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An Efficient CNN-based Model for Meat Quality Assessment: The Role of Artificial Intelligence Towards Sustainable Development

Ahmed Elmasry [1], **and Walid Abdullah** [1,*]

[1] Department of Computer Science, Faculty of Computers and Informatics, Zagazig University, Zagazig 44519, Egypt. Emails: a.elmasry24@fci.zu.edu.eg, waleed@zu.edu.eg.

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Abstract

The meat industry's pursuit of consistent and accurate quality assessment is essential to meet consumer demands and ensure food safety. Meat freshness is an important consideration when evaluating product quality and safety and has a significant impact on a consumer's purchasing decision. Traditional techniques that depend on visual inspection by humans are arbitrary and prone to discrepancies. In this paper, we propose a new deep learning architecture model based on convolutional neural networks (CNNs) for meat freshness classification. The model was trained on a meat images dataset to classify the red- meat images into two classes named "fresh" or "spoiled". The proposed model performance is compared against a set of deep transfer learning models. The obtained results show that the proposed model outperformed other models and achieved the best accuracy of 100% and 100% precision and recall in meat images quality classifications.

Keywords: Meat Quality; Deep Learning; Machine Learning; Computer Vision; Convolution Neural Network.

1 | Introduction

The meat industry plays a significant role in the global economy, the Global meat (beef, poultry, lamb, etc.) consumption continues to rise every year [1, 2]. The importance of quality in a consumer's purchase decision is increasing. Furthermore, studies reveal that the primary factor influencing a consumer's decision while making a purchase is the quality of the meat [3, 4]. Additionally, the value and price of these meat products directly correlate with their freshness and quality, making impartial classification essential [5].

Freshness is an important consideration when evaluating a product's quality and safety and has a significant impact on consumer purchases. The freshness decline can be measured in a variety of methods. these methods can be divided into two major measurement methods, subjective and objective methods [6, 7]. Most subjective methods rely on sensory evaluation, which includes eating and visual experiences. They can be hard to measure and heavily rely on the specific experience of the evaluators. On the other hand, objective evaluation methods based on analyzing the microorganisms and the physical and chemical properties of meat give

Corresponding Author: waleed@zu.edu.eg

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accurate results, but they can damage the meat product samples and are time-consuming methods, making it difficult for modern meat production companies to meet the demand for automated processing.

In recent years, The rapid development of computer technology and advancement of Artificial intelligence techniques such as Computer vision analysis, Machine learning, and deep learning techniques. This new technology provided an opportunity for researchers to develop an automated, objective method for evaluating the quality of meat [8]. The development of Computer vision and image processing technologies have been widely used in extracting image-based features and feature recognition related to detecting meat quality.in addition to machine learning techniques [9], Furthermore, by using machine learning techniques, systems can learn from data images of meat products and enhance their performance. By training machine learning algorithms to identify patterns in images, predictions of meat quality can be made based on that information [8, 10].

In this paper, we proposed a deep learning model architecture based on a Convolution neural network (CNN) for the Meat Quality Assessment task, The deep convolutional neural network architecture has been constructed and trained.to classify red meat images to images as "fresh" or "spoiled". A dataset consisting of 1896 images of spoiled and fresh meat products is utilized in this study to train the deep learning model. Convolutional Layers are a powerful tool that is used to extract an important feature from the image [11]. It can train and define patterns and edges or colors of the image, these features are used to distinguish between two classes of meat images with high accuracy.

The proposed model performance is compared against state-of-the-art deep transfer learning models such as Xception, Resnet50, and Mobilenet models. In terms of accuracy, precision, recall, F1 Score. And the results showed that. The proposed model outperformed all other models and achieved the best performance of 100 % accuracy and 100% precision and recall. experimental results which are explained in the paper, prove the power and usability of our proposed model to distinguish between fresh and spoiled meat products and identify the meat quality with high accuracy.

The rest of the paper is organized as follows. Section 2 lists and reviews some of the state-of-the-art techniques and related work in meat quality assessment and identification. Section 3 describes the utilized material and methods of this paper such as dataset and deep learning models including the proposed model. Section 4 provides the experiment setup and experimental results and discussions of the proposed models and other deep learning models for meat quality assessment and classifying. The implication of the proposed solution is presented in Section 5. Section 6 presents the conclusion of this paper.

