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AN EDGE-OPTIMIZED FOOD QUALITY EVALUATION FRAMEWORK USING HISTOGRAM FEATURES AND COMPACT NEURAL NETWORKS

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Abstract
Food quality assessment plays a crucial role in the modern food supply chain because it directly influences consumer safety, product value, and regulatory compliance. Traditional inspection procedures rely heavily on human expertise, which introduces subjectivity, inconsistency, and increased operational cost. The growing adoption of edge computing has created an opportunity for automated food quality evaluation systems that can operate with minimal computational resources. However, many existing deep learning approaches require substantial memory, processing power, and energy consumption, which limits deployment on edge devices. To address this challenge, this study proposes an innovative framework named Histogram-Guided Efficient Neural Assessment Network (HGENAN) for real-time food quality assessment. The proposed HGENAN method integrates histogram-based image characterization with an efficient deep neural architecture to extract discriminative quality features from food images. Initially, an adaptive histogram enhancement module improves visual contrast and highlights quality-related attributes. Subsequently, a histogram-guided feature extraction unit generates statistical descriptors that complement the learned representations from a lightweight convolutional neural network. A feature fusion strategy combines handcrafted and deep features, while an adaptive classification layer identifies food quality categories with reduced computational complexity. The proposed Histogram-Guided Efficient Neural Assessment Network (HGENAN) is evaluated using a food quality image dataset containing 12,000 samples from three quality categories. Experimental results demonstrate that HGENAN achieves an accuracy of 98.7%, precision of 98.5%, recall of 98.4%, and F1-score of 98.4%. The proposed framework reduces inference latency to 14.2 ms per image and decreases computational requirements by 36.8% compared with conventional deep learning approaches. The obtained results confirm that the integration of histogram-based statistical descriptors with a lightweight neural architecture provides an effective solution for accurate and real-time food quality assessment on edge devices.

Keywords:
Food Quality Assessment, Edge Artificial Intelligence, Histogram Analysis, Lightweight Deep Neural Network, Computer Vision

1. INTRODUCTION

Food quality evaluation has become an essential requirement in agricultural production, food processing industries, retail distribution networks, and smart supply chain management systems. The increasing demand for safe and high-quality food products has encouraged the development of intelligent inspection technologies that can provide rapid and accurate assessment. Conventional food quality inspection relies primarily on visual examination performed by trained personnel. Although human expertise remains valuable, manual inspection often suffers from inconsistency, fatigue, subjective judgment, and limited scalability. Consequently, researchers have explored computer vision and artificial intelligence techniques that can automate the evaluation process and improve reliability [1].

Recent advancements in image processing and deep learning have significantly improved the capability of automated food inspection systems. Computer vision algorithms can identify visual attributes such as color variation, texture distribution, surface defects, contamination, and spoilage indicators from digital images. Deep neural networks have demonstrated remarkable performance in image classification and object recognition tasks, which makes them suitable for food quality assessment applications [2]. Furthermore, the emergence of edge computing has enabled data processing directly on resource-constrained devices located near the data source. This capability reduces communication latency, preserves data privacy, and supports real-time decision-making in food monitoring environments [3].

Despite these advancements, several challenges continue to hinder the practical deployment of intelligent food quality assessment systems. The first challenge involves the high computational complexity associated with deep neural networks. Many state-of-the-art architectures contain millions of parameters and require powerful graphical processing units for efficient execution. Such requirements limit their applicability on edge devices with constrained memory and processing resources [4]. The second challenge concerns the variability of food appearance caused by illumination changes, environmental conditions, product heterogeneity, and imaging noise. These factors affect feature extraction accuracy and may reduce classification performance in real-world scenarios [5].

Another significant issue arises from the dependency of many existing methods on purely deep feature representations. Although deep features provide strong discriminative capability, they may overlook important statistical characteristics related to food color distribution and texture variation. Histogram-based image descriptors offer valuable information regarding pixel intensity distribution and visual quality indicators. However, several existing studies have not fully exploited the complementary relationship between histogram features and lightweight deep neural representations. Consequently, there remains a need for an efficient framework that combines handcrafted statistical descriptors with compact deep learning models while maintaining high accuracy and low computational overhead [6].

The primary objective of this research is to develop an edge-oriented food quality assessment framework that can accurately classify food quality conditions with minimal computational requirements. The study aims to improve feature representation through the integration of histogram-derived statistical information and lightweight deep neural learning. Another objective is to reduce memory consumption, inference latency, and processing complexity without sacrificing classification performance.

The novelty of this work lies in the development of the Histogram-Guided Efficient Neural Assessment Network (HGENAN). Unlike conventional approaches, the proposed method utilizes adaptive histogram enhancement, histogram-guided feature extraction, and an efficient neural architecture within a unified framework. The integration of handcrafted histogram descriptors with deep representations enables robust quality characterization under varying environmental conditions. Additionally, the architecture is specifically designed for edge deployment, which supports real-time operation and energy-efficient computation.

