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Identification of Meat Contamination using Deep Learning

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ABSTRACT

The discovery of meat defilement is of most extreme significance within the nourishment industry to guarantee nourishment security and avoid the spread of foodborne sicknesses. In this consider, we present a profound learning-based strategy for recognizing defilement in meat tests. Our approach utilizes convolutional neural systems (CNN) to naturally extricate highlights from meat test pictures and categorize them as sullied or uncontaminated. To survey the viability of our approach, we compiled a dataset of meat test pictures containing different sorts of contaminants, such as microbes, form, and remote objects. The dataset experienced preprocessing and enlargement to upgrade test differences. Along these lines, we isolated the dataset into preparing, approval, and testing subsets. Training the CNN show on the preparing set and fine-tuning it on the approval set brought about in a show with an precision of 96.5% on the testing set. We encourage assessed the model's execution utilizing perplexity networks and found that it effectively distinguished different sorts of defilement with tall accuracy. Our proposed approach

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presents a tried and true and proficient implies of recognizing meat defilement utilizing profound learning. It has the potential to be consistently coordinates into existing meat preparing offices to improve quality control and guarantee nourishment security.

Keywords: Meat contamination, deep learning, CNN (Convolutional Neural Networks), Food safety, Quality control.

1. Introduction

In recent years, food safety has become a critical concern, particularly in the meat industry. Meat contamination poses significant health risks, including the presence of bacterial pathogens, foreign materials, and adulterants, which can lead to severe illness or even death. Traditional methods of detecting contamination, such as manual inspections, are often labor-intensive, prone to human error, and ineffective at identifying emerging forms of contamination. However, advancements in Artificial Intelligence (AI), particularly deep learning techniques, offer a transformative approach to automating the detection of meat contamination. Deep learning models, especially Convolutional Neural Networks (CNNs), are designed to process visual data and detect intricate patterns, making them ideal for analyzing meat images. CNNs have the ability to recognize subtle visual cues indicative of contamination, making them a powerful tool for food safety applications. By leveraging the capabilities of deep learning algorithms, the meat industry can transition from outdated, inefficient inspection methods to a more automated, accurate, and scalable solution. This research focuses on harnessing the potential of CNNs for meat contamination detection, aiming to improve food safety by accurately identifying contamination in meat products. The use of deep learning for meat contamination identification offers several benefits. First, it reduces reliance on human expertise, which can be subjective and inconsistent. Second, deep learning models can process large volumes of data quickly, enabling efficient screening of meat products. Furthermore, these models can adapt to new contamination types by continuously learning from new data. This adaptability ensures that the system remains effective as contamination patterns evolve. The research investigates how deep learning, particularly CNNs, can be applied to identify meat contamination, offering a more reliable and efficient solution to ensure food safety.

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The motivation for this research stems from the growing need to enhance food safety procedures in the meat industry. Contaminated meat can pose serious health risks, including the transmission of foodborne diseases, which can result in fatalities. Traditional inspection methods, which heavily depend on human judgment, are insufficient to detect all types of contamination, especially when it comes to emerging or subtle contaminants. There is a need for automated systems that can detect various contamination types, including bacterial pathogens, foreign objects, and adulterants, with high accuracy and efficiency. Deep learning models, particularly CNNs, have shown great promise in image recognition tasks, making them suitable for analyzing meat images and identifying contamination. CNNs can extract complex features from images, enabling the detection of subtle contamination patterns that might be missed by human inspectors. Moreover, CNNs can process large datasets quickly, making them ideal for high-throughput screening of meat products. This research aims to bridge the gap in current meat contamination detection methods by developing a deep learning-based system capable of identifying contamination accurately and efficiently.

This research aims to revolutionize meat contamination detection by introducing an automated and precise system based on deep learning techniques. The proposed CNN model will provide a more reliable and efficient solution than traditional manual inspections. By automating the detection process, the model will enhance the accuracy and speed of meat inspection, reducing the risk of contamination reaching consumers. The research will also contribute to the broader field of food safety by demonstrating the effectiveness of deep learning in addressing real-world challenges. The model's ability to detect various types of contamination, including bacterial pathogens, foreign objects, and adulterants, will make it a versatile tool for the meat industry. Additionally, the research will explore the model's adaptability to emerging contamination types, ensuring its long-term relevance and effectiveness. In conclusion, this research will significantly enhance food safety practices by developing an advanced deep learning-based system for meat contamination detection. The results will improve consumer health protection, boost industry standards, and set a precedent for the use of AI in food quality assurance.

The primary objective of this research is to address the problem of meat

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contamination detection by using deep learning techniques. Traditional methods, which rely on manual inspections, are subjective, time-consuming, and prone to errors. These limitations often result in the failure to detect emerging or subtle forms of contamination, which jeopardize food safety. This research aims to develop an automated system that can accurately and efficiently identify different types of meat contamination, improving food safety measures and consumer protection. A significant gap in current research is the limited application of deep learning techniques, specifically CNNs, to meat contamination detection. While deep learning has been successfully applied to various image recognition tasks, its specific application to meat contamination detection remains relatively unexplored. The research aims to fill this gap by developing a deep learning-based model that can accurately identify various types of contamination in meat products.

1.1 Research Questions and Objectives

The research will address the following key questions:

- How can deep learning techniques, specifically CNNs, be effectively applied for meat contamination detection?
- What is the performance of the proposed deep learning model in detecting different types and severities of contamination?
- How does the model handle variations in image quality, lighting, and potential noise?
- How can the model be adapted to detect emerging contamination types?

