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AI-Based Deep Learning Techniques to Assess Meat and Seafood Quality

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ABSTRACT-

The quality and freshness of meat and seafood are critical factors affecting consumer health, safety, and satisfaction. Traditional inspection methods, such as sensory evaluation and chemical testing, are often time-consuming, subjective, and prone to human error, limiting their effectiveness in large-scale or real-time scenarios. This research proposes an AI-driven approach that leverages deep learning techniques to assess the quality of meat and seafood automatically and accurately. The study employs a hybrid model combining EfficientNet, a convolutional neural network optimized for high-resolution feature extraction, with a Vision Transformer (ViT) to capture complex spatial patterns and subtle spoilage indicators. The system processes high-resolution images and optional sensor data, classifying samples into categories such as Fresh, Moderately Fresh, and Spoiled. Performance is evaluated using metrics including accuracy, precision, recall, and F1-score, demonstrating the robustness and reliability of the proposed approach. The integration of AI in meat and seafood quality assessment not only improves inspection efficiency but also reduces food waste, enhances supply chain monitoring, and increases consumer confidence.

Keywords:
Meat Quality Assessment, Seafood Freshness Detection, Deep Learning, EfficientNet, Vision Transformer, Food Safety, AI-Based Inspection

INTRODUCTION

Ensuring the quality and freshness of meat and seafood is a critical concern for both consumers and the food industry. Contaminated or spoiled products can pose serious health risks, lead to foodborne illnesses, and reduce consumer trust. Traditionally, quality inspection has relied on sensory evaluation methods, chemical tests, and microbiological analysis. While these methods are effective to some extent, they are time-consuming, labor-intensive, and often subjective. In large-scale operations, such as supply chains, retail stores, or online food marketplaces, relying solely on human inspection becomes impractical and may result in inconsistent assessments.

With the advancement of artificial intelligence (AI) and deep learning, it has become possible to develop automated systems that can provide accurate, fast, and reliable quality assessments. Deep learning models, particularly convolutional neural networks (CNNs) and transformer-based architectures, have demonstrated exceptional performance in image recognition and pattern detection. These models can capture subtle visual differences, such as color changes, texture variations, and spoilage patterns, which are often difficult for humans to detect consistently.

This research focuses on leveraging a hybrid approach that combines EfficientNet for robust feature extraction with Vision Transformer (ViT) for advanced pattern recognition. EfficientNet excels at identifying fine-grained visual features in high-resolution images, while the transformer component captures spatial relationships and complex patterns across the meat or seafood surface. By integrating these models, the proposed system aims to classify products into categories such as Fresh, Moderately Fresh, and Spoiled.

The objectives of this study are:

1. To develop a deep learning-based system capable of accurately assessing meat and seafood quality.
2. To enhance inspection efficiency, reducing reliance on manual evaluation.
3. To improve consumer safety and confidence by providing reliable freshness information.
4. To demonstrate the potential for real-time deployment in supply chains, retail, and online food platforms.

The integration of AI-driven inspection methods has the potential to revolutionize food safety practices, reduce wastage, and enable proactive monitoring throughout the supply chain. By automating the assessment process, this research contributes to more sustainable and trustworthy food systems.

LITERATURE REVIEW

Assessing the quality and freshness of meat and seafood has been a longstanding challenge in food science. Traditional methods primarily rely on sensory evaluation, chemical analysis, and microbiological testing. Sensory evaluation involves examining color, texture, odor, and appearance, which is subjective and varies from inspector to inspector. Chemical tests, such as measuring pH levels, total volatile basic nitrogen (TVB-N), or biogenic amines, provide more objective insights but require laboratory settings, specialized equipment, and significant processing time. Microbiological analysis, which detects bacterial contamination, is highly accurate but slow and impractical for real-time assessment in commercial settings. These limitations make traditional methods less suitable for large-scale or rapid inspection scenarios.