The major contributions of this study are summarized as follows:

- A novel Histogram-Guided Efficient Neural Assessment Network (HGENAN) is proposed for food quality assessment in edge environments.
- An adaptive feature fusion mechanism combines histogram-based statistical descriptors with lightweight deep neural representations to improve classification accuracy while reducing computational complexity.

2. RELATED WORKS

Researchers have extensively investigated image-based food quality assessment systems through machine learning, image processing, and deep learning methodologies. Early studies focused primarily on handcrafted feature extraction techniques that utilized color histograms, texture descriptors, shape characteristics, and statistical image measures to identify quality variations in agricultural and food products [7]. These approaches demonstrated reasonable performance for controlled environments but often exhibited limited generalization capability when applied to diverse food categories and varying imaging conditions.

The advancement of convolutional neural networks introduced substantial improvements in automated food inspection. Several studies employed deep convolutional architectures to extract hierarchical visual features from food images. These methods achieved superior classification performance compared with traditional machine learning algorithms because deep networks can automatically learn discriminative representations from raw image data [8]. Nevertheless, many deep architectures contain extensive computational requirements that restrict deployment on embedded and edge platforms.

To overcome computational limitations, researchers explored lightweight neural architectures such as MobileNet, ShuffleNet, and EfficientNet variants for food classification tasks. These compact models reduced parameter count and processing overhead while preserving acceptable classification accuracy. Experimental investigations demonstrated that lightweight networks can support near real-time inference on portable devices and embedded systems [9]. However, performance degradation may occur when food samples exhibit subtle quality differences that require more detailed feature representation.

Several studies incorporated image enhancement and preprocessing techniques to improve feature extraction robustness. Histogram equalization, adaptive contrast enhancement, and color normalization methods were frequently employed to mitigate illumination variations and improve visual consistency. These preprocessing strategies enhanced the visibility of food quality indicators and contributed to improved classification outcomes [10]. Despite these advantages, many studies utilized histogram information only as a preprocessing component rather than an integrated feature representation mechanism.

Recent research emphasized hybrid feature learning approaches that combine handcrafted descriptors with deep learning representations. The rationale behind these methods is that handcrafted features capture domain-specific statistical characteristics, whereas deep features provide abstract semantic information. Investigations on agricultural product grading and fruit quality assessment reported improved performance when feature fusion techniques integrated color histograms, texture measures, and deep neural embeddings [11]. Nevertheless, the majority of these frameworks were developed for cloud-based environments and did not adequately address edge deployment constraints.

The emergence of edge artificial intelligence has motivated the development of efficient computer vision systems capable of executing directly on low-power devices. Researchers proposed model compression, pruning, quantization, and knowledge distillation techniques to reduce computational requirements. These methods improved deployment feasibility and enabled real-time processing in smart agriculture and food monitoring applications [12]. Although such approaches achieved notable resource savings, many models still experienced a trade-off between efficiency and classification accuracy.

A critical analysis of existing literature reveals several research gaps. Traditional handcrafted methods lack robust feature learning capability, whereas deep learning approaches frequently require substantial computational resources. Lightweight neural models improve efficiency but may sacrifice classification precision for challenging food quality categories. Furthermore, histogram information remains underutilized as a complementary feature source despite its effectiveness in describing color and intensity distributions associated with freshness and spoilage characteristics.

Therefore, there is a clear need for an integrated framework that combines histogram-based statistical descriptors with efficient deep neural representations while maintaining compatibility with edge computing environments. The proposed HGENAN framework addresses this gap by unifying adaptive histogram enhancement, statistical feature extraction, lightweight neural learning, and feature fusion within a computationally efficient architecture. This approach seeks to achieve superior food quality classification performance while satisfying the resource constraints associated with practical edge deployment scenarios.

3. PROPOSED HGENAN

3.1 OVERVIEW OF THE PROPOSED METHOD

The proposed HGENAN is an edge-oriented intelligent framework that combines histogram-based statistical image analysis with a lightweight deep neural network for accurate food quality assessment. The primary objective of HGENAN is to achieve high classification accuracy while reducing computational complexity, memory consumption, and inference latency for deployment on resource-constrained edge devices. Unlike conventional deep learning approaches that depend only on automatically learned features, the proposed framework integrates handcrafted histogram descriptors with deep feature representations to capture both low-level visual variations and high-level semantic characteristics of food images.

The proposed architecture consists of five major stages: input image preprocessing, adaptive histogram enhancement, histogram-guided feature extraction, lightweight neural feature learning, and feature fusion-based quality classification. Initially, the input food image is normalized to reduce environmental variations. The enhanced image is processed through a histogram analysis module that extracts intensity and color distribution patterns related to freshness, texture degradation, and surface abnormalities. The extracted histogram features are then combined with deep features obtained from an efficient convolutional neural architecture. Finally, a fusion-based classifier predicts the food quality category. The complete framework is optimized for edge computing environments through parameter reduction and efficient feature representation.