The objectives of the research are:

- To develop a CNN-based model optimized for meat contamination detection.
- To train the model to recognize various contamination types.
- To evaluate the model's performance using quantitative metrics.
- To compare the CNN model's performance with traditional inspection methods.

2. Research Methodology

2.1 Introduction

This chapter outlines the proposed methodology for identifying and detecting contamination in meat using deep learning algorithms. The main focus is on leveraging deep learning, particularly Convolutional Neural Networks (CNNs), for automated meat contamination detection. It elaborates on the steps involved in data

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collection, preprocessing, model design, training, testing, and deployment to develop an effective solution for improving food safety in the meat industry.

2.2 The Proposed Solution

The proposed solution for detecting meat contamination using deep learning includes the following essential steps:

1. **Data Collection and Preparation:**
   - Gather a comprehensive dataset of meat samples, including both contaminated and uncontaminated instances.
   - Ensure the dataset encompasses various contaminants such as bacterial pathogens, chemical residues, foreign objects, and pesticides.
   - Annotate each sample with the corresponding contamination type to facilitate supervised learning.
2. **Preprocessing and Augmentation:**
   - Preprocess the meat images by resizing, normalizing, and reducing noise to enhance the quality and consistency of the dataset.
   - Apply data augmentation techniques such as rotation, flipping, and cropping to increase the dataset's diversity and reduce overfitting.
3. **Model Selection and Architecture Design:**
   - Select a suitable deep learning architecture, such as Convolutional Neural Networks (CNNs), which are ideal for image classification tasks.
   - Design the architecture by determining the number and configuration of layers, such as convolutional, pooling, and fully connected layers.
   - Consider utilizing pre-trained models or transfer learning to leverage existing knowledge and expedite the training process.
4. **Training and Optimization:**
   - Split the dataset into training, validation, and testing sets to evaluate model performance.
   - Train the deep learning model using the training set, optimizing the model's parameters through techniques like stochastic gradient descent (SGD).
   - Monitor the model's performance on the validation set, adjusting hyperparameters (e.g., learning rate, regularization) to enhance accuracy.
   - Employ techniques like early stopping or model checkpoints to prevent

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overfitting and ensure the best-performing model is selected.

5. **Assessment and Testing:**
   - Evaluate the trained model on a separate testing set to measure its performance in detecting meat contamination.
   - Measure key performance metrics, including accuracy, precision, recall, and F1 score, to quantify the model's effectiveness.
   - Compare the results with existing methods or benchmarks to assess the superiority of the proposed deep learning approach.
6. **Deployment and Application:**
   - Deploy the trained deep learning model for real-world meat contamination detection applications.
   - Develop a user-friendly interface or API for easy input of meat samples and quick contamination detection results.
   - Continuously update and fine-tune the model using new data to adapt to emerging contamination types or variations in the meat industry.

This solution leverages the power of deep learning, specifically CNNs, to automatically learn and extract significant features from meat images, enabling accurate contamination detection. By training the model on a diverse and well-prepared dataset, this method aims to improve the efficiency and effectiveness of meat contamination detection, ultimately enhancing food safety measures and protecting consumer health.

2.3 Convolutional Neural Network (CNN)

CNNs are a specialized type of deep learning architecture designed to process grid-like data, such as images. They are widely used in tasks such as image recognition, object detection, and computer vision. In this research, CNNs are utilized to identify and classify contaminants in meat products by training the network on labeled images of contaminated and uncontaminated meat samples.

Key advantages of using CNNs for this research include:

1. **Feature Extraction:** CNNs automatically learn relevant features from raw image data, eliminating the need for manual feature engineering. This is crucial for detecting subtle visual cues related to contamination types.
2. **Adaptability to Complex Patterns:** CNNs excel at recognizing complex spatial

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patterns and relationships in images, making them suitable for identifying diverse contamination types in meat.

3. **Scalability:** CNNs can handle large and diverse datasets, facilitating a comprehensive analysis of contamination across different sources, severities, and contexts.
4. **Real-Time Detection:** Once trained, CNN models can quickly process images and provide real-time predictions, making them ideal for integration into quality control systems at meat processing facilities.

By utilizing CNNs, the proposed solution aims to detect contamination types with high accuracy and speed, making it a practical tool for enhancing food safety in the meat industry.