2 | Related Work

In this section, we review relevant literature on the utilization of machine learning (ML) and computer vision techniques in the assessment of meat quality. By examining previous studies, we aim to identify gaps and highlight key findings, methodologies, and advancements in the field of meat quality assessment.

In [12], Deep Spectral–Spatial Features in Hyperspectral Images were utilized for the detection of Red-meat product adulteration. This study examined the use of the deep CNN model for self-extraction spectral and spatial features and the support vector machines (SVM) model for handmade spectral and spatial features from meat images. A collection of scanned images of muscles from lamb, livestock, or pork were collected while considering the meat's condition (fresh, frozen, thawed, and sample packed and unpacked using a clear bag). According to the results, regardless of the condition of the products, the CNN model performs the best, with an overall classification accuracy of 94.4%. This study demonstrates the effectiveness of hyperspectral imaging systems as quick, accurate, and non-destructive methods for identifying adulteration in red meat products. Furthermore, this research demonstrates that deep learning techniques, like CNN networks, offer strong characteristics for categorizing the hyperspectral information of meat products.

Authors in [2] proposed a deep CNN model for classifying meat from images as “fresh” or “spoiled”. The meat images were acquired from a stable camera that monitored a tray of meat cubes for a long time and took one image every two minutes, the model was compared to feature-based SVM classifiers with different attributes such as Histogram Attribute (Hist), Gray Level Co-Occurrence Matrix (GSEM), and Bag of Features (BoF) and the results conducted that The proposed CNN architecture outperformed the SVM systems fed with different attributes, It gave better results than all others with accuracy of 99.62 and 99.58 for training and testing data respectively.

In [13], The Authors utilized a deep transfer learning method based Resnet-50 model for Beef Quality Classification, the authors proposed using a Generative Adversarial Network (GAN) to make image augmentation to overcome image resource limitation due to the few number of images in the utilized dataset. The proposed model was compared against classical deep learning models and the results demonstrated that the Resnet-50 has the best accuracy among them. It achieved an accuracy of 96.03%, 91.67%, and 88.89% in the training, testing, and validation phases, respectively.

Geronimo et al. [14]. used computer vision technology with near-infrared spectroscopy (NIS) for the detection and identification of chicken with wooden breast (WB), which causes changes in meat appearance, the authors Combined image analyses and spectral information obtained by NIR and computer vision with a SVM classification model to classify wooden breast in images. The experiments showed that the proposed method can identify WB correctly with an accuracy of 91.8%.

Another Study presents an implementation of the Principal Component Analysis (PCA) and SVM algorithms on an embedded system based on a Digital Signal Processor (DSP) for meat quality assessment applications to classify and predict the freshness of beef meat [15]. Eighty-one hue, saturation, and intensity (HSI) images of beef steak were utilized in the dataset for the study. Whereas the PCA serves as a projection and prediction model, and the SVM is utilized for the identification and classification of beef meat. The model's results demonstrated that the PCA prediction model was able to forecast the new unknown samples perfectly, while the SVM model was able to identify and classify the samples with a 100% success rate.

Computer vision and deep neural networks (DNNs) were also utilized in [8] to estimate the quality of the beef using the color score of the muscle of the beef meat, This classification model engine applies the Inception-V4 model the experiments conducted by four hundred beef rib-eye steaks were selected and purchased, the color score of the beef was determined by experts using normal color, model The best performance percentage of 90.0% was attained by the proposed DNN classifier, demonstrating that computer vision combined with the DNN method can produce an effective implementation for predicting beef quality based on color scores of beef muscle.

Several studies used Computer vision technology with different Machine learning models such as Linear regression and support vector machines for predicting, identifying, and classifying the quality of meat products based on extracted color features from the images such as HSI and HSL (hue, saturation, lightness) [16, 17]. The obtained results showed that computer vision methods can be employed for rapid analysis of the quality of meat products by predicting image color attributes of meat products.

