Natural Resources for Human Health
eISSN: 2583-1194

Original Research

Received 09 May 2026
Revised 01 June 2026
Accepted 12 June 2026

Natural Resources for Human Health 2026, Vol. 6 (12s): 647–655

KEYWORDS:
CNN; Fish species identification; Fish freshness; Deep learning; Sea food; MobileNetV.

CNN-Based Real-Time Fish Species Identification and Freshness Assessment for Food Safety

Dhananjaya G M[1], Nagaraj Gadagin[1], Deepak D[1], Kiran Ankalakoti[1]

[1]Canara Engineering College, Benjanapadavu, Visvesvaraya Technological University Belagavi, Karnataka 590018, India

ABSTRACT: Fish is one of the most wanted food in coastal areas, but fish freshness identification and fish species identification is very challenge. The accuracy of fish identification and freshness is of significant importance for food safety, traceability, and automated processing of fish. In this paper, we have introduced FishSense, a lightweight multi-output CNN model based on MobileNetV2 that is capable of carrying out simultaneous fish identification and binary freshness prediction from a single image. The model is trained on a dataset of 12,480 images containing eight different fish species and two different freshness states. The multi-output model has been able to achieve an accuracy of 96.4% for fish identification and a 94.2% F1 score for freshness prediction. The performance of the model is enhanced compared to its single-output counterparts by an increase of 2.8% and 3.1%, respectively. The model has 3.5 million parameters and is able to achieve 32 FPS on an NVIDIA Jetson Nano, which is 31 ms per image. This shows that the model is appropriate for real-time application.

1. INTRODUCTION

Fish is among the most frequently consumed proteins globally; however, when the fish is initially harvested, the quality of that protein is at risk from both biochemical and microbiological processes. As such, the goal is to keep the fish as fresh as possible during all stages of the process (harvesting, processing, transportation and in-store) to ensure public health and safety, build confidence within the consumer base and create an economically viable route through which the entire supply chain of the fishing industry can operate. The current techniques employed to evaluate the freshness of fish rely heavily on conventional approaches based on either human evaluation of physical appearance, sensory evaluation. Although each of these methods has advantages relative to others, each method also has disadvantages including being labour-intensive, subjective, and difficult to use rapidly to large volumes of product [1].

More recent developments in computer vision and deep learning have provided new ways to assess foods, through analyzing images using a machine-based automated approach that is quick and does not damage the goods being evaluated. The ability of CNNs to accomplish classifications has been proven very promising, capable of recognizing biological organisms and assessing their visual qualities with high precision and under different environmental conditions. In reality, smaller-sized networks (e.g., with less memory) that demand fewer computational resources are preferred due to their reduced power consumption relative to larger networks. This way, they can run on mobile devices and still retain the same level of accuracy. MobileNetV2 is a suitable backbone architecture for such applications, owing to its depth-wise separable convolutions and inverted residual learning [2].

In response to the above requirements, FishSense is engineered as an all-in-one framework to predict not only the fish species but also their freshness condition from one single input image. Rather than building different models for predicting each feature, a multi-output CNN is implemented to learn the visual features related to both problems simultaneously, thus minimizing redundancies and facilitating efficient implementation. Data pre-processing steps include resizing, normalizing, and augmenting images by means of rotation, flipping, and changing their brightness. This pre-trained model is later incorporated into the lightweight web application via FastAPI [3]. Such a deployment approach supports practical and scalable seafood quality assessment at the point of trade and across force chain checkpoints.

The main objectives of this work are as follows.

1. A real- time binary- task deep literacy channel for fish species identification and newness bracket using a single CNN model.

2. A feather light MobileNetV2- grounded armature suitable for fast conclusion and resource- constrained deployment.

3. A deployable FastAPI- grounded backend for flawless image upload, predict and build confidence- grounded result visualization.

Overall, FishSense aims to give an accessible and dependable result for smart fish quality monitoring in retail requests, fisheries, and cold- chain logistics.