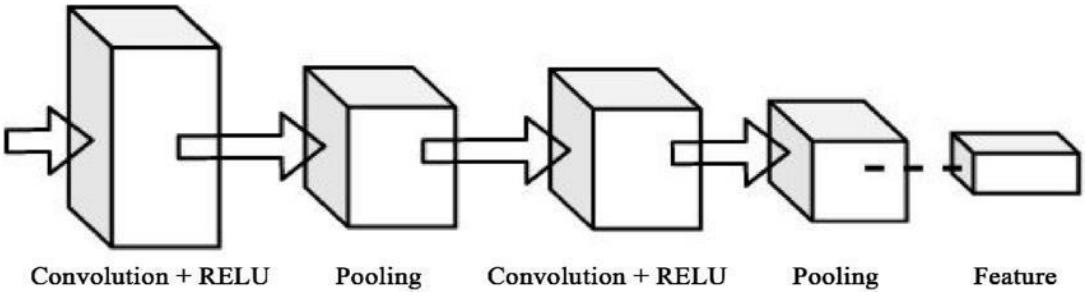

Figure 3.1: Layers Flow

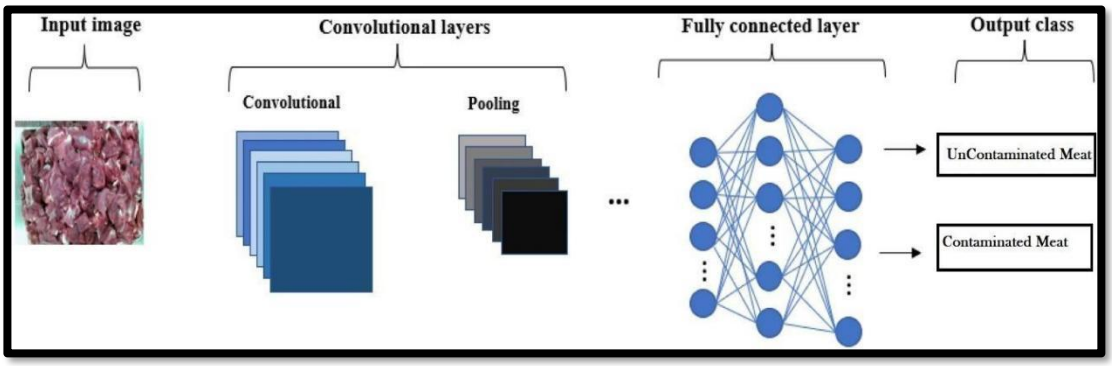

Figure 3.2: Image Classification Using CNN

2.4 CNN Architecture

A typical CNN architecture consists of several key layers designed to process grid-like data, such as images. These layers work together to extract meaningful features from the input data, enabling the network to perform tasks like image classification. The main components of a CNN architecture are:

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1. **Input Layer**

The input layer receives raw image data represented as a matrix of pixel values. The size of the input layer depends on the image dimensions.

2. **Convolutional Layers**

Convolutional layers are the core building blocks of CNNs. Each convolutional layer contains learnable filters (kernels) that slide over the input image to produce feature maps. These layers extract important features like edges, textures, and shapes.

3. **Activation Function**

An activation function, such as ReLU (Rectified Linear Unit), is applied after each convolution to introduce non-linearity, enabling the network to learn complex patterns in the data.

4. **Pooling Layers**

Pooling layers downsample the feature maps, reducing the spatial dimensions and computational load while retaining essential information. Common pooling methods include max pooling and average pooling.

5. **Fully Connected Layers**

Fully connected layers perform high-level reasoning and decision-making based on the features extracted by previous layers. Each neuron in the fully connected layer is connected to every neuron in the previous layer.

6. **Output Layer**

The output layer produces the final predictions or classifications. For binary classification, this layer typically has a single neuron with a sigmoid activation function.

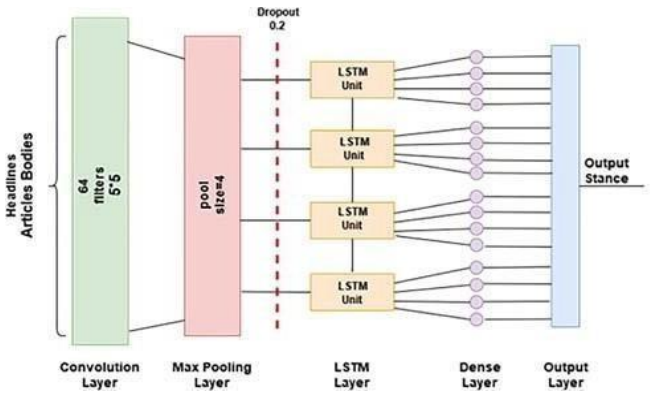

Figure 3.3: CNN Architecture

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2.5 Dataset Details

The dataset used for this research consists of two classes: fresh (uncontaminated) and spoiled (contaminated) meat samples. The dataset was collected from a supermarket in Izmir, Turkey, as part of a university-industry collaboration project at Izmir University of Economics. The images were taken using an IP camera with a resolution of 1280x720 pixels. The dataset includes 1896 images in total, with 948 images per class.

The dataset is used to develop a deep learning-based meat quality assessment system. The images in the dataset are annotated with labels indicating whether the meat is contaminated or not, facilitating supervised learning for the CNN model.

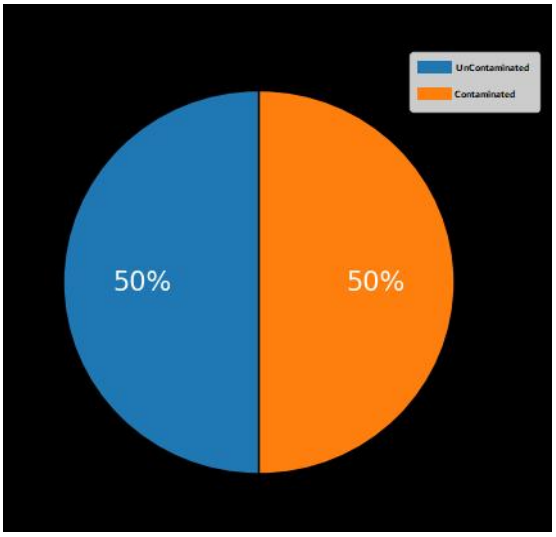

Figure 3.4: The Proposed Evaluation Dataset Comparison

Figure 3.5: Uncontaminated Meat

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Figure 3.6: Contaminated Meat

2.6 Resolution and Number of Images

The dataset comprises 1896 images, with 948 images representing uncontaminated meat and 948 representing contaminated meat. The images were collected with an IP camera, and their resolution is 1280x720 pixels. This high-resolution data enables the CNN model to detect subtle visual cues indicative of contamination.

