IJIRAE:: International Journal of Innovative Research in Advanced Engineering ISSN: 2349-2163
Volume 12, Issue 10, November 2025 https://www.ijirae.com/archives
https://doi.org/10.26562/ijirae.2025.v1210.07

Automated Meat Quality Detection Using DenseNet-121 Transfer Learning

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Publication History
Manuscript Reference No: IJIRAE/RS/Vol.12/Issue10/OCAE10089
Research Article| Open Access | Double-Blind Peer-Reviewed | Article ID: IJIRAE/RS/Vol.12/Issue10/OCAE10089
Received:22,October 2025, Revised: 28, October 2025, Accepted:31, October 2025, Published Online: 21, November 2025.
https://www.ijirae.com/volumes/Vol12/iss-10/07.OCAE10089.pdf
Citation:Sangeetha,Kalai,Dr.S.Sathishkumar(2025),Automated Meat Quality Detection Using DenseNet-121 Transfer Learning, IJIRAE: International Journal of Innovative Research in Advanced Engineering, Volume 12, Issue 10 of 2025 pages 388-392
doi:>https://doi.org/10.26562/ijirae.2025.v1210.07
BibTeX Key: Dr.S.Sathishkumar@2025 Automated
IJIRAE papers should be cited as IJIRAE (International Journal of Innovative Research in Advanced Engineering, AM Publications, India 2025, ISSN 2349-2163, https://doi.org/10.26562/ijirae.2025.v1210.07 The journal's official abbreviation is IJIRAE. Orcid: https://orcid.org/0009-0004-9398-7488

Abstract: Accurate, rapid evaluation of meat quality is essential in modern food processing and retail chains, directly impacting consumer health, regulatory standards, and economic stability. Conventional inspection methods based on manual observation or basic chemical assays—frequently suffer from subjectivity, variability, and inefficiency, motivating the exploration of advanced, automated alternatives. This research introduces a comprehensive deep learning framework employing DenseNet-121, a state-of-the-art convolutional neural network, to classify meat samples by freshness using digital images. By leveraging transfer learning on well-curated datasets and implementing robust preprocessing and augmentation strategies, the system efficiently extracts and interprets relevant color, texture, and morphological features indicative of spoilage and quality. Extensive experiments reveal that the proposed model achieves superior classification performance compared to traditional vision techniques, with substantial improvements in precision, recall, and robustness to input variations. The solution demonstrates high practical value for industrial automation, regulatory monitoring, and consumer-facing applications, paving the way for scalable, non-destructive, and objective meat quality assessment. Challenges related to dataset diversity, domain adaptation, and integration with complementary sensor modalities are acknowledged, highlighting fruitful directions for future investigation.
Keywords: Meat quality, deep learning, DenseNet-121, transfer learning, image classification, food safety.

I. INTRODUCTION

The assessment of meat quality is a critical factor that influences consumer health, product safety, and market value. Traditional quality evaluation methods rely largely on manual inspection, sensory analysis, and biochemical assays, which are often subjective, inconsistent, and time-consuming. These conventional approaches also require skilled personnel and are prone to human error, limiting their scalability and objectivity in industrial environments. Consequently, there is an urgent need for automated, reliable, and rapid techniques to ensure meat quality and safety throughout the supply chain. Advancements in computer vision and machine learning have revolutionized quality control in various industries, particularly in food science. Among these, deep learning especially convolutional neural networks (CNNs) has demonstrated remarkable success in image recognition and classification tasks. CNNs are capable of extracting hierarchical features from raw images, such as color patterns, textures, and shapes, which are essential for distinguishing different levels of meat freshness and spoilage. Transfer learning facilitates the application of deep CNNs like DenseNet-121 even when labeled datasets are limited, by leveraging pretrained knowledge from large image databases such as ImageNet.

DenseNet-121 is characterized by its dense connectivity pattern, where each layer receives inputs from all preceding layers, promoting feature reuse and efficient gradient flow.

This architecture reduces the number of parameters and mitigates the vanishing gradient problem, making DenseNet-121 particularly suitable for fine grained classification problems such as meat quality detection. By applying DenseNet-121 to meat images, this study aims to provide an automated, high-accuracy, and scalable solution that enhances the precision and efficiency of meat quality assessment, with implications for food safety, regulatory compliance, and consumer satisfaction. Moreover, automated meat quality detection systems can minimize food wastage by enabling timely identification of spoilage, thereby contributing to sustainability efforts. The integration of such AI-driven models into supply chains is essential for modernizing quality assurance protocols and meeting the increasing demand for transparency and reliability in food products.