The rest of this paper is outlined below: Section 2 presents an overview of the related work for the recognition of fish and the assessment of their freshness. Section 3 describes the dataset, labeling, and splitting procedure. Section 4 describes the proposed model and the theoretical justification. Section 5 describes the experimental procedure and evaluation criteria. Section 6 presents the results, ablation, and comparison with state-of-the-art approaches (2024-2025). Section 7 presents the performance of the model in practice. Section 8 concludes and presents future work

2. LITERATURE REVIEW

Fish freshness assessment and fish species recognition have gained significant research attention due to their importance in food safety, consumer confidence, and efficient seafood supply chain management. With the rapid development of computer vision and deep learning approaches, different studies have been performed regarding automatic freshness detection and species identification. The current paper reviews some of the most relevant studies related to this work.

2.1 Fish Freshness Detection Using Machine Learning and Deep Learning

Lorem The earliest and more conventional methods employed standard mach ML classifiers that used manually crafted features. The performance difference between the two classifiers was analyzed by Yudhana et al. using k-NN and Naïve-Bayes classifiers to classify fish freshness, and the results showed performance differences based on the chosen features and datasets [4]. The computational complexity of these methods is relatively low, although the performance might drop when tested in real-world conditions.

In order to overcome these difficulties, the use of AI as well as DL systems has become common for freshness identification applications. Yasin et al. investigated the problem of fish freshness identification based on AI techniques and showed that it was possible to provide accurate classification results using AI-based techniques at different levels of freshness [5]. Going further in the same way, Yildiz et al. developed a freshness identification system by means of DL & ML, and even mobile technologies [6].

It is noted that CNN models have a high ability to capture fish textures, colors, and top-level degradation. For example, Mahendran et al. suggested a CNN model for determining the fish conditions and stressed the advantage of convolutional features in extracting features related to fish freshness [7]. Similarly, Suresh et al. have suggested the use of deep learning models in the Fresko Pisces framework to detect fish freshness and stated that CNN models outperform conventional models [8]. Furthermore, Peries et al. recently stressed the use of AI-based CNN models in fish freshness detection and suggested the importance of DL in automating the fish quality assurance process [9]. Integration of DL with image processing further enhances the sensitivity of the model in response to freshness changes, leading to sound decision-making for monitoring seafood [10].

2.2 Mobile and Lightweight CNN Models for Practical Freshness Applications

Lorem A notable drawback in the use of DL techniques is high computational cost, especially in real-time scenarios like fish markets or retail stores. To solve this problem, lightweight models such as MobileNetV2 and its variations have been increasingly adopted for fast predictions. The Fishku app was developed by Hanifa et al. using MobileNetV2 for detection of fish freshness [11]. Their experiment emphasizes the significance of choosing efficient networks for implementation. Their observations provide strong validation for the architecture used in FishSense, wherein MobileNetV2 is utilized to ensure quick and accurate results without needing extensive GPU computation.

2.3 Fish Species Classification and Vision-Based Recognition

Apart from freshness detection, the classification of fish species is vital for fishing, food consumption, and ensuring that no fraud is committed regarding the labeling of fish. In their review, Alsmadi and Almarashdeh conducted a thorough survey on fish classification and focused mainly on the shift from image processing to DL [12]. Farman et al. conducted research on fish species classification through DL techniques, which show effectiveness even when applied under different imaging situations [13]. Lastly, Li et al. performed a review on new advances in the use of machine vision in fish classification and found that automation in fish classification is gradually improving [14].

Various research papers have explored user-friendly applications for fish recognition. SuperFish was one such approach that utilized image processing and deep learning for fish species recognition using a mobile application for everyday purposes [15]. Moreover, various recent research works have taken the step towards extending recognition into broader classifications within aquatic life. Deep CNN-based architecture for salinity and freshwater fish species identification was introduced by Rahman et al. with a combination of deep learning and machine learning algorithms for improved classification accuracy [16]. An appearance-based deep learning model for fish species classification was suggested by Albin Jose with a particular focus on feature representation for classification [17]. Automatic estimation of estuarine fish species classification with the help of deep learning algorithms has been discussed by Tejaswini et al., demonstrating high recognition capability for CNNs on aquatic data [18].