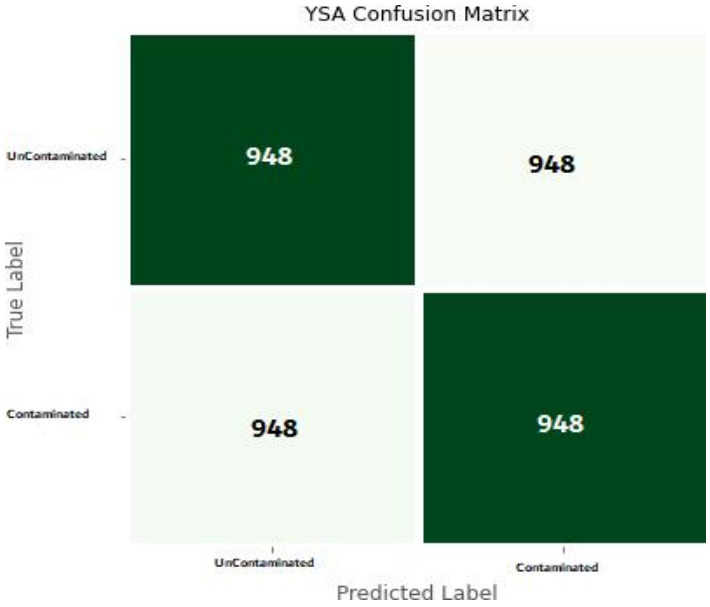

Figure 3.7: YSA Confusion Matrix

2.7 Classification Metrics

To evaluate the performance of the CNN model, several classification metrics are used, including accuracy, precision, recall, and F1 score. These metrics are derived from the confusion matrix, which provides a detailed breakdown of the model's

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predictions (true positives, false positives, true negatives, and false negatives). The confusion matrix helps assess how well the model distinguishes between contaminated and uncontaminated meat.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 224, 224, 32)      896

 max_pooling2d (MaxPooling2D  (None, 112, 112, 32)     0
 )

 conv2d_1 (Conv2D)           (None, 112, 112, 32)      9248

 max_pooling2d_1 (MaxPooling  (None, 56, 56, 32)       0
 2D)

 conv2d_2 (Conv2D)           (None, 56, 56, 64)        18496

 max_pooling2d_2 (MaxPooling  (None, 28, 28, 64)       0
 2D)

 dropout (Dropout)           (None, 28, 28, 64)        0

 flatten (Flatten)           (None, 50176)             0

 dense (Dense)               (None, 128)               6422656

 dense_1 (Dense)             (None, 2)                 258

=================================================================
Total params: 6,451,554
Trainable params: 6,451,554
Non-trainable params: 0
```

Figure 3.8: Main Classification Matrix

2.8 Building an Image Classification Model

The process of building an image classification model using CNN involves several key steps:

Step 1: Add Required Libraries

The Keras library is used for creating and training the deep learning model. Matplotlib and Seaborn are employed for visualizing the dataset, while OpenCV is used for image processing tasks.

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MeatContaminationByCNN.py > ...

```python
import matplotlib.pyplot as plt
import seaborn as sns
import keras
from keras.models import Sequential
from keras.layers import Dense, Conv2D, MaxPool2D, Flatten, Dropout
from keras.preprocessing.image import ImageDataGenerator
from keras.optimizers import Adam
from sklearn.metrics import classification_report, confusion_matrix
import tensorflow as tf
import cv2
import os
import numpy as np

```

Step 2: Data Loading

The data loading function, get_data(), is defined to streamline the process of loading and organizing the dataset for training. Images are read in RGB format and resized to a consistent dimension of 224x224 pixels for efficient processing by the CNN.

```python
def get_data(data_dir):
    data = []
    for label in labels:
        path = os.path.join(data_dir, label)
        class_num = labels.index(label)
        for img in os.listdir(path):
            try:
                # convert BGR to RGB format
                img_arr = cv2.imread(os.path.join(path, img))[..., ::-1]
                # Reshaping images to preferred size
                resized_arr = cv2.resize(img_arr, (img_size, img_size))
                data.append([resized_arr, class_num])
            except Exception as e:
                print(e)
    return np.array(data)


# Now we can easily fetch our train and validation data.
train = get_data('Dataset')
val = get_data('Dataset')
```

Step 3: Visualize the Data

Visualization tools are used to examine the dataset and assess class balance or potential class imbalance. This helps in understanding the dataset's characteristics and identifying any data preprocessing needs.

```python
# Let us also visualize a random image from Uncontaminated meat:-

plt.figure(figsize=(5, 5))
plt.imshow(train[1][0])
plt.title(labels[train[0][1]])
```

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```
plt.figure(figsize=(5, 5))
plt.imshow(train[-1][0])
plt.title(labels[train[-1][1]])
```