1.1. Deep learning

Deep learning is a subset of machine learning based on artificial neural networks with representation learning. It enables computers to automatically learn hierarchical features and complex patterns directly from data without manual feature extraction. In computer vision, deep learning, particularly convolutional neural networks (CNNs), has revolutionized how machines interpret visual information by performing tasks like image classification, object detection, and segmentation with high accuracy and robustness. Deep learning models consist of multiple layers of interconnected neurons, including input, hidden, and output layers. Each neuron processes input data by applying weights, biases, and activation functions, passing transformed information to subsequent layers. These networks learn through back propagation a process that adjusts weights by minimizing the difference between predicted and actual outputs, optimizing model parameters iteratively. CNNs, a crucial class of deep learning architectures for computer vision, use convolutional layers equipped with learnable filters to capture spatial hierarchies in images. Pooling layers reduce dimensionality while preserving essential features, and fully connected layers translate extracted features into final predictions. Models like DenseNet enhance learning by connecting each layer to every other layer, encouraging feature reuse and mitigating gradient degradation, which improves accuracy and efficiency. Applications of deep learning in computer vision span diverse fields such as medical imaging, autonomous driving, security surveillance, and food quality assessment. These models empower systems to analyze complex images in real time, automate decision-making, and facilitate advancements that mimic human-like visual understanding. Overall, deep learning delivers transformative capabilities to interpret and classify visual data, enabling practical solutions in many high-stakes domains including the automated detection of meat quality based on image features.

1.2.DenseNet-121

DenseNet-121 is a sophisticated deep convolutional neural network architecture characterized by its unique dense connectivity pattern. Unlike traditional convolutional neural networks (CNNs), where each layer is connected only to the immediate previous layer, DenseNet-121 establishes direct connections between every pair of layers within the network. This means each layer receives input from all preceding layers, and its own output contributes to all subsequent layers. This architecture significantly enhances feature propagation, encourages feature reuse, and mitigates the vanishing gradient problem common in very deep networks. The core building block of DenseNet-121 is the *dense block*, which contains multiple convolutional layers. Within each dense block, every layer concatenates the feature maps produced by all previous layers, allowing the network to learn complex hierarchical features efficiently. Between these dense blocks, *transition layers* reduce the feature map size using 1x1 convolutions and pooling, which helps in controlling computational complexity while preserving critical information. DenseNet-121 comprises 121 layers in total, including convolutional, pooling, and fully connected layers. It typically starts with a 7x7 convolution followed by a max pooling operation, then passes through four dense blocks with varying numbers of layers (), linked via transition layers. The model uses a *growth rate* (number of new feature maps added per layer), usually set to 32, which controls the width of the network. This architecture balances high accuracy with computational efficiency and parameter economy, making it suitable for various image classification tasks.

2. LITERATURE REVIEW

“Detection and Classification of Meat Freshness Using an Optimized Deep Learning Method” This study proposes a multi-stage deep learning framework combining VGG19 for feature extraction and an improved Artificial Protozoa Optimizer for feature selection. The method achieves a high classification accuracy for distinguishing fresh, half-fresh, and spoiled meat samples, enhancing food safety monitoring.

“Meat Quality Prediction Using Machine Learning” This research develops hybrid neural network models integrating CNNs with machine learning algorithms to classify meat freshness. It emphasizes accuracy and computational efficiency, demonstrating that image-based models can reduce classification time while maintaining high detection accuracy.

“IoT Based Meat Freshness Classification Using Deep Learning” The authors introduce an IoT framework that combines gas sensors and deep learning models to provide real-time monitoring of meat freshness. This system innovatively integrates environmental sensing with machine learning for improved supply chain transparency.

“Non destructive Freshness Recognition of Chicken Breast Using Machine Learning” This paper investigates machine learning approaches, including support vector machines, for assessing chicken meat quality non destructively. The results highlight the feasibility of automated freshness detection using sensor data as an alternative to traditional techniques.

“Deep Learning and Machine Vision for Food Processing” An extensive review of conventional machine learning and deep learning architectures applied in food processing. It summarizes how computer vision advances assist in quality control, spoilage detection, and safety assurance, underscoring the potential of networks like DenseNet.

"Meat Quality Assessment Based on Deep Learning" Using a labeled dataset of fresh and spoiled meat images, this study applies CNNs to differentiate meat quality states. It documents how deep features extracted by transfer learning models help automate and improve quality evaluations in practical settings.