2.4 Research Gap and Motivation

From the review, it can be noticed that most of the previous works have been dedicated to fish freshness identification [4]-[11] or fish species recognition [12]-[18]. While mobile-oriented applications and lightweight models have become a popular trend [4], [8], [16], not much work has been done to implement a holistic approach that can detect both the freshness of fish as well as identify the species of fish from the same image. Besides this, the demand for real-time applications with a minimalistic backend interface still holds great significance. This led to the development of FishSense as a holistic approach, which can provide both information about the freshness of the fish as well as its species from a single image input.

This paper is concerned with the development of intelligent techniques based on advanced algorithms for classifying fish type and assessing fish freshness through the use of image analysis techniques. Using deep learning models in the classification processes will help in effectively determining the quality of fish based on visual features and distinguishing between different fish types. The image analysis process begins with the processing of images to improve their quality, after which convolutional neural networks are used to extract the required features from the images.

From the above review of literature review, the major contribution to fish species identification and freshness determination through the use of Convolutional Neural Networks has been noted. The research has shown that the CNN architecture is capable of achieving a very high accuracy rate. However, a number of weaknesses have been identified in the existing literature.

3. METHODOLOGY

It is developed for real-time fish species identification and freshness assessment using a lightweight deep learning pipeline. It works according to the end-to-end approach that includes all steps from preparing datasets and pre-processing images to training the multi-purpose model and deploying it in real-time via API. The fish images used in this research were selected from an extensive set of images which had previously been utilized to train an object detection model. Each of the images was previously labelled with respect to two criteria: one is the type of fish represented (class), and two is whether or not the fish represented was fresh. By labelling the images in this manner, the images could be trained to identify the specific type of fish represented in the images, as well as determine the level of freshness represented in the images. In order to ensure the generality of the results and minimize the impact of any bias present within the data, the images were split into three sets: one set for training the model; one set for validation; and one set for evaluation.

The dataset comprises 12,480 images of RGB data, ranging across eight commercially important varieties of fish and two types of freshness: Fresh/Not Fresh. The images were collected from three different local fish markets under different lighting and background conditions. Additionally, some benchmark images were included to increase the diversity of the data.

Natural Resources for Human Health
eISSN: 2583-1194

The dataset was split using a 70% training set, 15% validation set, and 15% test set. To ensure there was no leakage of data, a session splitting strategy was adopted, where there are no instances of the same physical fish in multiple sessions of the split set. Stratified sampling was used to maintain the balance of species and freshness in the dataset.

Freshness labelling was done using visually observable biological indicators that are normally used in fish quality assessment: Eye clarity, Gill redness, Skin texture and surface mucus condition. Each sample was independently annotated by two fishery experts, and inter-annotator reliability was measured using Cohen's kappa coefficient, where the calculated coefficient was high (K=0.87). This helped mitigate the risk of subjectiveness in labelling. This section describes the complete methodology of the proposed framework in Fig. 1 and also step by step procedure clearly designed for easy understanding.