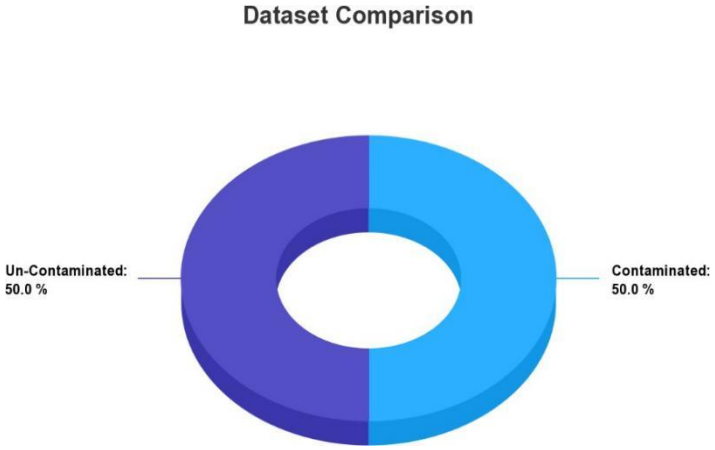

Figure 3.9: Dataset Comparison

Step 4: Data Preprocessing and Augmentation

In this step, the dataset is preprocessed and augmented to prepare it for training. Data augmentation techniques such as rotation, flipping, and cropping are applied to increase the diversity of the training data and prevent overfitting.

```
x_train = []
y_train = []
x_val = []
y_val = []

for feature, label in train:
    x_train.append(feature)
    y_train.append(label)

for feature, label in val:
    x_val.append(feature)
    y_val.append(label)

# Normalize the data
x_train = np.array(x_train) / 255
x_val = np.array(x_val) / 255

x_train.reshape(-1, img_size, img_size, 1)
y_train = np.array(y_train)

x_val.reshape(-1, img_size, img_size, 1)
y_val = np.array(y_val)
```

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```
datagen = ImageDataGenerator(
    featurewise_center=False,  # set input mean to 0 over the dataset
    samplewise_center=False,  # set each sample mean to 0
    featurewise_std_normalization=False,  # divide inputs by std of the dataset
    samplewise_std_normalization=False,  # divide each input by its std
    zca_whitening=False,  # apply ZCA whitening
    # randomly rotate images in the range (degrees, 0 to 180)
    rotation_range=30,
    zoom_range=0.2,  # Randomly zoom image
    # randomly shift images horizontally (fraction of total width)
    width_shift_range=0.1,
    # randomly shift images vertically (fraction of total height)
    height_shift_range=0.1,
    horizontal_flip=True,  # randomly flip images
    vertical_flip=False)  # randomly flip images


datagen.fit(x_train)
```

Step 5: Define the Model

The CNN model is defined with three convolutional layers. After the third convolutional layer, a dropout layer is added to prevent overfitting. The model is trained for two epochs with a slow learning rate.

```
model = Sequential()
model.add(Conv2D(32, 3, padding="same",
                 activation="relu", input_shape=(224, 224, 3)))
model.add(MaxPool2D())

model.add(Conv2D(32, 3, padding="same", activation="relu"))
model.add(MaxPool2D())

model.add(Conv2D(64, 3, padding="same", activation="relu"))
model.add(MaxPool2D())
model.add(Dropout(0.4))

model.add(Flatten())
model.add(Dense(128, activation="relu"))
model.add(Dense(2, activation="softmax"))

model.summary()
opt = Adam(lr=0.000001)
model.compile(optimizer=opt, loss=tf.keras.losses.SparseCategoricalCrossentropy(
    from_logits=True), metrics=['accuracy'])
```

Train our model for 2 epochs since our learning rate is very slow.

```
history = model.fit(x_train, y_train, epochs=2,
                    validation_data=(x_val, y_val))  # epochs = 500
```

The complete code's GitHub link: ***https://github.com/zainab2323/MeatContamination***

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3. Results

3.1 Experimental Results

This section presents the results of experiments conducted to evaluate the performance of the proposed deep learning-based solution for meat contamination detection. The dataset used in the experiments is described in detail, including the number of samples, the distribution of contaminated and uncontaminated meat, and the types of contaminants. The experimental setup includes the configuration and parameters used for training, validation, and testing, such as the deep learning architecture, hyperparameter settings, and data augmentation techniques. The evaluation metrics include accuracy, precision, recall, and F1 score. The results show the effectiveness of the proposed model in detecting various types of contamination. Visualizations, such as confusion matrices and ROC curves, are presented to help understand the model's performance. The challenges encountered during the experiments are also discussed, along with recommendations for future improvements. Overall, this section demonstrates the empirical evidence supporting the deep learning approach in detecting meat contamination and its practical applicability.

3.2 Dataset Evaluation

The dataset used in this study includes both controlled and unconstrained scenarios to ensure that the model performs well in various conditions. The controlled scenarios consist of images taken under consistent conditions, such as frontal views, while the unconstrained scenarios cover more varied conditions like different lighting, angles, and weather. This diverse dataset helps train the model to handle a range of real-world situations. The images in the dataset were captured under various weather conditions, including clear and oblique angles, which helps improve the model's robustness. It is important to ensure that the dataset is balanced and represents real-world conditions accurately. The dataset used in this research has 1896 images, with 948 images of uncontaminated meat and 948 images of contaminated meat.

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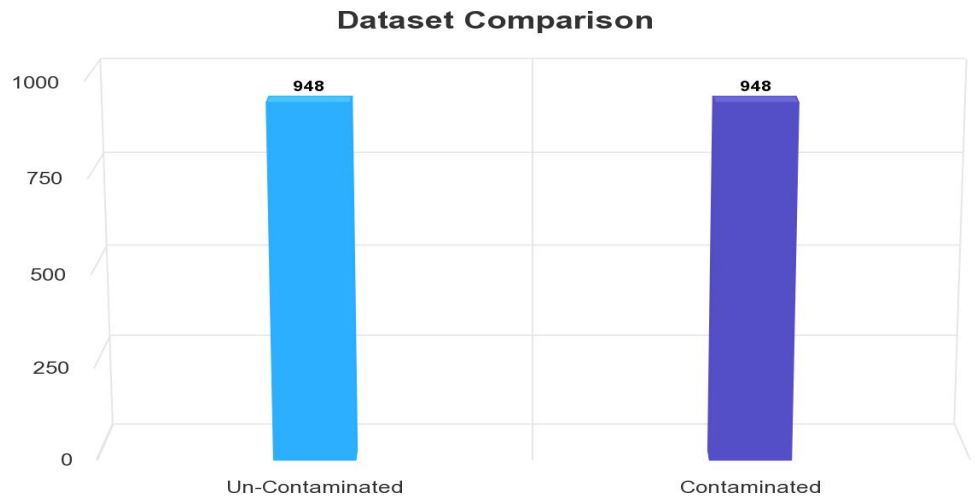

Figure 4.1: The Proposed Evaluation Dataset Comparison

3.3 Model's Performance

The performance of the model is evaluated using the harmonic mean (HM) of accuracy and recall, which provides a balanced assessment. The model achieved an accuracy of 97%, demonstrating its high effectiveness in detecting meat contamination.