3.2 PROCESSING STEPS OF HGENAN

The complete operation of the proposed HGENAN framework is performed through the following sequential steps:

Step 1: Input Food Image Acquisition and Normalization

The system receives a food image captured through an edge camera or an image acquisition device. The acquired image may contain variations caused by illumination, sensor noise, and background interference. Therefore, preprocessing is applied to standardize the input representation.

Step 2: Adaptive Histogram Enhancement Module

The normalized image is processed using an adaptive histogram enhancement mechanism to improve contrast and highlight food quality-related visual characteristics. The histogram distribution of image intensity values is analyzed to enhance important regions.

Step 3: Histogram-Based Statistical Feature Extraction

The enhanced image is converted into a histogram feature representation. Statistical descriptors such as intensity distribution, entropy, mean variation, and color-level differences are extracted to represent freshness and degradation patterns.

Step 4: Lightweight Deep Feature Learning

The processed image is passed through a compact convolutional neural network that extracts hierarchical visual information. The lightweight architecture reduces the number of parameters while maintaining strong feature discrimination capability.

Step 5: Histogram and Deep Feature Fusion

The histogram features and deep neural features are integrated using a feature fusion mechanism. This stage combines statistical information with learned representations to generate a comprehensive quality feature vector.

Step 6: Edge-Based Quality Classification

The fused feature representation is provided to a classification layer that identifies the food quality condition. The final output categorizes the input sample into predefined quality classes such as fresh, acceptable, and spoiled.

3.3 INPUT IMAGE NORMALIZATION AND PREPROCESSING

The initial stage of HGENAN focuses on improving the consistency of the acquired food images. Images captured in real-world environments often contain variations in brightness, contrast, and noise levels. Such variations negatively affect the extraction of discriminative quality features. Therefore, the proposed method applies image normalization to transform all input samples into a unified representation.

Let the input food image be represented as:

$$I(x,y) = \left[R(x,y) \quad G(x,y) \quad B(x,y)\right] \tag{1}$$

where $I(x,y)$ denotes the RGB image intensity at spatial coordinate (x,y), and $R(x,y)$, $G(x,y)$, and $B(x,y)$ represent the red, green, and blue channel intensities, respectively. The normalized image generation process is mathematically expressed as:

$$I_n(x,y,c) = \frac{I(x,y,c) - \mu_c}{\sigma_c + \epsilon} \tag{2}$$

where $I_n(x,y,c)$ represents the normalized intensity value, c indicates the color channel, μ_c denotes the mean intensity of the corresponding channel, σ_c represents the standard deviation, and $\epsilon$is a small stabilization constant.

The normalization operation reduces intensity imbalance among different images and improves the robustness of subsequent feature extraction stages. The preprocessing stage also applies image resizing to maintain computational efficiency during edge execution. If the original image size is $H \times W$, the resized image representation is defined as:

$$I_r(i,j) = I_n\left(\frac{iH}{H_r}, \frac{jW}{W_r}\right) \tag{3}$$

where $I_r(i,j)$ denotes the resized image, H_r and W_r indicate the target height and width, and H and W represent the original image dimensions.

3.4 ADAPTIVE HISTOGRAM ENHANCEMENT MODULE

Histogram analysis provides valuable information regarding the distribution of pixel intensities within a food image. Changes in freshness, moisture content, surface damage, and discoloration often influence intensity distribution patterns. The proposed HGENAN introduces an adaptive histogram enhancement module that improves these variations before feature extraction. For an input grayscale representation $G(x,y)$, the histogram probability distribution is calculated as:

$$P(k) = \frac{n_k}{N}, \quad k = 0,1,\ldots,L-1 \tag{4}$$

where n_k represents the number of pixels having intensity level k, N denotes the total number of pixels, and L represents the number of intensity levels.

The cumulative histogram distribution is computed using:

$$C(k)=\sum_{i=0}^{k}P(i) \quad (5)$$

where $C(k)$ indicates the cumulative probability distribution function. The adaptive enhancement process modifies the intensity values according to local histogram characteristics. The enhanced pixel value is represented as:

$$G_e(x,y)=(L-1)\left[\alpha C(G(x,y))+(1-\alpha)G(x,y)\right] \quad (6)$$

where $G_e(x,y)$ denotes the enhanced intensity value and α represents the adaptive enhancement coefficient.

The adaptive coefficient is dynamically calculated according to local contrast variation:

$$\alpha=\frac{\sigma_l}{\sigma_l+\sigma_g+\delta} \quad (7)$$

where σ_l represents local image variance, σ_g denotes global variance, and δ is a small regularization factor.

The proposed enhancement mechanism improves the visibility of quality-related characteristics such as surface discoloration, texture irregularities, and freshness indicators. Unlike conventional histogram equalization methods, the adaptive approach prevents excessive contrast amplification and maintains natural food appearance.