While these studies have made significant strides in automating meat quality assessment, there remains a need for robust, some of these studies lack high accuracy in the classification of meat quality. Some other methods lack a small dataset of data to train the machine learning system. Our study aims to contribute to this continuous conversation by developing and evaluating the proposed convolutional neural network (CNN) powerful architecture model specifically designed for classifying fresh meat based on visual attributes by utilizing a large dataset to train the proposed model.

3 | Materials and Methods

In this section, the experimental procedures and methodology employed in our study to develop and evaluate the proposed CNN model architecture are detailed. In addition, we outline the utilized dataset used, the preprocessing steps, and the models' training procedures.

3.1 | Utilized Dataset Description

In this paper, we use the Meet Quality Dataset [18]. which consists of 1896 images and consists of 2 classes “fresh” and “spoiled”, Each Class of data has 984 images. The Data Set was collected by IP Camera with a resolution of 1280 * 720. Expert data has been provided as a reference label at the same time as taking images.

3.2 | Data Preprocessing

The data set is entered into the system to be pre-processed to improve the performance of deep learning models. In this paper, the Preprocessing step was done by normalizing the data to speed up the convergence speed. This method is based on rounding the pixels of the images from 0 to 1 through an Eq. (1).

$$I' = I/255 \quad (1)$$

where I' is a normalized image, I the input image, and the grayscale image's maximum intensity value per pixel is represented by 255.

3.3 | Building Deep Learning Models

In this work, a group of deep learning models were trained using the Transfer Learning technique [19], namely Xception, ResNet50, and MobileNet, and a comparison was made between them and the proposed model.

3.3.1 | Xception

Xception [20] is a novel convolutional neural network architecture inspired by Inception. Inception modules have been replaced with depthwise separable convolutions.

3.3.2 | ResNet50

Resnet [21] is a convolutional neural network based on the skip Connection technique. The benefit of skip connection is avoiding the vanishing gradient problem. This paper used Resnet 50 which consists of 50 layers (48 convolutional layers, one maxpooling, and one averagePoling).

3.3.3 | MobileNet

MobileNet [22] is a version of the CNN model introduced by Google and is based on the DepthWise separable convolution which consists of two main stages first Stage is depthwise convolution Applies one Convolution Filter for Each input Channel Second stage applies pointwise Convolution to make a linear combination between all output.

3.4 | Proposed Model

The proposed deep learning model is based on CNN, it consists of two convolutional layers used to extract an important feature from the image. Convolutional layers perform convolutions on the input image using a collection of learnable filters, or kernels, to extract important features from images [11]. CNNs have demonstrated advances in a variety of computer vision tasks. followed by Maxpooling which is used to downsample the image by extracting the maximum value from the feature map, pooling layers help reduce the feature maps by a constant factor, and as a result, it helps in highlighting the most important features. Maxpooling layers are used followed by Dropout layers to avoid overfitting through comprises a random selection of neurons that are deactivated. The following GlobalAverage pool is used to downsample the input by averaging the width and height of it. Finally, a fully connected layer, followed by a drop-down layer, and then the output layer. Figure 1 shows the architecture of the proposed model.

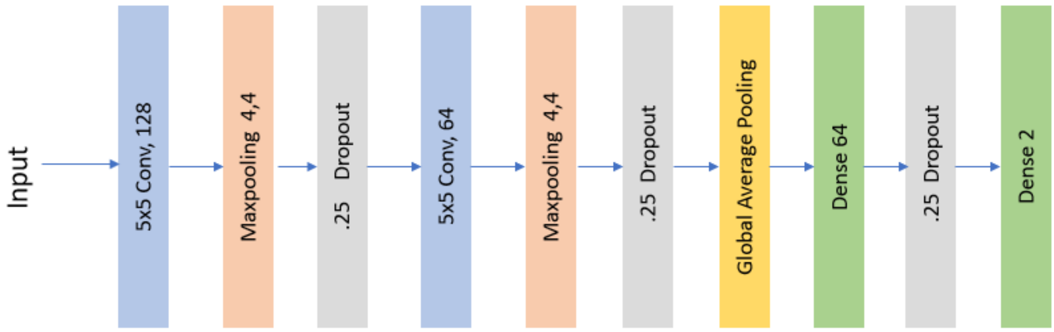

Figure 1. The proposed model architecture.