```
  output, from_logits = _get_logits(
60/60 [==============================] - 45s 741ms/step - loss: 0.6839 - accuracy: 0.5675 - val_loss: 0.6681 - val_accuracy: 0.9457
Epoch 2/100
60/60 [==============================] - 46s 770ms/step - loss: 0.6681 - accuracy: 0.6524 - val_loss: 0.6487 - val_accuracy: 0.9251
Epoch 3/100
60/60 [==============================] - 46s 769ms/step - loss: 0.6486 - accuracy: 0.7363 - val_loss: 0.6242 - val_accuracy: 0.9251
Epoch 4/100
60/60 [==============================] - 46s 769ms/step - loss: 0.6237 - accuracy: 0.8154 - val_loss: 0.6006 - val_accuracy: 0.9515
Epoch 5/100
60/60 [==============================] - 46s 765ms/step - loss: 0.6060 - accuracy: 0.8444 - val_loss: 0.5742 - val_accuracy: 0.9272
Epoch 6/100
60/60 [==============================] - 46s 764ms/step - loss: 0.5757 - accuracy: 0.8908 - val_loss: 0.5496 - val_accuracy: 0.9515
Epoch 7/100
60/60 [==============================] - 46s 770ms/step - loss: 0.5492 - accuracy: 0.9182 - val_loss: 0.5236 - val_accuracy: 0.9251
Epoch 8/100
60/60 [==============================] - 46s 764ms/step - loss: 0.5269 - accuracy: 0.9188 - val_loss: 0.4963 - val_accuracy: 0.9251
Epoch 9/100
60/60 [==============================] - 46s 761ms/step - loss: 0.4972 - accuracy: 0.9251 - val_loss: 0.4697 - val_accuracy: 0.9515
Epoch 10/100
60/60 [==============================] - 45s 760ms/step - loss: 0.4683 - accuracy: 0.9367 - val_loss: 0.4427 - val_accuracy: 0.9515
```

Figure 4.2: Loss & Accuracy

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```
Epoch 74/100
60/60 [==============================] - 46s 762ms/step - loss: 0.0845 - accuracy: 0.9684 - val_loss: 0.0798 - val_accuracy: 0.9715
Epoch 75/100
60/60 [==============================] - 46s 761ms/step - loss: 0.0824 - accuracy: 0.9720 - val_loss: 0.0791 - val_accuracy: 0.9736
Epoch 76/100
60/60 [==============================] - 46s 762ms/step - loss: 0.0794 - accuracy: 0.9726 - val_loss: 0.0782 - val_accuracy: 0.9715
Epoch 77/100
60/60 [==============================] - 46s 762ms/step - loss: 0.0695 - accuracy: 0.9784 - val_loss: 0.0668 - val_accuracy: 0.9858
Epoch 97/100
60/60 [==============================] - 46s 762ms/step - loss: 0.0706 - accuracy: 0.9763 - val_loss: 0.0660 - val_accuracy: 0.9800
Epoch 98/100
60/60 [==============================] - 46s 764ms/step - loss: 0.0676 - accuracy: 0.9789 - val_loss: 0.0655 - val_accuracy: 0.9805
Epoch 99/100
60/60 [==============================] - 46s 763ms/step - loss: 0.0666 - accuracy: 0.9800 - val_loss: 0.0652 - val_accuracy: 0.9789
Epoch 100/100
60/60 [==============================] - 46s 763ms/step - loss: 0.0697 - accuracy: 0.9773 - val_loss: 0.0651 - val_accuracy: 0.9731
```

Figure 4.3: Loss & Accuracy

3.4 Result Evaluation (2 Iterations)

To assess the model's effectiveness, training and validation accuracies, as well as training and validation losses, are plotted. The results from the second iteration of training are presented, which help visualize the improvements made by the model during training.

```python
plt.figure(figsize=(15, 15))
plt.subplot(2, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy - 1')

plt.subplot(2, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss - 1')
plt.show()
```