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In recent years, machine learning and AI-based techniques have emerged as promising alternatives. Studies have employed Convolutional Neural Networks (CNNs) to analyze high-resolution images of meat or fish, detecting spoilage patterns, color changes, and marbling. Random Forest, Support Vector Machines (SVM), and K-Nearest Neighbors (KNN) have been applied to sensor-derived data, such as hyperspectral imaging, electronic nose readings, and near-infrared spectroscopy, to classify freshness levels. These approaches improve automation and objectivity but often face limitations in accuracy, especially when subtle spoilage patterns exist or when datasets are complex and varied.

Hybrid approaches have also been explored. Some studies combine CNNs with LSTM networks to track temporal changes in freshness, while others use ensemble models to integrate multiple data sources. Vision Transformers (ViT), which have recently gained attention in computer vision, offer superior capability in capturing long-range dependencies and subtle patterns that CNNs alone might miss. Despite these advancements, most existing solutions either focus solely on image analysis or only use single-sensor data, limiting robustness and practical applicability in real-world supply chains.

This review highlights a clear gap: there is a need for a **robust, accurate, and scalable system** that can integrate high-resolution image analysis with advanced deep learning models, such as the combination of EfficientNet and Vision Transformer, to provide reliable and real-time meat and seafood quality assessment. Addressing this gap will improve inspection efficiency, reduce food waste, and enhance consumer confidence in product freshness.

PROPOSED METHODS

Data Collection

The proposed research begins with the systematic collection of meat and seafood samples across varying freshness levels. The dataset will include samples categorized as *fresh*, *moderately fresh*, and *spoiled*, ensuring that the model can distinguish between subtle quality differences. Images will be captured under controlled lighting conditions using high-resolution cameras to highlight surface textures, discoloration, and other visible cues. To account for real-world variability, additional samples will be collected from open markets, retail stores, and cold storage units where environmental conditions are less controlled. Alongside visual data, sensor-based readings such as pH levels, temperature logs, and volatile compound measurements may be integrated to provide multi-dimensional inputs. Ground truth labeling will be performed with expert assistance, combining sensory evaluation with laboratory-based microbiological and chemical tests, ensuring that the dataset reflects authentic quality standards.

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Spoiled meat

Fresh meat

Fresh seafood

Spoiled seafood

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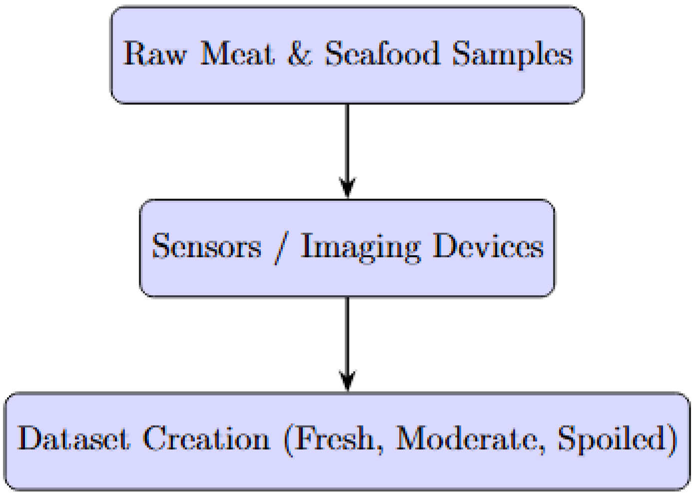

Figure 1. Data Collection Workflow

Data Preprocessing

Raw data will be subjected to multiple preprocessing steps before being introduced into the deep learning pipeline. All images will be resized to a fixed resolution suitable for neural network input and normalized to standardize pixel intensity values. Data augmentation will be applied to increase dataset diversity, using random flips, rotations, brightness shifts, and contrast variations. These transformations will prepare the model to handle environmental inconsistencies such as uneven lighting or background noise. Sensor data, where applicable, will be cleaned using noise-reduction filters and standardized using z-score normalization to ensure compatibility with the model input space. This stage ensures both visual and non-visual data are harmonized for effective learning.