3.5 | Deep Learning Models Hyperparameters Tuning

At this stage, deep learning models were created with the default parameters. All models were compiled to determine the used loss function. the Adam Optimizer was used to measure the error rate, and the evaluation metrics were used to evaluate its performance. The Categorical cross entropy (CCE) loss function is used to optimize the initial weights of certain DL models to increase classification accuracy. The loss function is mathematically defined as shown in Eq. (2).

Minimize: $\text{loss(CCE)} = -\sum_{i=1}^{M} y_i \cdot \log \breve{y}_i$ (2)

Where y_i is true value $\breve{y}_i$ is shorthand for a vector that contains all of the outputs that were predicted based on the training samples.

All deep learning models were trained using Adam optimizer, with a learning rate of .0001, and applying mini-batch gradient descent to minimize error [23, 24]. it is calculated by the CCE Loss function by updating the weights on a small sample of images from the training dataset. The number of images in the training Data Set is 1516 and we use batch size 32 This means weights change 48 times for each epoch. Figure 2 shows the proposed system for Meat Quality Classification.

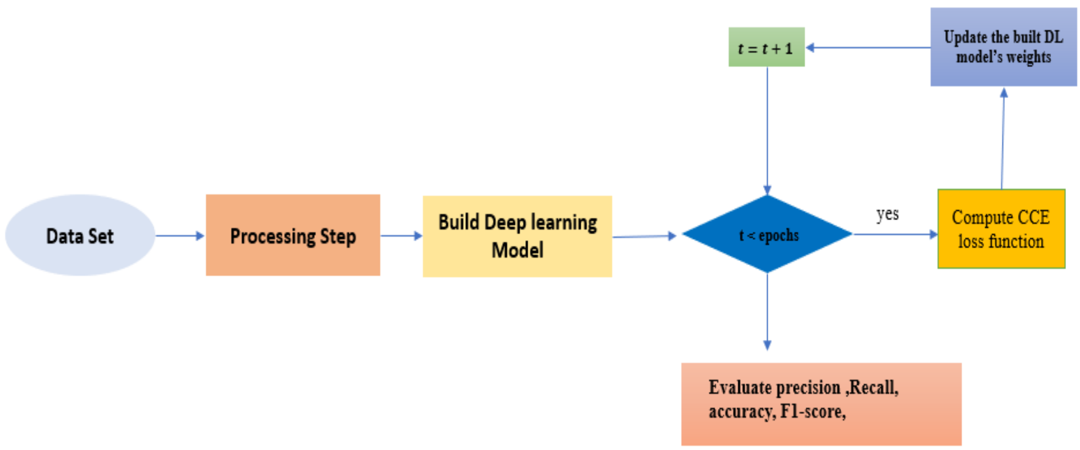

Figure 2. The proposed system for meat quality classification.

4 | Results and Discussions

In this section, the performance of the proposed model and the deep transfer learning models (Xception, ResNet50, and MobileNet) were measured with the utilized dataset for this study. After that, the proposed methods are thoroughly evaluated and compared against state-of-the-art deep transfer learning models In terms of accuracy, precision, recall, and F1 Score.

4.1 | Experimental Environment Setup

The Experiments were conducted on a Kaggle environment, with a Nvidia Tesla P100 GPU and RAM of 16 GB, the deep learning models were built using Python version 3.7.6 and Keras version 2.3.1 [25].

4.2 | Evaluation Metrics

In order to evaluate the utilized Deep learning models (Xception, ResNet50, and MobileNet) against the proposed model, the comparison is made between these models with the Proposed model by training the models in the Meet Quality Data Set [18]. through a set of metrics namely, Accuracy, precision, recall, and F1-score.