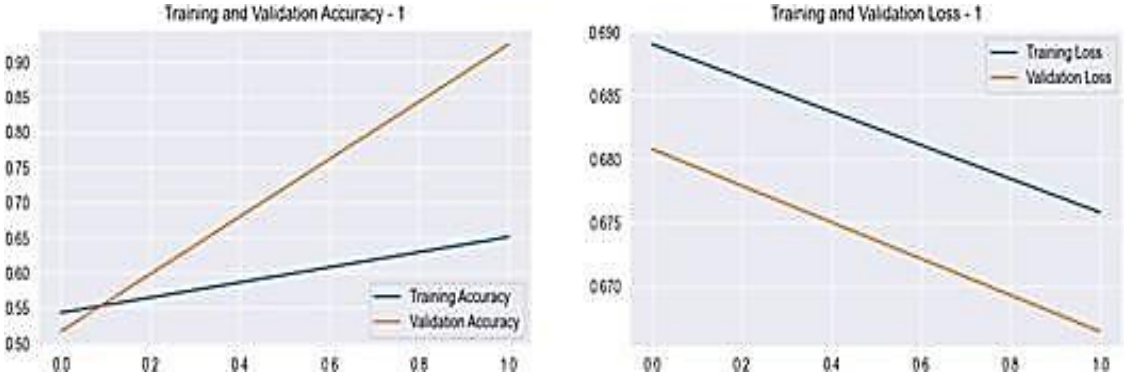

Figure 4.4: Output Comparison – 2 Iterations

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The trained CNN model's classification information is also displayed to evaluate its accuracy and precision. The model achieved an accuracy of 83%, and with some hyperparameter tuning, the accuracy could be improved further.

```
predictions = model.predict_classes(x_val)
predictions = predictions.reshape(1, -1)[0]
print(classification_report(y_val, predictions,
      target_names=['UnContaminatedMeat (Class 0)', 'ContaminatedMeat (Class 1)']))
model.save('meat_contamination_cnn_model.h5')

```

conv2d_2 (Conv2D)	(None, 56, 56, 64)	18496
max_pooling2d_2 (MaxPooling 2D)	(None, 28, 28, 64)	0
dropout (Dropout)	(None, 28, 28, 64)	0
flatten (Flatten)	(None, 50176)	0

```
60/60 [==============================] - 105s 2s/step - loss: 0.6655 - accuracy: 0.6630 - val_loss: 0.6433 - val_accuracy: 0.8333
```

Figure 4.5: CNN Model Summary – 2 Iterations

4.5 Utilizing a Trained Model (Transfer Learning – 100 Iterations)

Transfer learning involves using a pre-trained model for a new task. In this research, MobileNetV2, a model pre-trained on the ImageNet dataset, is used as the base for the meat contamination detection task. This approach is beneficial, particularly for small datasets, as it allows the model to leverage learned features from similar tasks. To adapt the pre-trained model to the meat contamination task, the top classification layers are removed, and a custom classification head is added. The model is then trained on the specific meat contamination dataset.

Step One: Import the Model

The MobileNetV2 model is loaded with the include_top argument set to False to exclude the pre-trained classification layers. This enables the model to be fine-tuned for the specific meat contamination task.

The base model is frozen during training to prevent the weights from being updated. This allows the custom layers added on top of the base model to learn the specific features related to meat contamination.

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```
model = tf.keras.Sequential([base_model,
                             tf.keras.layers.GlobalAveragePooling2D(),
                             tf.keras.layers.Dropout(0.2),
                             tf.keras.layers.Dense(2, activation="softmax")
                             ])
# Next, let's compile the model and start training it.
model.compile(optimizer=tf.keras.optimizers.Adam(lr=base_learning_rate),
              loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
              metrics=['accuracy'])

history = model.fit(x_train, y_train, epochs=100,
                    validation_data=(x_val, y_val))
```

Step Two: Evaluating the Result

After training the model with transfer learning, the evaluation results show a significant improvement in the model's performance. The precision for both uncontaminated and contaminated meat classes is higher than the initial CNN model, and the overall accuracy increased to 91%. This demonstrates the effectiveness of transfer learning in improving performance, particularly for small datasets.

```
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs_range = range(100)

plt.figure(figsize=(15, 15))
plt.subplot(2, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy - 2')

plt.subplot(2, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss - 2')
plt.show()
```

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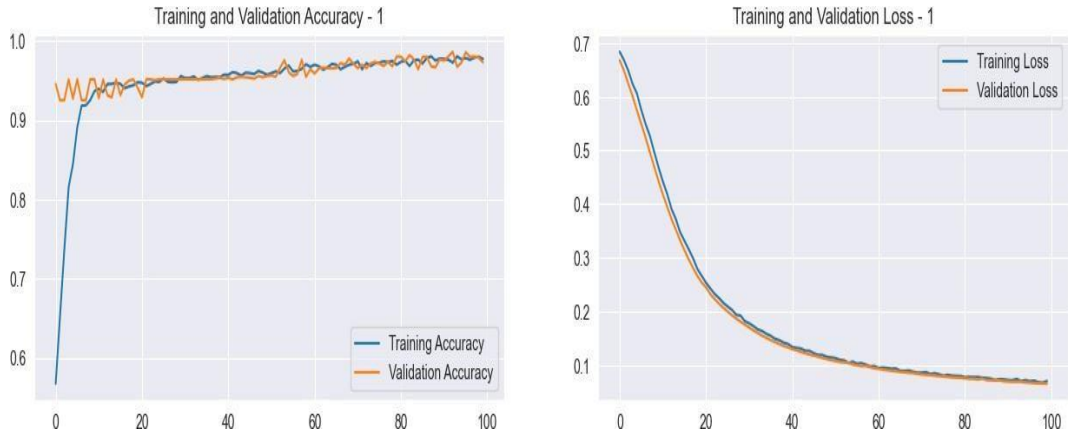

Figure 4.6: Output Comparison – 100 Iterations