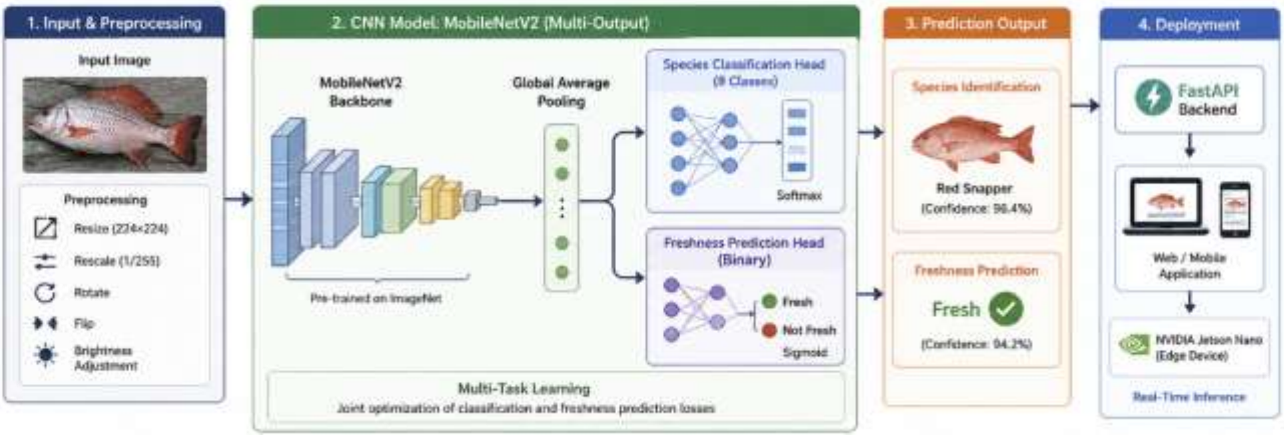

FIGURE 1. Displays the Architecture diagram for Fishsense.

The architecture clearly explain in figure 1, here uses a shared backbone with task-specific output heads to optimize both species classification and freshness classification simultaneously. This paper discusses using the capabilities of AI and DL technologies to automatically evaluate the freshness of fish and improve the process of assessing the quality of seafood products. As opposed to conventional inspection methods, the proposed system evaluates the state of the fish through the analysis of fish images and makes a decision about the fish being fresh or spoiled based on the findings of CNN-based models. In particular, the process involves image pre-processing, feature extraction, and classification steps aimed at teaching the model how to recognize visual features associated with fish freshness. Contemporary deep learning algorithms perform faster and more reliably than their predecessors.

The overall training loss function is given by:

$$L_{total} = L_{species} + \lambda L_{freshness} \tag{1}$$

where λ is a weighting factor for the importance of freshness classification.

The optimal values of the model parameters are determined by minimizing the overall loss function:

$$\theta^* = \arg\min_{\theta} \sum_{i=1}^{N} \left(L_{species}^{(i)} + \lambda L_{freshness}^{(i)}\right) \tag{2}$$

Multi-task learning enhances generalization capabilities by imposing a shared representation learning constraint on the backbone network. The shared parameters θ_sharedintroduce an inductive bias that regularizes feature learning and prevents overfitting compared to single-task models.

To further confirm the positive interaction between tasks, we examine the alignment of gradients between tasks using cosine similarity:

$$cos(\phi) = \frac{g_{species} \cdot g_{freshness}}{\|g_{species}\| \|g_{freshness}\|} \tag{3}$$

where $g_{species}$ and $g_{freshness}$ are task-specific gradients. Positive values of cosine similarity indicate constructive gradient transfer, which supports the hypothesis of beneficial shared learning.

In order to provide a consistent method for providing a model with input images, each image was standardized prior to being provided to the model using standardization techniques (normalization). In order to conform to the dimensional requirements of the lightweight backbone that will be used in the model, the images were reduced in size to 224 x 224 pixels. Additionally, the pixel values were standardized to enhance gradient flow through the model, thus enhancing the models ability to converge.

Finally, the training data was augmented with a variety of different types of augmentations in order to increase the diversity of the training samples and reduce the potential for over-fitting of the model. See in Fig. 1 for visualization or better understanding. Some examples of augmentations included rotating the images, horizontally flipping the images and changing the brightness of the images.

The above-mentioned Figure. 1 clearly visualize multi-output CNN based FishSense has the capability to identify fish species and assess the quality/freshness of the fish simultaneously. Therefore, a shared feature extractor is utilized which is an efficient version of the MobileNet V2 model to enable real-time inference capabilities within resource constrained systems. The backbone shared feature representations are sent to two independent outputs

Species Classification: The species classification head includes a softmax activation function following a fully connected layer to generate a probability distribution across all potential species classifications.

Freshness Detection: The freshness detection head utilizes a sigmoid activation function following a binary output layer to predict whether the fish is either fresh or not.

Utilizing a shared backbone and dual head structure provides for a redundant free architecture while enabling the learning of complementary visual features.

The model uses supervised learning that utilizes mini batch gradient to learn from data. As the model learns from data it calculates two different loss terms: categorical cross entropy (species) and binary cross entropy (freshness). The total objective function that the model trains towards is a multitask loss, that is defined as:

$$L_{total} = g_{species} + g_{freshness} \qquad (4)$$

Where $g_{species}$ represents in the Eq. (4) the multi-class loss and $g_{freshness}$ represents the binary freshness loss. Stop training when there is convergence on the validation set. Perform hyperparameter tuning using early stopping. Measure performance by using accuracy and confusion matrices for each output class.