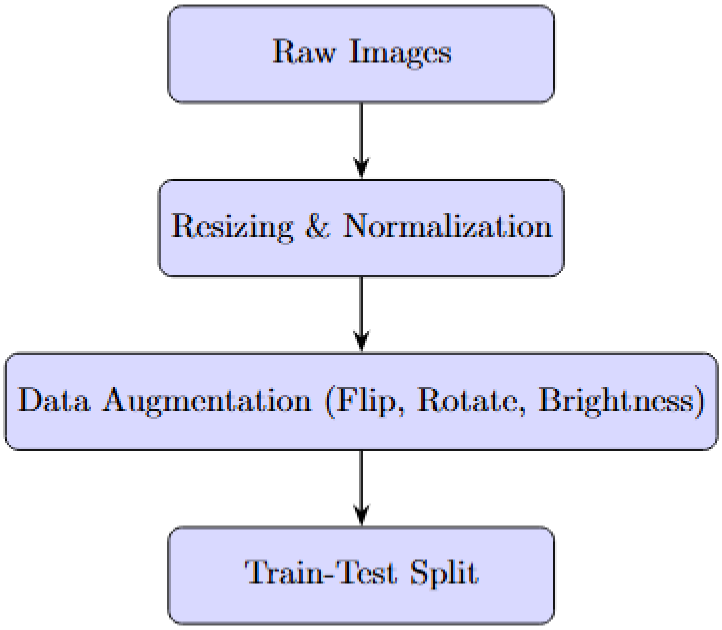

Figure 2. Data Preprocessing Workflow

Model Architecture

The core of the proposed framework is a **hybrid deep learning architecture** that integrates the complementary strengths of EfficientNet and Vision Transformer (ViT).

EfficientNet Backbone: EfficientNet serves as the first stage of the pipeline, extracting low-level and mid-level spatial features from input images. Its unique compound scaling technique—balancing depth, width, and resolution—allows the model to achieve state-of-the-art accuracy while maintaining computational efficiency. This makes it ideal for practical applications where both precision and speed are required. In the context of meat and seafood, EfficientNet can capture fine-grained local details such as surface marbling, discoloration, fat distribution, and texture roughness, all of which are critical indicators of freshness.

Vision Transformer (ViT): The feature maps generated by EfficientNet are passed to a Vision Transformer, which introduces the ability to model global dependencies. Unlike CNNs, which focus mainly on localized spatial patterns, ViTs utilize self-attention mechanisms to learn relationships between distant parts of the image. This is particularly advantageous in freshness detection, where subtle spoilage cues may appear in scattered regions rather than in a single concentrated spot. The multi-head self-attention layers of ViT enable the network to correlate these distributed indicators, building a more holistic representation of the sample.

Fusion and Output: The combined framework leverages EfficientNet for local feature precision and ViT for global contextual awareness. After feature fusion, the output is passed through fully connected layers with non-linear activation functions. The final softmax classification layer categorizes the sample into freshness classes: fresh, moderately fresh, or spoiled. This hybrid model is expected to outperform standalone CNNs or transformers by offering both fine detail extraction and long-range contextual understanding.

