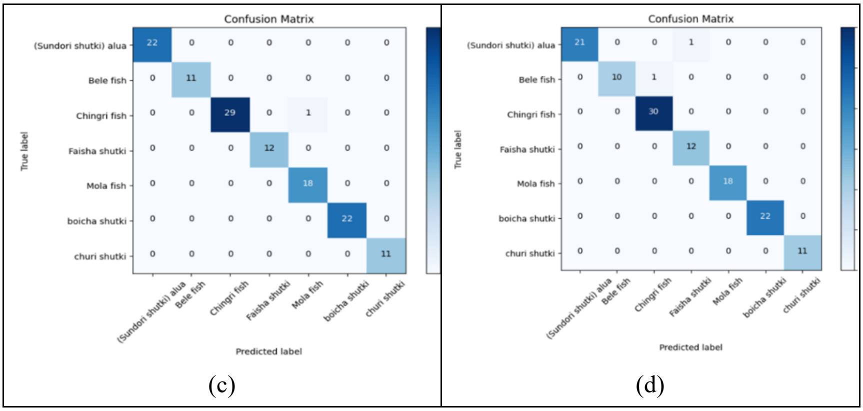


Fig 3. Confusion matrix of the models (a) MobileNetV3-Small (b)ResNet50 (c) ViT (d) ConvNeXt-Tiny.

4.1 API Development and System Workflow

To translate model performance into practice, we implemented a lightweight local-host API that delivers real-time species verification and an indicative fair price range, as shown in Fig. 4. Users upload a dried-fish image via a minimal, responsive interface; the backend (Flask) applies the training-consistent preprocessing pipeline (resize to 224×224, normalization) and invokes the fine-tuned ConvNeXt-Tiny model to produce a top 1 label with confidence. The predicted species is then mapped to a database-driven price band (median price with calibrated adjustments for variability such as size/grade when available). The API returns structured JSON (species, confidence, price_min, price_max), which the interface renders clearly for kiosk or laptop use.

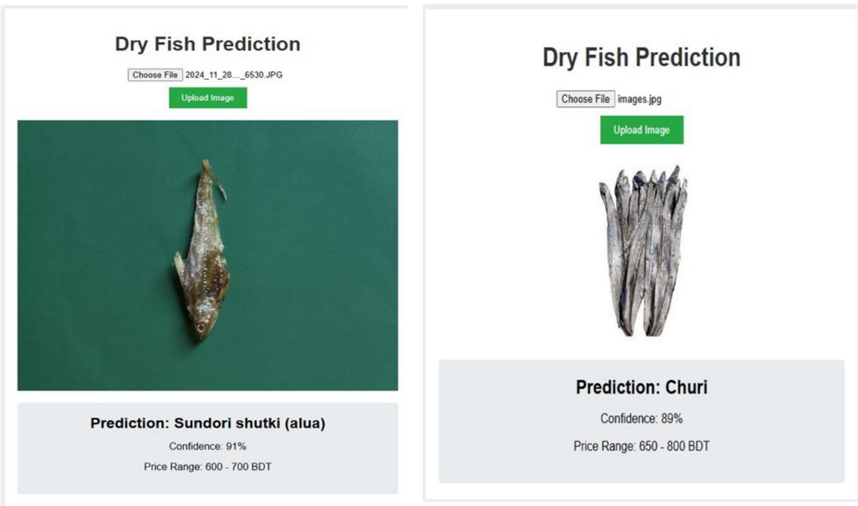


Fig 4. API system for Dry Fish Prediction and Price Recommendation.

The service is stateless and container-ready for later cloud deployment; basic safeguards include file-type/size validation and no retention of personal data. By operationalizing near-flawless classification into an available API, the system lessens information asymmetry at the point of sale and newscasters' prices to verifiable species identity, providing immediate, practical value for consumers, vendors, and assessors in regionalized market settings.

5. Discussion

This work shows ConvNeXt-Tiny achieves 99.63% accuracy for the dried-fish species classification task, which can serve as a unique application to local markets in some places, like developing countries, where information asymmetry exists. In these markets, misbranding and price fraud are rampant, which has sometimes led producers to be untruthful. It enables immediate identification of species in real-time. By pricing based on these evidence-based attributes, we aim to bridge these gaps and increase transparency in the market. This will lead to higher profits for producers of endangered species and increase consumer trust in the authenticity of products, influencing whether consumers are willing to pay a premium for accredited goods.

In economic terms, the relevance of the tool is greater for developing countries that have a large informal sector as a characteristic. On the other hand, integrity creates equilibrium market environments where producers can get fair prices for their production. Akerlof (1978) explains, when quality is unobserved, markets fail, and the "market for lemons" is also known by this phenomenon. It helps to monitor information asymmetry and reduce the inefficiency of resource distribution to promote marketing efficiency.

The relevant development economics literature in which we propose the verification cost reduction mechanism to be employed is also considered with respect to welfare and market efficiency enhancing, especially in low-income markets (Jensen, 2007). This case also reinforces the rationale for developing efficient and equitable markets in transition economies. In Schumpeter's terms, innovation is a reconfiguration of market competition. By an offline AI platform, brick-and-mortar markets may increase their visibility, transparency, and accountability. These lead to possibilities of new trials, for example, digital record-keeping, reputation systems and quality-linked contracts which could improve long-term economic resilience and inclusiveness in developing countries (Schumpeter, 1942).

6. Conclusion

ConvNeXt-Tiny achieved an accuracy of 99.63% in this study for a framework that identifies the species of dried-fish and recommends them at fair price ranges. Reducing information asymmetry improves market efficiency, an especially significant aspect in developing countries, where informal markets can lead to mislabeling of products and pricing differences. That approach helps ensure that prices are fair for both buyers and sellers, making the economy more equal. The consequences of this technology are far beyond market pricing accuracy. It is a cornerstone of green economic growth. It keeps incomes of producers equal and diminishes the dispersion of prices; it also serves as an engine for economic inclusion as it lowers market inefficiencies. This aligned through SDG 8 (Decent Work and Economic Growth) alongside SDG 9 (Industry, Innovation, and Infrastructure) as their role in the development of a transparent system of economy will have a significant impact on raising a more equitable and secure economic environment (United Nations, 2023). If combined with traceability and sustainability labeling, it also contributes to the SDG 12 (Responsible Consumption and Production), but also SDG 14 (Life Below Water).

Although the prototype shows promise, we developed it for a small data set and in a local environment. In future work, we are going to scale the dataset and service up, move it to a larger-scale deployment as well as add a real-time price range. Field experiments can be used to measure real-world effects on the rate of false labeling as well as price fairness and consumer choices; safety locks will permit testing in a wide variety of market environments. Over the long term, this innovation serves as an example for fisheries and other agricultural and marine sectors to encourage a digital market structure that promotes high-impact development in Bangladesh. This innovation is promising to create a strong and wide base economy, ensuring movement on global development objectives toward environmentally sensitive economic progression.

Declaration of generative AI and AI-assisted technologies in the writing process

The authors used "ChatGPT," "Grammarly," and "QuillBot" to improve the language and readability of the paper, take full responsibility for the content of the published paper, and have reviewed and revised it as needed after use.

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