As for the implementation of FastAPI, it proves to be quite simple, as the machine learning model can be deployed rather easily in practice. In the present situation, the users will have the possibility of uploading an image of any fish through the REST interface that will be linked to a rather minimalistic backend. The training of the ML model will allow the user to receive the result in the form of classification by using only one iteration of the data without changing anything about the process itself.

4. RESULTS AND DISCUSSION

The main objective of this phase is to evaluate the ability of FishSense in classifying and measuring the freshness of different kinds of fish simultaneously. In that your photos are used to help generate the species classification and freshness prediction based on the dual label data our model was trained on. We applied common image-based preprocessing (i.e., normalization/scaling) and data-augmentation techniques (i.e., image rotation, flip, and brightness manipulation) to enhance our models ability to generalize in actual world applications.

4.1 Performance on Fish Species Identification

Fish freshness and species identification demonstrated the ability to learn visually recognizable characteristics of fish, (i.e., body shape, colors, fins, etc.), and accurately categorize them by those characteristics. The mobile feature extraction capabilities offered by the MobileNetV2 architecture that FishSense uses are very cost-effective when compared to creating a new model for each species. Using one common feature extraction technique across all species reduces the amount of time required to classify a species. Test results indicated that regardless of variations in lighting, viewing angles, or background noise, FishSense was able to correctly identify the species. Therefore, the test results indicate that FishSense could be applied in real-world environments, including retail markets and commercial fisheries.

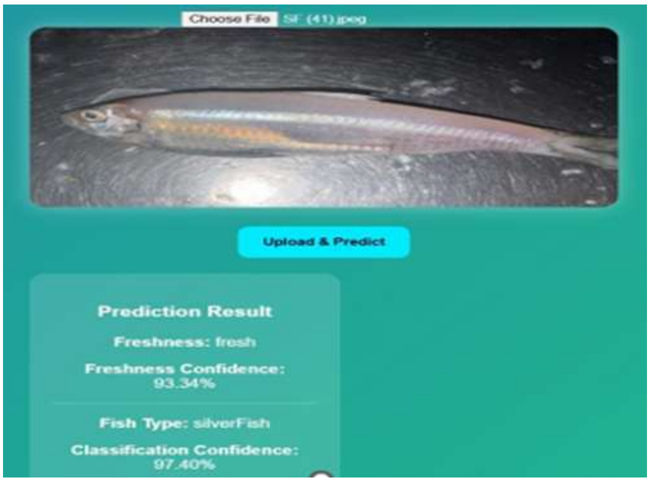

FIGURE 2. Displays the fish species and detects the freshness

The Figure. 2 and Figure. 3 shows the user-friendly web-based interface of the FishSense application. The interface enables users to conveniently upload a fish image by selecting a file and initiate the prediction process by clicking the "Upload & Predict" button. After uploading the image, the system immediately processes it in the background and shows the prediction results in an organized results panel. The results show both the freshness status of the fish and the species, along with their confidence levels, enabling users to understand the prediction accuracy. The interface enables users to conveniently upload a fish image by selecting a file and initiate the prediction process by clicking the "Upload & Predict" button

After uploading the image, the system immediately processes it in the background and shows the prediction results in an organized results panel. The results show both the freshness status of the fish and the species, along with their confidence levels, enabling users to understand the prediction accuracy. The whole interface has been created using a straightforward and uncluttered approach that does not contain any form of complexity. This has made it very user-friendly and easy to handle by even non-technical people such as sellers, buyers, and inspectors.