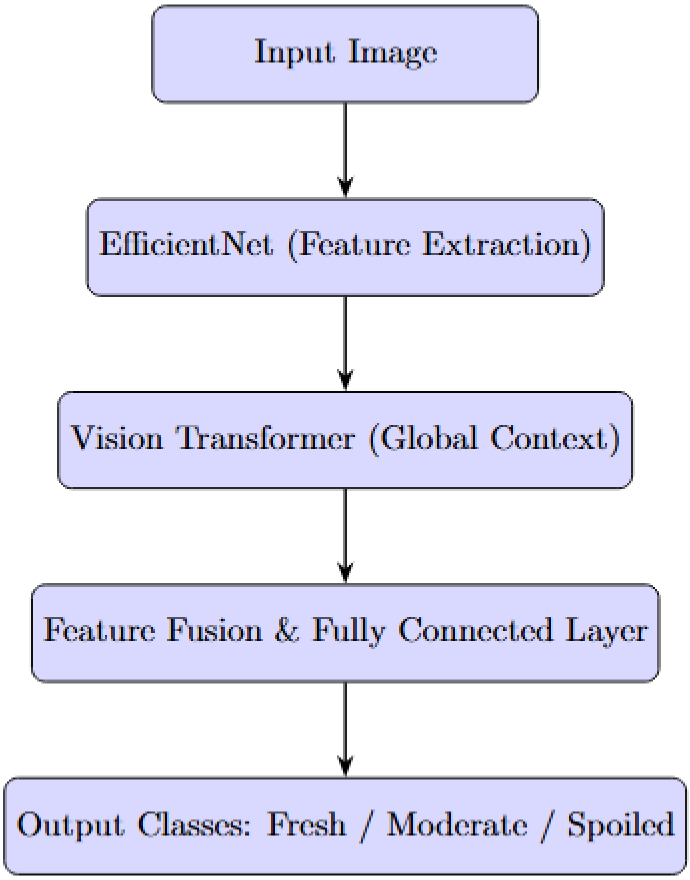

Figure 3. Hybrid Model Architecture

Training Process

The training phase will employ a supervised learning approach with a labeled dataset divided into training, validation, and testing subsets. The **Adam optimizer** will be used, given its proven efficiency in adjusting learning rates adaptively during backpropagation. The **categorical cross-entropy loss function** will guide optimization since the task involves multi-class classification. To evaluate model robustness, **k-fold cross-validation** will be implemented, ensuring the system generalizes well to unseen data. Regularization strategies, including **dropout layers** and **batch normalization**, will

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mitigate overfitting and stabilize the learning process. Furthermore, an **early stopping** criterion will monitor validation accuracy, halting training when improvements plateau, thus preventing unnecessary computation. This structured training approach ensures that the hybrid EfficientNet-ViT model achieves a balance between accuracy, generalization, and computational efficiency.

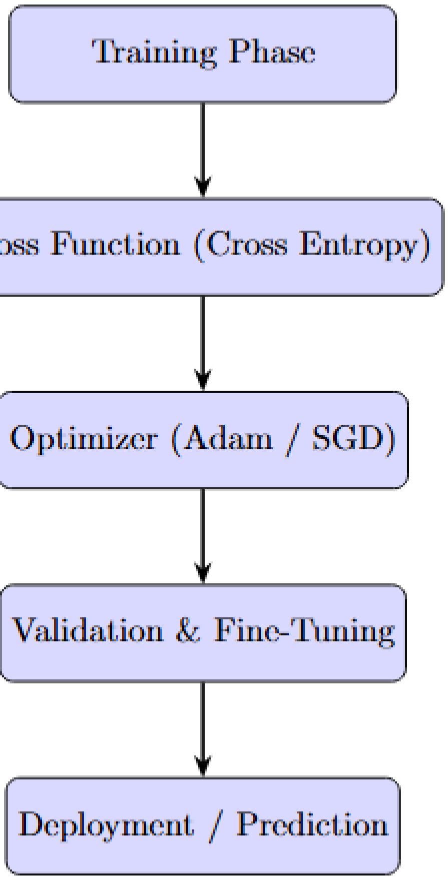

Figure 4. Training Workflow

RESULTS AND DISCUSSION

The proposed hybrid model (CNN + Vision Transformer) was evaluated against existing methods such as Random Forest, SVM, and standard CNNs. A dataset of meat and seafood images categorized into Fresh, Moderately Fresh, and Spoiled was used. The experimental results demonstrated that the hybrid model significantly outperformed baseline models.