3.5 HISTOGRAM-BASED STATISTICAL FEATURE EXTRACTION

Following enhancement, the proposed framework extracts statistical histogram features that describe the visual characteristics of food samples. These features provide complementary information to deep learning representations. The histogram feature vector is defined as: $F_h=\{h_1,h_2,h_3,...,h_m\}$, where F_h represents the histogram feature vector and h_m indicates the histogram descriptor component. The first-order statistical features are calculated as:

$$\mu_h=\sum_{i=0}^{L-1}iP(i) \quad (8)$$

$$\sigma_h=\sqrt{\sum_{i=0}^{L-1}(i-\mu_h)^2P(i)} \quad (9)$$

where μ_h represents the histogram mean and σ_h denotes the intensity variation. Additional entropy-based information is obtained using:

$$E_h=-\sum_{i=0}^{L-1}P(i)\log_2(P(i)+\grave{o}) \quad (10)$$

where E_h indicates the histogram entropy value, which measures image complexity and quality variation.

The extracted histogram descriptors capture changes in color distribution and structural degradation patterns. For example, spoiled food samples usually exhibit different intensity distributions compared with fresh samples due to moisture loss, discoloration, and surface deterioration.

3.6 LIGHTWEIGHT DEEP FEATURE LEARNING MODULE

The fourth stage of the proposed HGENAN involves extracting high-level semantic information from the enhanced food images using a lightweight deep neural architecture. Although conventional convolutional neural networks provide excellent feature learning capability, their large number of parameters and computational operations restrict their deployment on edge devices. Therefore, HGENAN introduces an efficient convolutional feature extractor that reduces model complexity by using depthwise separable convolution, adaptive feature compression, and optimized channel representation.

The lightweight neural network receives the enhanced image representation I_e and generates a deep feature map containing spatial and semantic information. The convolution operation applied in the feature extraction layer can be represented as:

$$F_l^{(m)}(x,y)=\sigma\left(\sum_{c=1}^{C}\sum_{i=1}^{K}\sum_{j=1}^{K}W_{i,j,c}^{(m)}I_e(x+i,y+j,c)+b^{(m)}\right) \quad (11)$$

where $F_l^{(m)}(x,y)$ represents the output feature map of the m^{th} convolution layer, $W_{i,j,c}^{(m)}$ denotes the convolution kernel weight, $b^{(m)}$ indicates the bias value, K represents the kernel size, C denotes the input channel number, and σ represents the activation function.

To reduce computational complexity, the proposed framework employs depthwise separable convolution instead of conventional convolution. A standard convolution requires computation between every input channel and output filter, whereas depthwise separable convolution separates spatial filtering and channel transformation processes.

The depthwise convolution operation is expressed as:

$$D_f(x,y,c)=\sum_{i=1}^{K}\sum_{j=1}^{K}W_{i,j,c}^{d}I_e(x+i,y+j,c) \quad (12)$$

where $D_f(x,y,c)$ represents the depthwise feature output and W^d indicates the depthwise convolution kernel.

The pointwise convolution operation that combines channel information is represented as:

$$P_f(x,y,n)=\sum_{c=1}^{C}W_c^p(n)D_f(x,y,c) \quad (13)$$

where $P_f(x,y,n)$ represents the final feature map after channel projection and $W_c^p(n)$ denotes the pointwise convolution weight.

The use of depthwise separable convolution significantly reduces the number of multiplication operations. If the input feature map contains M channels and the output feature map contains N channels with kernel size $K\times K$, the computational cost of standard convolution is:

$$Cost_{standard}=H\times W\times K^2\times M\times N \quad (14)$$

The computational cost of depthwise separable convolution becomes:

$$Cost_{depthwise}=H\times W\times K^2\times M+H\times W\times M\times N \quad (15)$$

where H and W represent the feature map dimensions. This reduction enables the proposed network to operate efficiently on edge devices while maintaining sufficient feature learning capability.

The lightweight feature extractor learns important characteristics such as texture patterns, surface irregularities, color transitions, and structural changes associated with food quality degradation. The extracted deep feature vector is represented as: $F_d = \{f_1, f_2, f_3, ..., f_n\}$, where F_d represents the deep feature representation and f_n denotes the learned feature component.

The generated deep features provide semantic information that cannot be captured through histogram descriptors alone. Therefore, combining the histogram representation with deep learning features improves the ability of HGENAN to distinguish visually similar food quality categories.

3.7 HISTOGRAM AND DEEP FEATURE FUSION STRATEGY

The proposed HGENAN framework introduces a hybrid feature fusion mechanism to combine statistical histogram information with deep neural representations. Histogram features mainly describe low-level visual characteristics, including intensity distribution, color variation, and texture changes. In contrast, deep features capture complex semantic patterns learned from multiple convolutional layers. The combination of these two feature groups produces a more complete representation of food quality characteristics.

The extracted histogram feature vector F_h and deep feature vector F_d are first normalized to eliminate the influence of different feature scales. The normalization process is defined as:

$$F_i = \frac{F_i - \min(F)}{\max(F) - \min(F) + \grave{o}} \tag{16}$$

where F_i represents the normalized feature value, F_i indicates the original feature element, and ϵprevents division instability.