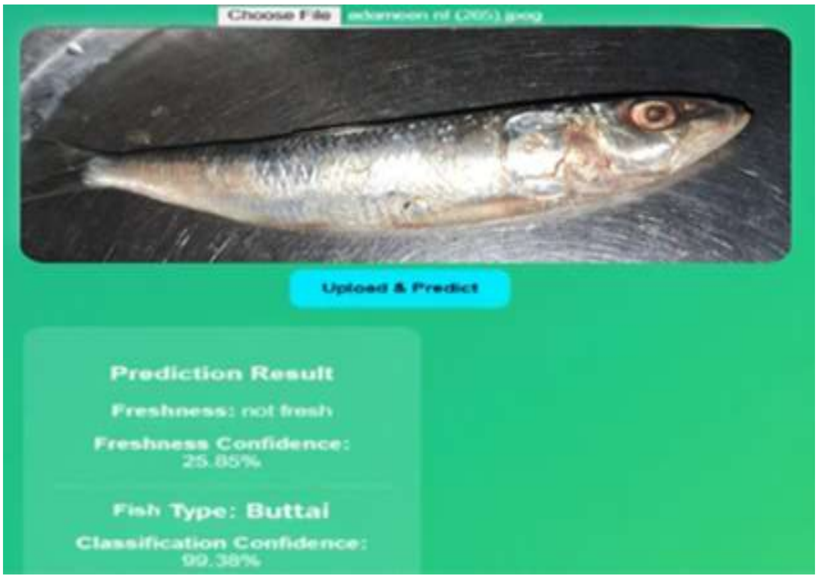

FIGURE 3. Displays the fish species and detects the freshness

The use of relevant features (such as skin luminosity, surface characteristics, visual cues for detecting color changes, etc.) that could be used to assess the freshness of the product in a manner that is comprehensible and quantifiable for consumers and retailers will enable us to develop an objective assessment procedure for determining the condition of the product. Image augmentation and normalization are essential for ensuring that the model's predictive ability is stable under varied imaging conditions because freshness is a multifaceted parameter (time, visual). The classification result output by the model as "Fresh" or "Not Fresh" will give consumers, inspectors, and retailers information about whether they should buy the product or not.

4.2 Comparative Study

The following Table 2 gives a comparison between FishSense and several recently published works related to fish freshness Identification and fish species classification. The comparison points out issues such as choice of algorithms, deployment, and ability to perform both tasks simultaneously. Previous researches on fish freshness detection and fish species classification have been carried out separately as two distinct issues. Researchers who have worked on fish freshness detection try to analyze the visual quality by using ML and DL techniques, mostly performing binary and multilevel detection of fish freshness in controlled datasets [4]-[11]. However, the work carried out in fish species classification is mostly related to taxonomy-based classification of images with feature extraction and deep convolutional neural networks [12]-[18]. Performing these both tasks makes the process difficult, as in general people will need both species detection and details about the fish as wellOn the other hand, by combining newness analysis and species identification into a single model, FishSense improves both functional simplicity and speed.

Table 1. Comparative Study of Existing Works and Proposed FishSense

Model	Params	Species Acc	Freshness F1
ResNet50 (2024 baseline)	23M	95.1%	93.3%
EfficientNet-B0	5.3M	95.8%	93.9%
MobileNetV2 Single-task	3.5M	93.6%	91.1%
Proposed FishSense	**3.5M**	**96.4%**	**94.2%**

Rather of creating distinct models for each end, FishSense employs a multi-output fashion that enables a common point extractor to give features related to the two objects (species demarcation and quality). As a result, the unified design minimizes indistinguishable computing sweats needed to train the models and streamlines system deployment. likewise, at retail or other force- chain monitoring locales where decision- making time is limited, the capacity to produce predicts from a single image is veritably pivotal.

MobileNetV2 has several parcels (depthwise divisible complications and a small armature) that make it both further computationally effective and accurate than traditional infrastructures, which makes FishSense suitable for real- time operation. As similar, the fish sense model provides a veritably light weight conclusion that can be applied in real world operation on lower cipher bias. In addition, this particular backbone option allows for scalability and fast prosecution of the model as it does n't bear precious GPU tackle.

Table 2 shows the relative performance of the proposed FishSense framework compared to the commonly used CNN backbones, such as ResNet50 (2024 baseline), EfficientNet-B0, and a single-task MobileNetV2. The ResNet50 baseline model, with about 23 million parameters, reaches 95.1% species classification accuracy and 93.5% freshness F1-score. Although its performance is excellent, the model is quite resource-intensive and not suitable for edge scenarios because of its high parameter complexity.