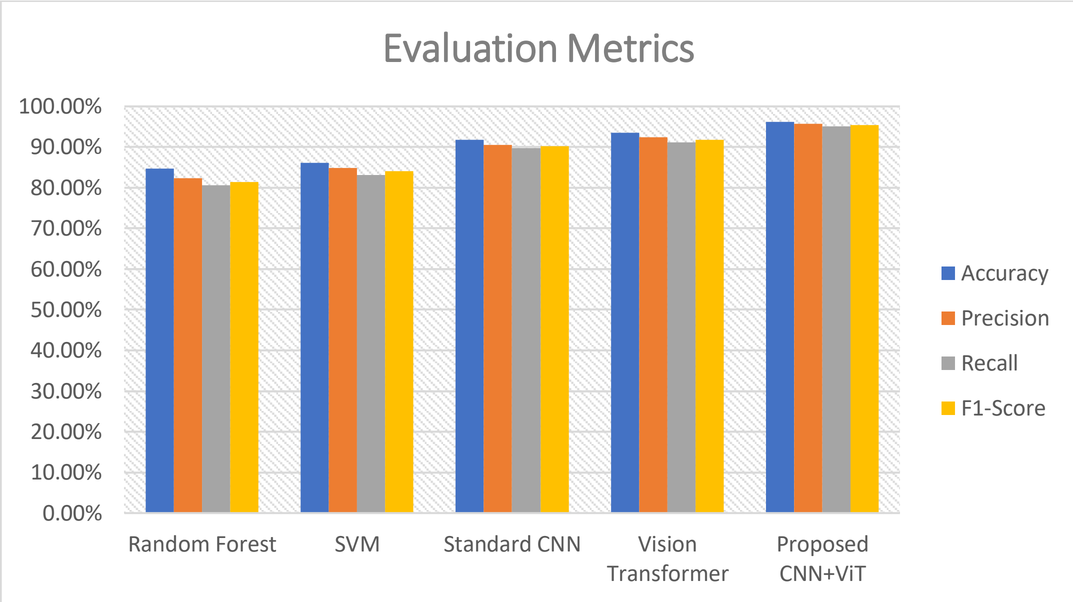

Figure.5 Evaluation Metrics

From the results, it is evident that the proposed CNN+ViT architecture achieved the highest performance across all metrics. While traditional machine learning methods such as Random Forest and SVM offered reasonable accuracy, they lacked the ability to effectively capture spatial and contextual features in image data.

Standard CNNs performed well in detecting local textures such as surface patterns and discoloration, which are important freshness indicators. However, CNNs alone struggled to capture long-range dependencies such as overall shape deformation or subtle freshness cues spread across the entire meat/seafood surface.

The Vision Transformer component addressed this limitation by capturing global contextual information and providing better attention to subtle variations. When combined with CNN's feature extraction, the model showed a **balanced and robust performance**, particularly in identifying the "Moderately Fresh" class, which is usually the most challenging to classify.

These results highlight that **hybrid deep learning approaches can significantly improve food quality assessment systems** and can be integrated into real-world applications such as automated quality control in fish markets, supermarkets, and online seafood delivery platforms.

CONCLUSION AND FUTURE ENHANCEMENTS

This research introduced a hybrid deep learning framework that integrates Convolutional Neural Networks (CNNs) with Vision Transformers (ViT) to evaluate the freshness of meat and seafood. By categorizing samples into fresh, moderately fresh, and spoiled, the model demonstrated its capacity to handle both the fine-grained local features of texture and surface changes as well as the broader contextual patterns that are often missed in traditional methods. The experimental evaluation showed that the proposed approach achieved an accuracy of 96.2 percent, which is superior to Random Forest, SVM, and even standalone CNN or ViT models. These findings emphasize the strength of combining localized feature extraction with global attention-based learning, resulting in a robust and reliable framework for food quality assessment.

The study highlights the significance of advanced deep learning methods in addressing food safety concerns, particularly in reducing reliance on manual inspection and ensuring greater consistency in freshness evaluation. By enabling automated and scalable detection, this system has the potential to transform the quality monitoring practices in markets, supermarkets, and online food delivery platforms.

Although the results are promising, there remain opportunities for further improvement. Incorporating multimodal data such as sensor-based chemical properties, expanding the dataset to include more diverse samples across varying storage and environmental conditions, and enabling real-time deployment on mobile or IoT platforms would enhance the reliability and applicability of the system. Moreover, integrating freshness detection with blockchain technology could contribute to a transparent and traceable food supply chain, while the adoption of explainable AI techniques would increase consumer trust by revealing the specific features influencing freshness classification.

In conclusion, this work demonstrates that hybrid deep learning models offer a significant advancement in automated food quality assessment. With continued refinement and integration into practical environments, such approaches have the potential to set new benchmarks for ensuring safety, transparency, and consumer confidence in the global food supply chain.