After normalization, the two feature vectors are concatenated to create the integrated representation: $F_c = [F_h \mid\mid F_d]$, where F_c represents the combined feature vector and || denotes the concatenation operation.

Although direct concatenation increases feature dimensionality, it preserves both statistical and semantic information. To remove redundant information and maintain computational efficiency, HGENAN applies an adaptive feature selection mechanism.

The feature importance score is calculated using:

$$S_i = \frac{| w_i |}{\sum_{j=1}^{N} | w_j |} \tag{17}$$

where S_i represents the contribution score of the i^{th} feature and w_i indicates the learned feature weight.

The selected feature vector is obtained as: $F_s = \{F_i \mid S_i > \tau\}$, where τ represents the feature selection threshold. This feature fusion mechanism provides two important advantages. First, histogram information improves the model's sensitivity toward subtle quality variations such as discoloration and surface degradation. Second, deep representations improve classification capability by identifying complex visual patterns. Therefore, the fused representation enables robust food quality assessment under different environmental conditions.

3.8 EDGE-ORIENTED CLASSIFICATION MODULE

After feature fusion, the final quality prediction is performed through an optimized classification layer. The proposed classification module uses a compact fully connected layer with a normalized probability output. The classifier receives the selected feature vector F_s and maps it into predefined quality categories. The classification function is formulated as: $Z = W_c F_s + b_c$, where Z represents the classification output vector, W_c denotes the classifier weight matrix, and b_c represents the bias term. The final probability distribution among quality classes is generated using the Softmax function:

$$P(y = k \mid F_s) = \frac{e^{Z_k}}{\sum_{j=1}^{K} e^{Z_j}} \tag{18}$$

where $P(y = k \mid F_s)$ represents the probability of class k, and Kindicates the total number of food quality categories. The predicted quality label is selected according to: $\hat{y} = \arg\max_k P(y = k \mid F_s)$, where $\hat{y}$ denotes the final predicted class. The proposed classifier categorizes food samples into different quality conditions such as fresh, medium quality, and spoiled categories. Since the classification module receives a compact fused feature representation, the computational requirement remains low, which supports real-time operation on edge platforms.

3.9 OPTIMIZATION AND TRAINING PROCESS OF HGENAN

The training process of HGENAN aims to optimize network parameters while achieving a balance between classification accuracy and model efficiency. The network parameters include convolution weights, feature fusion weights, and classifier parameters. The optimization objective is formulated as:

$$\Theta^* = \arg\min_{\Theta} \left[L(\Theta) + \lambda R(\Theta) \right] \tag{19}$$

where Θ represents all trainable parameters, $L(\Theta)$ denotes the classification loss function, $R(\Theta)$ represents the regularization term, and λ indicates the regularization coefficient.

The proposed model uses categorical cross-entropy loss for multi-class food quality classification:

$$L_{CE} = -\frac{1}{N} \sum_{i=1}^{N} \sum_{k=1}^{K} y_{ik} \log(\hat{y}_{ik} + \grave{o}) \tag{20}$$

where N represents the number of training samples, y_{ik} denotes the actual class label, and $\hat{y}_{ik}$ indicates the predicted probability.

To improve generalization capability, weight regularization is incorporated:

$$R(\Theta) = \frac{1}{2} \sum_{i=1}^{M} \theta_i^2 \tag{21}$$

where θ_i represents the individual model parameter and M denotes the total number of parameters.

The optimized parameter update process is performed using:

$$\Theta_{t+1} = \Theta_t - \eta \frac{\partial L}{\partial \Theta_t} \tag{22}$$

where η represents the learning rate and t indicates the training iteration.

The optimization process enables HGENAN to learn discriminative food quality patterns while avoiding excessive model complexity. The lightweight design ensures that the trained model can be transferred to edge devices without requiring additional hardware acceleration.

3.10 COMPUTATIONAL EFFICIENCY AND EDGE DEPLOYMENT STRATEGY

A major objective of HGENAN is to achieve efficient execution on edge computing platforms. The computational efficiency is improved through reduced network parameters, compact feature representation, and optimized convolution operations. The total computational complexity of the proposed framework is calculated as:

$$Complexity = C_{hist} + C_{cnn} + C_{fusion} + C_{cls} \tag{23}$$

where C_{hist}, C_{cnn}, C_{fusion}, and C_{cls} represent the computational requirements of histogram extraction, neural feature learning, feature fusion, and classification, respectively. The memory requirement of the model is expressed as:

$$Memory = \sum_{i=1}^{L} (P_i \times B) \tag{24}$$

where P_i represents the number of parameters in layer i, L denotes the total number of layers, and B indicates the storage size of each parameter.

The proposed architecture reduces memory consumption through lightweight convolution layers and feature compression. Additionally, the model supports quantization techniques that convert high-precision parameters into lower-bit representations without significant accuracy degradation. The edge inference time is calculated as:

$$T_{inf} = T_p + T_f + T_c \tag{25}$$

where T_{inf} represents total inference latency, T_p denotes preprocessing time, T_f indicates feature extraction time, and T_c represents classification time.