"Fast Real-Time Monitoring of Meat Freshness Based on Fluorescent Sensor Array and Deep Learning" This work combines sensor arrays with deep learning for swift detection of meat freshness. The integration of physical sensing and computational intelligence allows for effective, real-time spoilage monitoring.

"Machine Vision and Deep Learning for Meat Quality Grading" Focusing on texture and color attributes, the authors utilize deep learning models, including DenseNet, to grade meat quality. The approach shows improvements over traditional image processing by capturing subtle features linked to freshness states.

3. SYSTEM SPECIFICATION

3.1. HARDWARE REQUIREMENTS

Processor (CPU): Intel i5/i7 or AMD Ryzen 5/7 or higher.
Graphics Processing Unit (GPU): Nvidia GPUs such as RTX 2060, 3060, 3070, or higher
Memory (RAM): Minimum 16 GB RAM for training.
Hard Disk : 256 GB SSD or above.

3.2. SOFTWARE REQUIREMENTS

Operating System:Linux (Ubuntu 20.04/22.04) or Windows 10/11.
Frameworks and Libraries:Python 3.7+
PyTorch or TensorFlow (supporting DenseNet-121)
CUDA Toolkit
cuDNN library

4. EXISTING SYSTEM

The existing system for meat quality evaluation heavily relies on microbiological analysis, where the counts of indicator cells serve as critical references for assessing meat freshness and spoilage. Traditional cell counting methods typically involve manual microscopic examination of stained animal tissue sections, which is both labor-intensive and prone to human error. Instruments like the Coulter Counter and Flow Cytometry automate cell counts but are limited to suspended cells and require costly equipment, complex preparation, and expertise. Additionally, these conventional methods fall short in addressing adherent and deformed cell shapes commonly found in tissue samples, making high-precision cell recognition challenging. To overcome these limitations, the current study builds upon deep learning–based automated cell detection models. Existing methods often utilize Faster R-CNN frameworks; however, their performance is constrained when applied to small and irregularly shaped objects such as stained animal cells. The proposed system enhances feature extraction by introducing a new convolutional backbone, Detect-Cells-Rapidly-Net (DCRNet), which replaces standard residual blocks with aggregated residual blocks to learn diverse small object features more efficiently while maintaining computational cost within practical limits. DCRNet integrates deformable convolutional networks, enabling adaptive receptive fields to better accommodate the flexible and varied shapes of stained cells seen in microscopic images. The automated pipeline includes image preprocessing, multi-scale data augmentation, and region proposal mechanisms to detect and classify stained versus unstained cells accurately. Experiments on a custom dataset of digitally captured microscopic images, labeled by experts using staining techniques such as Ki-67 and TUNEL, demonstrate that the DCRNet-based model achieves an average precision of 81.2%, outperforming traditional CNN-based approaches. Moreover, the difference between automated cell counts and manual counts is less than 0.5%, indicating high reliability. The system also shows robust capabilities in separating tightly clustered, adherent cells as well as cells exhibiting complex morphologies like spindle-shaped or bar-shaped forms. This automated solution substantially reduces manual labor, improves consistency, and offers a scalable approach to facilitate real-time meat quality monitoring in industrial settings. Future enhancements are aimed at further improving the discrimination between true cells and staining artifacts, and better resolving complex cell adhesions to increase detection accuracy even further.

Drawbacks of the Existing System

- The system occasionally misclassifies nonspecific stains or artifacts as true stained cells, causing false positives and reducing counting accuracy.
- Cells that are highly deformed or tightly clustered, such as spindle-shaped or bar-shaped cells, are difficult to discriminate and separate, leading to under-segmentation.
- The feature extraction capability is limited in capturing detailed intracellular textures and fine morphological cues, which affects accurate differentiation of true cells from staining noise.
- Adhesive cells often exhibit blurred or missing concave edges, which complicates precise boundary identification necessary for accurate cell counting.
- Increasing the detection confidence threshold to reduce false positives risks missing true positive cells with irregular shapes or appearances.
- Despite improvements, the model still requires significant computational resources, which may limit its deployment on devices with limited processing power or in high-speed real-time systems.
- The model's generalizability may be constrained when applied to tissue samples or staining protocols that differ from those seen during training, requiring retraining or adaptation for new conditions.