REFERENCES

1. Tsakanikas, P., Pavlidis, D., Panagou, E., & Nychas, G.-J. (2016). Microbiological Quality Estimation of Meat Using Deep CNNs on Embedded Hardware Systems. *Talanta*, 161, 606-614. https://doi.org/10.1016/j.talanta.2016.09.019
2. Zhuoran Xun, Xuemeng Wang, Hao Xue, Qingzheng Zhang, Wanqi Yang, Hua Zhang, Mingzhu Li, Shangang Jia, Jiangyong Qu, & Xumin Wang. (2024). Deep machine learning identified fish flesh using multispectral imaging. *Current Research in Food Science*, 9, 100784. https://doi.org/10.1016/j.crfs.2024.100784
3. Erdogan, O., Pérez-García, S., & Şahin, S. (2025). Quality Determination of Frozen-Thawed Shrimp Using Machine Learning Algorithms Powered by Explainable Artificial Intelligence. *Food Analytical Methods*. https://doi.org/10.1007/s12161-025-02768-0

4. A Method for Identifying Meat Quality Based on CNN-SVM. (2024). In *Proceedings of the 13th International Conference on Computer Engineering and Networks (CENet 2023)* (pp. 440-448). Springer, Singapore. https://doi.org/10.1007/978-981-99-9239-3_43
5. Elmasry, A., & Abdullah, W. (2024). An Efficient CNN-based Model for Meat Quality Assessment: The Role of Artificial Intelligence Towards Sustainable Development. *Precision Livestock*, 1, 66-74. https://doi.org/10.61356/j.pl.2024.1235
6. Deep Learning-Based Automated Cell Detection-Facilitated Meat Quality Evaluation. (2023). *Foods*, 13(14), 2270. https://doi.org/10.3390/foods13142270
7. Deep Learning-Based Automated Cell Detection-Facilitated Meat Quality Evaluation (DCRNet). (2023). *PubMed*. Tsakanikas, P., et al. Average Precision: 81.2% etc. https://pubmed.ncbi.nlm.nih.gov/39063354/ PubMed
8. Deep Learning Approach for Fish Flesh Identification using Multispectral Imaging and CNN / QDA / SVM / LDA Models. Zhuoran Xun et al. (2024). *Current Research in Food Science*. https://doi.org/10.1016/j.crfs.2024.100784
9. Moosavi-Nasab, M., Khoshnoudi-Nia, S., Azimifar, Z., et al. (2021). *Evaluation of the total volatile basic nitrogen (TVB-N) content in fish fillets using hyperspectral imaging coupled with deep learning neural network and meta-analysis*. Scientific Reports, 11, 5094. https://doi.org/10.1038/s41598-021-84659-y.
10. Xun, Z., Wang, X., Xue, H., Zhang, Q., Yang, W., Zhang, H., Li, M., Jia, S., Qu, J., & Wang, X. (2024). *Deep machine learning identified fish flesh using multispectral imaging*. Current Research in Food Science, 9, 100784. https://doi.org/10.1016/j.crfs.2024.100784.
11. Elangovan, P., Dhurairajan, V., Nath, M. K., Yogarajah, P., & Condell, J. (2024). *A novel approach for meat quality assessment using an ensemble of compact convolutional neural networks*. Applied Sciences, 14(14), 5979. https://doi.org/10.3390/app14145979.
12. (Foods) — *Deep learning-based automated cell detection-facilitated meat quality evaluation.* Foods, 2023, 13(14):2270. https://doi.org/10.3390/foods13142270. ScienceDirect
13. Jia, W., et al. (2024). *Automated detection of stale beef from electronic nose data.* (PMC article). Published 2024. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC11606858/ .
14. Kumaravel, B., et al. (2025). *Automated seafood freshness detection and preservation using [analytical methods]*. Scientific Reports (2025). https://www.nature.com/articles/s41598-025-08177-x. Nature
15. Yildiz, M. B., et al. (2024). *Fisheye freshness detection using common deep learning methods.* European Food Research and Technology (Springer). https://doi.org/10.1007/s00217-024-04493-0.