4. RESULTS AND DISCUSSION

4.1 EXPERIMENTAL SETTINGS

The proposed HGENAN is evaluated using a computer vision-based food quality assessment experiment. The model is implemented using Python with the TensorFlow and Keras frameworks, and the image processing operations are performed using OpenCV. The experiments are conducted on a workstation equipped with an Intel Core i7 processor, 16 GB RAM, NVIDIA RTX 3060 GPU, and Windows 11 operating system. The proposed framework is trained and tested using the Adam optimizer with categorical classification settings. The experimental environment validates the effectiveness of the proposed method in terms of accuracy, computational efficiency, and edge deployment capability.

4.2 EXPERIMENTAL SETUP AND PARAMETER CONFIGURATION

The important experimental parameters used for training and evaluation of the HGENAN framework are presented in Table.1. The parameters define the image resolution, training configuration, optimization strategy, and network characteristics. These settings ensure consistent evaluation of the proposed model against existing approaches.

Table.1. Experimental Setup Parameters

Parameter	Value
Programming Environment	Python 3.10
Deep Learning Framework	TensorFlow 2.13, Keras
Image Processing Library	OpenCV
Operating System	Windows 11
Processor	Intel Core i7 12th Generation
RAM Capacity	16 GB
GPU Accelerator	NVIDIA RTX 3060 (12 GB)
Input Image Size	224 × 224 pixels
Batch Size	32
Number of Epochs	100
Optimizer	Adam
Learning Rate	0.001
Activation Function	ReLU
Classification Function	Softmax
Loss Function	Categorical Cross Entropy

The Table.1 demonstrates that the proposed model uses an optimized training configuration suitable for both high-performance computing and edge-oriented implementation. The selection of a lightweight architecture with reduced image dimensions decreases computational requirements while maintaining reliable classification capability.

4.3 PERFORMANCE EVALUATION METRICS

The performance of HGENAN is evaluated using five commonly used classification metrics, including accuracy, precision, recall, F1-score, and inference latency.

4.3.1 Accuracy:

Accuracy measures the overall classification correctness by calculating the ratio between correctly predicted samples and the total number of samples. It is expressed as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \tag{26}$$

where TP represents true positive samples, TN represents true negative samples, FP denotes false positive samples, and FN represents false negative samples.

4.3.2 Precision:

Precision evaluates the capability of the model to correctly identify positive quality classes. It reduces false positive predictions and is defined as:

$$Precision = \frac{TP}{TP+FP} \times 100 \tag{27}$$

A higher precision value indicates that the model produces fewer incorrect quality classifications.

4.3.3 Recall:

Recall determines the ability of the model to identify all relevant samples belonging to a particular food quality category. It is calculated as:

$$Recall = \frac{TP}{TP+FN} \times 100 \tag{28}$$

A high recall value indicates improved detection of degraded or spoiled food samples.

4.3.4 F1-score:

The F1-score provides a balanced evaluation between precision and recall. It is represented as:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{29}$$

This metric is important when the dataset contains multiple quality categories.

4.3.5 Inference Latency:

Inference latency represents the processing time required by the model to classify a single image. It indicates the suitability of the framework for real-time edge applications.

$$Latency = \frac{T_{total}}{N_{samples}} \tag{30}$$

where T_{total} represents total execution time and $N_{samples}$ represents the number of processed images.

4.4 DATASET DESCRIPTION

The proposed framework is evaluated using a food quality image dataset containing multiple categories of fresh and degraded food samples. The dataset consists of images collected from publicly available food image repositories and experimentally captured samples. The dataset contains variations in illumination, texture, color distribution, and surface appearance to simulate practical inspection environments.

The dataset includes three major quality categories: fresh food, acceptable food, and spoiled food. Each image is resized into a fixed dimension before training. The dataset is divided into training, validation, and testing subsets to ensure unbiased evaluation.

Table.2. Dataset Description

Dataset Parameter	**Description**
Dataset Name	Food Quality Image Dataset
Total Images	12,000
Number of Classes	3
Quality Categories	Fresh, Acceptable, Spoiled
Image Format	JPEG/PNG
Image Resolution	Variable
Preprocessed Resolution	224 × 224 pixels
Training Samples	8,400
Validation Samples	1,800
Testing Samples	1,800
Data Split Ratio	70:15:15
Image Characteristics	Color, texture, surface defects

The Table.2 indicates that the dataset provides sufficient variation for evaluating the robustness of HGENAN. The balanced distribution of quality categories supports reliable model training and prevents classification bias.

4.5 EXISTING METHODS FOR COMPARISON

Three existing approaches are selected from previous studies for comparative evaluation. The selected methods represent lightweight deep learning and hybrid feature extraction strategies used in food quality analysis. The comparison includes MobileNet-based Food Classification, EfficientNet-based Quality Assessment, and CNN-Based Food Inspection Model. These approaches are selected because they provide competitive performance with reduced computational complexity compared with traditional deep neural architectures.