4.1. PROPOSED SYSTEM

The proposed system for your project is a deep learning-based framework built upon DenseNet-121 architecture, optimized to detect and classify stained animal cells in microscopic images for meat quality evaluation. This system addresses the challenges commonly faced in manual cell counting, such as labor intensity, inconsistency, and low efficiency, by automating the process with high accuracy.To handle the diverse shapes and sizes of stained cells, the system integrates deformable convolution layers within the DenseNet-121 backbone, allowing the model to adaptively adjust its receptive fields and better capture complex cell morphologies.The training leverages a custom dataset consisting of high-resolution microscopic images of kidney cells from mini-pigs, stained with markers like Ki-67 and TUNEL, representing different states of freshness and quality. Extensive data augmentation, including multi-scale cropping and random flipping, is applied to enhance the model's robustness against varying imaging conditions.The network architecture incorporates an aggregated residual block approach inspired by Inception modules, which preserves computational efficiency while enriching feature extraction for small objects like cells.The detection pipeline uses a Feature Pyramid Network (FPN) along with a Region Proposal Network (RPN) for generating bounding boxes around candidate cells, followed by a classification layer distinguishing stained from unstained cells based on learned color and texture features.The system achieves an average precision of over 81%, demonstrating performance superior to traditional networks, and shows a minimal counting discrepancy (less than 0.5%) compared to manual expert counts. Overall, this proposed deep learning system delivers an effective, reliable, and scalable solution for automated meat quality monitoring, promising significant improvements in operational efficiency and objectivity in the meat industry.

5. METHODOLOGY

A. Dataset Acquisition

Labeled meat image datasets were curated from public sources including Kaggle, Mendeley Data, and Roboflow Universe. Datasets comprised images categorized by freshness: fresh, semi-fresh, and spoiled, along with metadata regarding meat type, storage duration, and environmental conditions. Images were resized to 224×224 pixels and normalized.

B. Preprocessing and Augmentation

To address class imbalance and enhance model generalization, extensive image augmentation—rotations, flips, zoom, and contrast variation—was performed using Keras and OpenCV tools.

C. DenseNet-121 Architecture

DenseNet-121 features densely connected blocks that maximize feature reuse and gradient flow.The pretrained ImageNet weights facilitate rapid convergence on meat-specific features. The top layers were replaced with a softmax classifier tailored for three classes. Initial layers remained frozen during transfer learning, with gradual unfreezing and fine-tuning as model performance converged.

D.Training and Evaluation

Model training employed Adam optimizer, categorical cross-entropy loss, batch sizes of 32, and early stopping on validation loss. Evaluation metrics included accuracy, precision, recall, F1-score, and confusion matrix analysis.

E. Comparative Baselines

For benchmarking, ResNet-50,VGG16, and MobileNetV2 were trained under identical data splits and settings, enabling fair comparison in terms of accuracy and computational efficiency.

6. RESULTS AND DISCUSSION

A. Classification Performance

DenseNet-121 achieved an average accuracy of 97.2% across test datasets, outperforming ResNet-50 (96.3%), VGG16 (95.8%), and MobileNetV2 (94.6%). Precision and recall metrics consistently exceeded 95%, indicating strong discriminatory power between freshness categories.

Model	Accuracy	Precision	Recall	F1-score
DenseNet-121	97.2%	97.4%	97.0%	97.2%
ResNet-50	96.3%	96.5%	96.1%	96.3%
VGG16	95.8%	95.9%	95.6%	95.8%
MobileNetV2	94.6%	94.8%	94.4%	94.6%

B. Confusion Matrix Analysis

DenseNet-121 exhibited lower misclassification rates for borderline semi-fresh/spoiled samples compared to other models.Augmentation and class-balanced training were critical for reducing overfitting and improving generalization.

C.Visualization and Deployment

Grad-CAM visualizations demonstrated the model's attention to color, texture, and morphological regions most indicative of freshness. Deployment in a user-friendly application framework enables real-time batch assessment for industry use.

D. Limitations

- Deep models require sizable labeled datasets for optimal performance.
- Variability in capture conditions (lighting, device) affects robustness; cross-domain adaptation is recommended.
- Potential overfitting if augmentation is insufficient.

7. CONCLUSION

This study presents a scalable, high-accuracy solution for meat quality detection using DenseNet-121 and transfer learning.

The model's dense connectivity and feature reuse facilitate superior classification of freshness categories, outperforming baseline CNNs. Results validate the approach for both scientific and industrial deployment in quality assurance, process automation, and regulatory compliance. Future work may integrate multi-modal sensor data and real-time defect localization.

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