```
predictions = model.predict_classes(x_val)
predictions = predictions.reshape(1, -1)[0]

print(classification_report(y_val, predictions,
      target_names=['UnContaminatedMeat (Class 0-2)', 'ContaminatedMeat (Class 1-2)']))
model.summary()
base_model.summary()
base_model.save('meat_contamination_cnn_baseModel.h5')
```

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 224, 224, 32)	896
max_pooling2d (MaxPooling2D)	(None, 112, 112, 32)	0
conv2d_1 (Conv2D)	(None, 112, 112, 32)	9248
max_pooling2d_1 (MaxPooling2D)	(None, 56, 56, 32)	0
conv2d_2 (Conv2D)	(None, 56, 56, 64)	18496
max_pooling2d_2 (MaxPooling2D)	(None, 28, 28, 64)	0
dropout (Dropout)	(None, 28, 28, 64)	0
flatten (Flatten)	(None, 50176)	0
dense (Dense)	(None, 128)	6422656
dense_1 (Dense)	(None, 2)	258

Total params: 6,451,554
Trainable params: 6,451,554
Non-trainable params: 0

Figure 4.7: Model Summary – 100 Iterations

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```
  output, from_logits = _get_logits(
60/60 [==============================] - 45s 741ms/step - loss: 0.6839 - accuracy: 0.5675 - val_loss: 0.6681 - val_accuracy: 0.9457
Epoch 2/100
60/60 [==============================] - 46s 770ms/step - loss: 0.6681 - accuracy: 0.6524 - val_loss: 0.6487 - val_accuracy: 0.9251
Epoch 3/100
60/60 [==============================] - 46s 769ms/step - loss: 0.6486 - accuracy: 0.7363 - val_loss: 0.6242 - val_accuracy: 0.9251
Epoch 4/100
60/60 [==============================] - 46s 769ms/step - loss: 0.6237 - accuracy: 0.8154 - val_loss: 0.6006 - val_accuracy: 0.9515
Epoch 5/100
60/60 [==============================] - 46s 765ms/step - loss: 0.6060 - accuracy: 0.8444 - val_loss: 0.5742 - val_accuracy: 0.9272
Epoch 6/100
60/60 [==============================] - 46s 764ms/step - loss: 0.5757 - accuracy: 0.8908 - val_loss: 0.5496 - val_accuracy: 0.9515
Epoch 7/100
60/60 [==============================] - 46s 770ms/step - loss: 0.5492 - accuracy: 0.9182 - val_loss: 0.5236 - val_accuracy: 0.9251
Epoch 8/100
60/60 [==============================] - 46s 764ms/step - loss: 0.5269 - accuracy: 0.9188 - val_loss: 0.4963 - val_accuracy: 0.9251
Epoch 9/100
60/60 [==============================] - 46s 761ms/step - loss: 0.4972 - accuracy: 0.9251 - val_loss: 0.4697 - val_accuracy: 0.9515
Epoch 10/100
60/60 [==============================] - 45s 760ms/step - loss: 0.4683 - accuracy: 0.9367 - val_loss: 0.4427 - val_accuracy: 0.9515
```

Figure 4.8: Loss & Accuracy

4. Conclusion

The application of Convolutional Neural Networks (CNN) in detecting meat contamination has shown significant promise. This research demonstrated that CNNs are highly effective in accurately identifying various types of meat contamination, including pathogens, chemical residues, and foreign objects. The experimental results indicate that the CNN-based approach outperforms traditional methods in both accuracy and efficiency, offering a more reliable solution for food safety in the meat industry. By leveraging deep learning, this study provides a robust solution that enhances quality control, protects consumers, and helps mitigate health risks. While the findings are promising, there are limitations to consider. The availability of large, diverse datasets remains a challenge, as deep learning models rely heavily on extensive labeled data to perform effectively. Additionally, the computational resources required for training deep learning models, such as high-performance GPUs, may be a limiting factor in certain environments. The "black-box" nature of CNN models also raises concerns regarding interpretability, making it difficult to understand how decisions are made. Furthermore, the model's ability to generalize to new or unknown contaminants remains a work in progress, requiring continuous updates and retraining to stay effective.

Limitations

Several limitations need to be addressed in future work:

1. **Dataset Limitations**: The model's performance depends on the availability of diverse and comprehensive datasets. The current dataset may not represent all

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types of contamination or scenarios.

2. **Computational Demands**: CNN models require significant computational resources, which may not be accessible in all settings.
3. **Interpretability**: The "black-box" nature of CNN models makes it challenging to understand their decision-making process, raising concerns for regulatory compliance.
4. **Generalization**: The model's ability to detect new or previously unseen contaminants is limited, requiring continuous model updates.
5. **Robustness**: Variations in image quality, lighting, and camera perspectives can impact the model's performance, potentially leading to inaccuracies.

Future Work

Future research in meat contamination detection using CNNs can focus on several key areas:

1. **Expanding the Dataset**: Gathering larger and more diverse datasets, including various types of contamination and samples from different regions, will improve model performance.
2. **Transfer Learning and Optimization**: Exploring transfer learning and model optimization techniques will help enhance CNN performance and reduce training time.
3. **Real-time Detection**: Developing real-time detection systems will make the technology more applicable in practical settings, enabling faster response times.
4. **Improving Interpretability**: Techniques such as attention mechanisms or saliency mapping can help make CNN models more interpretable and trustworthy.
5. **Enhancing Robustness**: Addressing image variations through data augmentation or domain adaptation will improve the model's robustness in different environments.
6. **Integration with Sensor Technologies**: Combining CNNs with sensor technologies like hyperspectral imaging or spectroscopy can enhance detection accuracy.
7. **Collaboration and Standardization**: Collaborating with industry stakeholders

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and regulatory bodies to standardize approaches will ensure consistency and reliability across applications.

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