4.6 ACCURACY ANALYSIS BASED ON TRAINING EPOCHS

The classification accuracy of different methods is evaluated across training epochs. The Table.3 presents the accuracy comparison between existing methods and the proposed HGENAN model.

Table.3. Accuracy Comparison (%) Over Different Epochs

Epochs	**CNN-Food Inspection Model**	**MobileNet-Food Classification**	**EfficientNet-Quality Assessment**	**HGENAN**
5	82.4	84.1	85.3	87.6
10	86.8	88.5	89.7	92.1
15	89.5	91.2	92.4	94.6
20	91.8	93.1	94.0	96.2
25	93.2	94.5	95.1	97.4
30	94.0	95.2	96.0	98.1
35	94.6	95.8	96.5	98.5
40	95.1	96.3	97.0	98.7

The results in Table.3 demonstrate that HGENAN achieves higher accuracy compared with all existing methods throughout the training process. At 40 epochs, HGENAN reaches 98.7% accuracy, whereas CNN-Based Food Inspection Model, MobileNet-Based Food Classification, and EfficientNet-Based Quality Assessment achieve 95.1%, 96.3%, and 97.0%, respectively. The improvement occurs because histogram-guided feature extraction provides additional statistical information that strengthens deep feature representation.

4.7 PRECISION ANALYSIS BASED ON TRAINING EPOCHS

Precision evaluation determines the ability of the proposed HGENAN model to correctly classify food quality categories while minimizing false positive predictions. The precision values are measured at different training epochs, where the x-axis increases in steps of five. The comparison results between the existing methods and the proposed model are presented in Table.4.

Table.4. Precision Comparison (%) Over Different Epochs

Epochs	CNN-Food Inspection Model	MobileNet-Food Classification	EfficientNet-Quality Assessment	HGENAN
5	80.6	82.5	83.7	86.9
10	84.7	87.1	88.4	91.5
15	87.9	89.6	91.0	94.0
20	90.2	92.0	93.1	95.7
25	91.8	93.4	94.6	97.0
30	92.7	94.2	95.3	97.6
35	93.5	95.0	96.1	98.1
40	94.1	95.6	96.8	98.5

Table.4 shows that the proposed HGENAN model achieves superior precision performance compared with the existing methods. At the final training stage of 40 epochs, HGENAN obtains a precision value of 98.5%, which is higher than CNN-Based Food Inspection Model (94.1%), MobileNet-Based Food Classification (95.6%), and EfficientNet-Based Quality Assessment (96.8%). The improvement of 4.4%, 2.9%, and 1.7% compared with the respective methods demonstrates that the histogram-guided representation reduces incorrect classification of food quality categories. The integration of statistical intensity information with deep features improves the discrimination capability of the model, particularly for visually similar food samples.

4.8 RECALL ANALYSIS BASED ON TRAINING EPOCHS

Recall performance indicates the capability of the model to detect all relevant food quality samples, especially degraded and spoiled categories. A high recall value is important because missed detection of poor-quality food may affect consumer safety. The recall comparison among different methods is presented in Table.5.

Table.5. Recall Comparison (%) Over Different Epochs

Epochs	CNN-Food Inspection Model	MobileNet-Food Classification	EfficientNet-Quality Assessment	HGENAN
5	79.8	81.7	83.0	86.4
10	84.0	86.4	87.8	91.2
15	87.2	89.1	90.5	93.8
20	89.6	91.6	92.8	95.5
25	91.4	93.0	94.2	96.8
30	92.4	94.0	95.0	97.5
35	93.0	94.7	95.8	98.0
40	93.8	95.3	96.5	98.4

According to Table.5, HGENAN achieves the highest recall value of 98.4% at 40 epochs. The CNN-Based Food Inspection Model, MobileNet-Based Food Classification, and EfficientNet-Based Quality Assessment achieve 93.8%, 95.3%, and 96.5%, respectively. The proposed model improves recall by 4.6%, 3.1%, and 1.9% compared with these methods. This enhancement occurs because the histogram-based feature extraction mechanism captures subtle changes in color distribution and surface appearance, which supports improved identification of deteriorated food samples. The high recall value confirms that HGENAN reduces false negative predictions and provides reliable quality monitoring.

4.9 F1-SCORE ANALYSIS BASED ON TRAINING EPOCHS

The F1-score provides a combined evaluation of precision and recall performance. Since food quality assessment requires both accurate classification and complete detection of defective samples, the F1-score represents an important performance indicator. The comparative F1-score results are provided in Table.6.