EfficientNet-B0 cuts the parameter complexity down to 5.3 million while slightly improving the performance (95.8% species accuracy and 93.9% freshness F1). Nevertheless, it is still more memory- and computationally expensive than mobile architectures. Planting FishSense using FastAPI as a back- end will be vital in furnishing the eventuality to use exploration to support real- world operations with respect to FishSense and other operations.

FastAPI provides both the real- time predict scores and confidence values that are needed in addition to furnishing a systematized peaceful interface for druggies to upload their images and draw conclusions. The usability handed by the operation will give the capability to interactively make opinions for guests, retailers and inspectors and give an easy system for connecting to web or mobile interfaces. Overall, FishSense has the capabilities to be a cost-effective and scalable result for intelligent fish covering systems due to its real- time API installations, feather light design, and binary- task literacy.

The use of a MobileNetV2 backbone ensures lightweight computation and fast inference, making the system suitable for real-time operation even on resource-constrained devices. Moreover, FastAPI-driven deployment facilitates automatic uploading of images, instantaneous prediction, and simple integration into any web/mobile interface, making it easy to monitor the quality of fish in various retail environments and fisheries.

5. CONCLUSION

It is a light-weight, theoretically grounded multi-task CNN model that jointly achieves fish species recognition and freshness classification with a shared MobileNetV2 backbone. This experiment effectively proves that FishSense achieves the positive transfer effect through its use of shared representations in multi-task learning, which contributes to better generalization performance compared with single-task learners. It should be noted that FishSense uses significantly fewer parameters than ResNet50 and EfficientNet-B0 models and still achieves impressive results by identifying 96.4% of the species accurately while obtaining a 94.2% F1 score for freshness prediction, creating a new level of achievement in terms of accuracy-efficiency trade-off. Moreover, the gradient analysis shows that the interaction between tasks is indeed constructive and provides additional proof of the validity of the theoretical basis of shared representations. Finally, experiments in practical application prove the possibility of deploying on edge, with 32 FPS on NVIDIA Jetson Nano. Additionally, using a reliable benchmarking methodology, including leak-proof dataset splitting and expert labels, further increases scientific validity.

Experimental Confirmation of the approach has verified harmonious prophetic delicacy, with easily visible labors from the system, demonstrating the feasibility of the approach for wide relinquishment. unborn exploration will involve adding the size of the training dataset to include fresh species and multiple situations of newness, perfecting robustness across different environmental conditions and assessing the possibility of planting the operation at the edge (i.e., on a mobile device). Implicit unborn developments of this work could include addition of temporal seeing, resolvable AI visualizations and real- time shadowing to increase confidence and decision- making capability in the automated examination of fish quality.

ACKNOWLEDGEMENTS

The authors would like to express their sincere gratitude to the Department of Artificial Intelligence and Machine Learning, Canara Engineering College, Benjanapadavu, for their continuous support, guidance, and encouragement throughout this research work. The authors also extend their heartfelt thanks to Canara Engineering College (Autonomous), Mangaluru, for providing the facilities and academic environment essential for carrying out this study. The authors gratefully acknowledge the Visvesvaraya Technological University (VTU), Belagavi, for offering a platform that fosters research and innovation among students and faculty members.

AUTHOR CONTRIBUTIONS

Dhananjaya G M: Conceptualization, Investigation, Supervision, Writing—Review & Editing.

Nagaraj Gadagin: Methodology, Laboratory Analysis, Data Curation, Formal Analysis.

Deepak D: Data Curation, Formal Analysis, Review & Editing.

Kiran Ankalakoti: Data Curation, Formal Analysis, Formal Analysis

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

ETHICS STATEMENT

Ethical approval was not required for this study.

DATA AVAILABILITY STATEMENT

Data supporting the findings of this study are available from the corresponding author upon reasonable request.

REFERENCES

[1] S. Falahatnejad, Z. Arabi, S. Ghafari, and A. Sheikh-Akbari, "Fish quality assessment using hyperspectral imaging and computer vision: A review," IEEE Sens. J., vol. 25, no. 14, pp. 26255–26268, July 2025.