- **Accuracy:** This metric is calculated from the number of correct predictions for all categories to the total number of predictions. The equation is as follows

$$\text{Accuracy} = \frac{(\text{TP}+\text{TN})}{(\text{TP}+\text{FP}+\text{TN}+\text{FN})} \tag{3}$$

- **Precision:** This measure is calculated from the number of correct predictions for a category to the total number of predictions in the same category. The equation is as follows

$$\text{Precision} = \frac{\text{TP}}{(\text{TP}+\text{FP})} \tag{4}$$

- **Recall:** This statistic is used to display the proportion of accurately predicted samples for a class compared to all samples of the same class in a dataset. This metric can be calculated as follows.

$$\text{Recall} = \frac{\text{TP}}{(\text{TP}+\text{FN})} \tag{5}$$

- **F1 Score:** This metric is calculated by the harmonic mean of precision and recall. The equation as follows

$$\text{F1 Score} = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \tag{6}$$

4.3 | Experimental Results

The proposed model and the mentioned models were trained on 80% of the Quality Meet data, and the remaining images were tested. The image was resized to 224,224 and normalized to a division of 255. Table 1 shows the performance of models with different metrics (accuracy, precision, recall, and F1-score). The proposed model achieved the best accuracy with 1.0 the Xception model achieved the lowest accuracy with 0.963. Figure 3 shows the Rank of each model with different matrices. The proposed model achieved the highest rank, followed by the ResNet50 model. Figure 4 shows the Confusion Matrix used to describe the performance of a Proposed model from a Visualizes and Summarize it.

Table 1. Performance of the deep learning models.

Model	Accuracy	Precision	Recall	F1 Score
Xception	0.963	0.966	0.963	0.963
ResNet50	0.979	0.979	0.979	0.979
MobileNet	0.979	0.979	0.979	0.979
Proposed Model	**1.0**	**1.0**	**1.0**	**1.0**

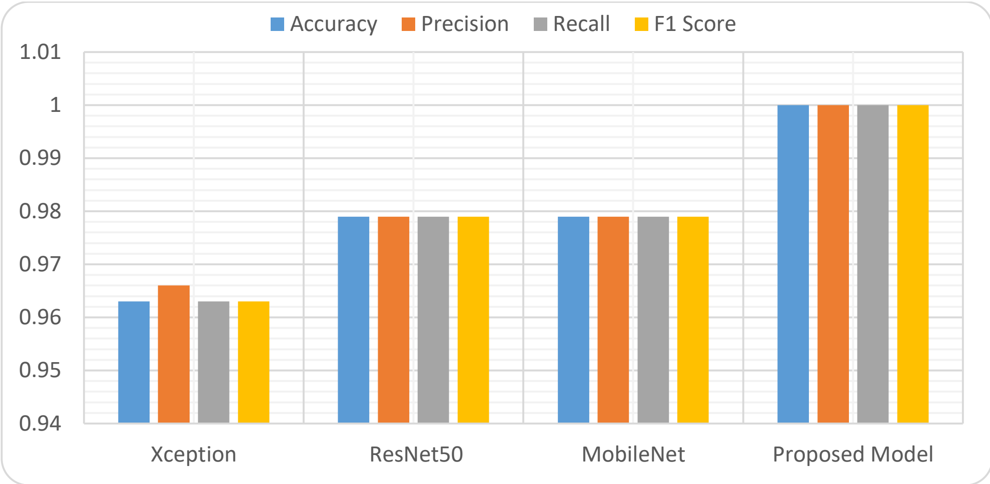

Figure 3. The proposed model Performance against other models.

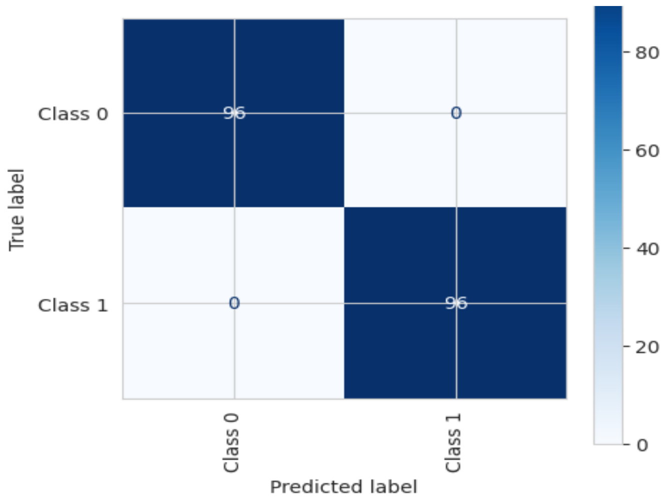

Figure 4. Confusion matrix of the proposed model.