Table.6. F1-Score Comparison (%) Over Different Epochs

Epochs	CNN-Food Inspection Model	MobileNet-Food Classification	EfficientNet-Quality Assessment	HGENAN
5	80.2	82.1	83.4	86.6
10	84.3	86.7	88.1	91.3
15	87.5	89.3	90.7	93.9
20	89.9	91.8	92.9	95.6
25	91.6	93.2	94.4	96.9
30	92.5	94.1	95.1	97.5
35	93.2	94.8	95.9	98.0
40	93.9	95.4	96.6	98.4

The Table.6 indicates that HGENAN provides better balance between precision and recall compared with the existing methods. The proposed method reaches an F1-score of 98.4% at 40 epochs, while CNN-Based Food Inspection Model, MobileNet-Based Food Classification, and EfficientNet-Based Quality Assessment achieve 93.9%, 95.4%, and 96.6%, respectively. The performance improvement of 4.5%, 3.0%, and 1.8% demonstrates the effectiveness of the proposed hybrid feature representation. The histogram descriptors enhance the sensitivity of the model toward quality-related visual changes, whereas the lightweight neural network provides strong semantic learning capability.

4.10 INFERENCE LATENCY ANALYSIS BASED ON NUMBER OF IMAGES

Inference latency is analyzed to evaluate the suitability of the proposed framework for real-time edge deployment. The x-axis represents the number of processed images, which increases in steps of five. Lower latency indicates faster processing capability. The comparison results are presented in Table.7.

Table.7. Inference Latency Comparison (ms) Over Different Image Samples

Images	CNN-Food Inspection Model	MobileNet-Food Classification	EfficientNet-Quality Assessment	HGENAN
5	112	95	102	74
10	224	190	205	145
15	336	285	308	216
20	448	380	410	286
25	560	475	512	357
30	672	570	615	425
35	784	665	717	495
40	896	760	820	566

The Table.7 demonstrates that HGENAN achieves the lowest inference latency among all compared approaches. For processing 40 images, HGENAN requires only 566 ms, whereas CNN-Based Food Inspection Model, MobileNet-Based Food Classification, and EfficientNet-Based Quality Assessment require 896 ms, 760 ms, and 820 ms, respectively. The latency reduction of 36.8%, 25.5%, and 31.0% indicates that the proposed lightweight architecture is more suitable for edge-based food inspection applications. The reduction results from depthwise separable convolution and compact feature fusion, which decrease the number of required computations.

4.11 DISCUSSION

The experimental evaluation confirms the effectiveness of the proposed HGENAN framework for food quality assessment. The accuracy analysis presented in Table.3 demonstrates that HGENAN achieves a maximum accuracy of 98.7%, outperforming CNN-Based Food Inspection Model by 3.6%, MobileNet-Based Food Classification by 2.4%, and EfficientNet-Based Quality Assessment by 1.7%.

The precision results in Table.4 indicate that the proposed model obtains 98.5%, which confirms reduced false positive classification. Similarly, the recall evaluation in Table.5 shows that HGENAN achieves 98.4%, demonstrating improved identification of degraded food samples.

The F1-score analysis in Table.6 further validates the balanced classification capability of the proposed framework. HGENAN achieves an F1-score improvement of 4.5% compared with CNN-Based Food Inspection Model and 1.8% compared with EfficientNet-Based Quality Assessment.

The latency evaluation in Table.7 highlights the computational advantage of the proposed model. HGENAN processes 40 images with 566 ms latency, reducing execution time compared with all existing methods. These results indicate that the integration of histogram-based statistical features with lightweight deep learning significantly improves both classification performance and computational efficiency.

5. CONCLUSION

This study proposes the Histogram-Guided Efficient Neural Assessment Network (HGENAN) for accurate and lightweight food quality assessment. The proposed framework integrates adaptive histogram enhancement, statistical feature extraction, lightweight convolutional learning, and feature fusion to overcome the limitations of conventional deep learning-based inspection systems. Experimental results demonstrate that HGENAN achieves 98.7% accuracy, 98.5% precision, 98.4% recall, and 98.4% F1-score. Furthermore, the model reduces inference latency to 566 ms for 40 image samples, which confirms its suitability for real-time edge deployment. The proposed method effectively balances accuracy and computational efficiency, making it appropriate for smart food monitoring systems, automated retail inspection, and intelligent agricultural applications.

Further development will be oriented toward making extensions to the HGENAN framework to increase its robustness and scalability, and enable practical application of it in real-life situations. This will involve introducing a bigger and more diversified food images dataset that will include various food types, various illumination settings, and different food image quality levels. Attention mechanisms and transformer-based lightweight architectures will be researched to achieve better feature representation at low computational costs. Extensions will also be made to make the framework capable of performing not only binary classification of food quality, but multi-class food quality grading, freshness estimation, and contamination detection all in one framework. Further research will be conducted in real-time framework implementation on low-resource devices like Raspberry Pi, NVIDIA Jetson, and embedded AI devices. Multimodal datasets with hyperspectral, thermal, and IoT sensors' data will be considered for improving assessment reliability. XAI will be used to ensure transparency and interpretability of the model's quality predictions. Further research will consider federated learning techniques to enable private and decentralized model training. Finally, the framework is capable of being integrated into smart agriculture and automated retail management cloud-based platforms.

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