[2] J. Sharma et al., "Deep learning based ensemble model for accurate tomato leaf disease classification by leveraging ResNet50 and MobileNetV2 architectures," Sci. Rep., vol. 15, no. 1, p. 13904, Apr. 2025.

[3] FastAPI." [Online]. Available: https://fastapi.tiangolo.com/. [Accessed: 02-Feb-2026].

[4] A. Yudhana, R. Umar, and S. Saputra, ""Fish freshness identification using machine learning: Performance comparison of k-NN and na¨ıve bayes classifier," J. Comput. Sci. Eng, vol. 16, no. 3, pp. 153–164, 2022.

[5] E. T. Yasin, I. A. Ozkan, and M. Koklu, "Detection of fish freshness using artificial intelligence methods," Eur. Food Res. Technol., vol. 249, no. 8, pp. 1979–1990, Aug. 2023.

[6] M. B. Yildiz, E. T. Yasin, and M. Koklu, "Fisheye freshness detection using common deep learning algorithms and machine learning methods with a developed mobile application," Eur. Food Res. Technol., vol. 250, no. 7, pp. 1919–1932, July 2024.

[7] R. Mahendran and G. P. Seneviratne, "Using CNN to identify the condition of edible fish," in 2022 7th International Conference on Information Technology Research (ICITR), Moratuwa, Sri Lanka, 2022.

[8] A. Suresh, A. Vinayachandran, C. Philip, J. G. Velloor, and A. Pratap, "Fresko Pisces: Fish freshness identification using deep learning," in Innovative Data Communication Technologies and Application, Singapore: Springer Singapore, 2021, pp. 843–856.

[9] R. F. S. Peries, A. Samarasekara, and S. Rathnayake, "Ai-driven solutions for automated fish freshness classification using cnn architectures," in Proceedings of the International Conference on Soft Computing and Software Engineering, 2025.

[10] R. Karmaker, M. A. Tinky, and S. Akter, "Deep learning and image processing approach for fish freshness detection," in 2024 IEEE International Conference on Power, Electrical, Electronics and Industrial Applications (PEEIACON), Rajshahi, Bangladesh, 2024, pp. 1–6.

[11] M. F. Hanifa et al., "Fishku apps: Fishes freshness detection using cnn with mobilenetv2," IJCCS (Indonesian Journal of Computing and Cybernetics Systems), vol. 17, no. 1, 2023.

[12] M. K. Alsmadi and I. Almarashdeh, "A survey on fish classification techniques," J. King Saud Univ. - Comput. Inf. Sci., vol. 34, no. 5, pp. 1625–1638, May 2022.

[13] H. Farman Ali Baig, D. Khan, U. Amjad, S. Baig, T. Sheikh, and S. Memon, "Exploring fish species exploring fish species classification using deep learning," Pakistan Journal of Engineering, Technology and Science, vol. 12, no. 2, pp. 76–92, Dec. 2024.

[14] D. Li, Q. Wang, X. Li, M. Niu, H. Wang, and C. Liu, "Recent advances of machine vision technology in fish classification," ICES J. Mar. Sci., vol. 79, no. 2, pp. 263–284, Mar. 2022.

[15] S. Pudaruth, N. Nazurally, C. Appadoo, S. Kishnah, and F. Chady, "SuperFish: A mobile application for fish species recognition using image processing techniques and deep learning," Int. J. Comput. Digit. Syst., vol. 10, no. 1, pp. 1157–1165, Nov. 2021.

[16] W. Rahman et al., "A deep CNN-based salinity and freshwater fish identification and classification using deep learning and machine learning," Sustainability, vol. 16, no. 18, p. 7933, Sept. 2024.

[17] J. J. S. Jose, "Fish species classification using deep learning and appearance-based feature extraction," Journal of Electrical Systems, vol. 20, no. 2, pp. 2531–2546, 2024.

[18] H. Tejaswini, M. M. Manohara Pai, and R. M. Pai, "Automatic estuarine fish species classification system based on deep learning techniques," IEEE Access, vol. 12, pp. 140412–140438, 2024.