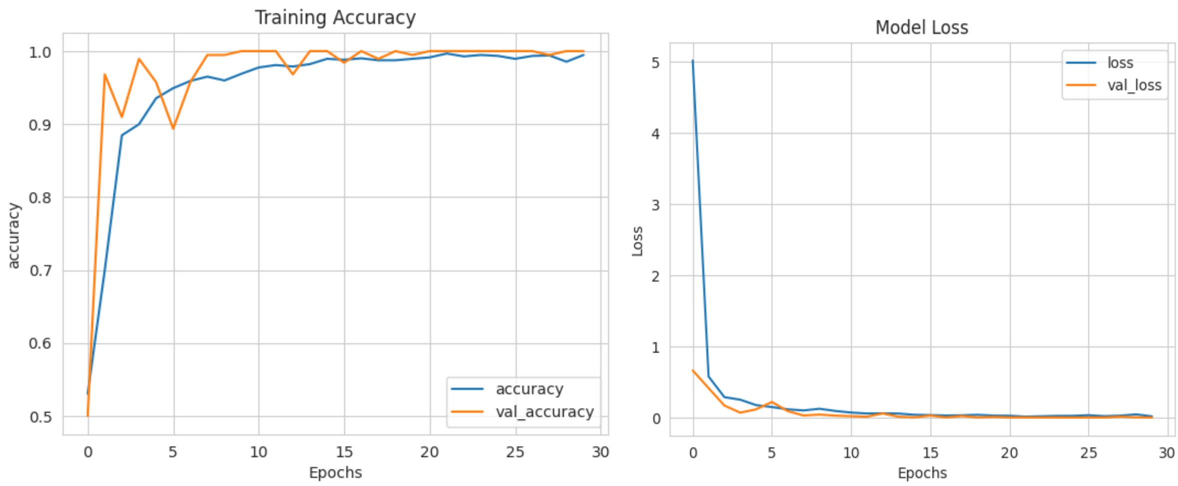

Figure 5. Loss and accuracy curves of the proposed model on the utilized Dataset.

5 | Implications

The meat industry plays a significant role in the global economy. Global meat consumption continues to rise every year, and the importance of quality in a consumer's purchase decision is increasing. Furthermore, the value and price of these meat products directly correlate with their freshness and quality, making impartial classification essential. Automating the process of evaluating meat and detecting spoiled meat using artificial intelligence techniques such as deep learning models can help meat production companies to meet the demand for automated processing, This ensures the safety of food for the buyer and has significant economic implications for the meat industry and trade.

Ensuring the quality of food is in line with Egypt's Vision 2032 and relevant to many of the important Sustainable Development Goals (SDG) such as Zero Hunger [26], which aims to end hunger, achieve food security and improved nutrition, and promote sustainable agriculture, also it is relevant to good health, Economic Growth and Industry, Innovation Goals, which makes Ensuring the quality of meat one of the most important and influential fields in this time.

6 | Conclusion and Future Work

In this study, we propose a new deep learning architecture model based on convolutional neural networks (CNNs) for meat freshness classification. The model was trained on a meat images dataset to classify the red-meat images into two classes named "fresh" or "spoiled". and its performance was compared against a set of deep transfer learning models in terms of Accuracy, precision, recall, and F1 score. The experimental results demonstrated that the proposed model outperformed other models and achieved the best accuracy pereion and recall of 100 % and 100% in meat image quality classifications and predictions. The results proved the power and usability of our proposed model to distinguish between fresh and spoiled meat products and identify the meat quality with high accuracy. Future directions may include utilizing an Enhanced dataset for training the CNN model which may improve its generalization ability and robustness across a wider range of meat types, cuts, and processing conditions. Furthermore, investigating alternative CNN architectures or fine-tuning hyperparameters could lead to further improvements in classification accuracy and efficiency, particularly in handling complex visual features associated with meat quality.

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Author Contribution

All authors contributed equally to this work.

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Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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