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Early Detection of Chicken Breast Contamination with Salmonella Bacteria Using Artificial Intelligence (Deep Learning) Technique

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Abstract - *Detecting Salmonella contamination in chicken breast meat is a critical priority for the food industry, especially when it comes to talking about unseen infected regions of chicken breast meat. A novel intelligent system leveraging deep learning (ResNet) is introduced, incorporating Histogram Equalization (HE) to enhance training image quality. This preprocessing step improves feature extraction, enabling the model to identify previously undetectable regions of contamination. The system achieves 97% accuracy (with generalization) and 95% without, outperforming comparable methods by 1%. By integrating deep learning into food safety technologies, this approach can protect public health, boost consumer confidence, and enhance sustainability, particularly in developing nations like Syria, as well as in industrialized countries.*

Key Words: Salmonella contamination, Artificial Intelligence, Deep Learning, Accuracy, Histogram Equalization.

1. INTRODUCTION

On one hand, healthy chicken is a high-quality protein source, providing all essential amino acids needed for muscle growth, tissue repair, and immune function. It is also rich in B vitamins (B6, B12, niacin), which boost energy metabolism and support brain health. Additionally, chicken contains iron and zinc, enhancing oxygen transport and strengthening the body's defence system, making it a powerful food for overall vitality [1]. On the other hand, contamination with Salmonella bacteria poses serious health risks, including severe food poisoning with symptoms like vomiting, diarrhea, fever, and abdominal cramps. In vulnerable groups (children, elderly, immunocompromised individuals), it can lead to life-threatening complications such as sepsis or meningitis [2]. Additionally, antibiotic-resistant Salmonella strains are emerging, making infections harder to treat and increasing public health concerns. Early detection of contamination with Salmonella is the best way to avoid such serious health risks.

Artificial Intelligence (AI), particularly Convolutional Neural Networks (CNNs), has significantly advanced the detection of Salmonella contamination in food, offering faster, more accurate, and scalable solutions compared to traditional methods [3, 4]. However, poor accuracy of prediction related to existing of Salmonella contamination leads to providing dangerous food to individuals.

1.1 Statement of Problem

Developing intelligent systems for detection of existing of Salmonella contamination manly depend on training the system on high-quality images. Therefore, good pre-processing step is critical to increase accuracy of prediction. Figure 1 illustrates the problem.

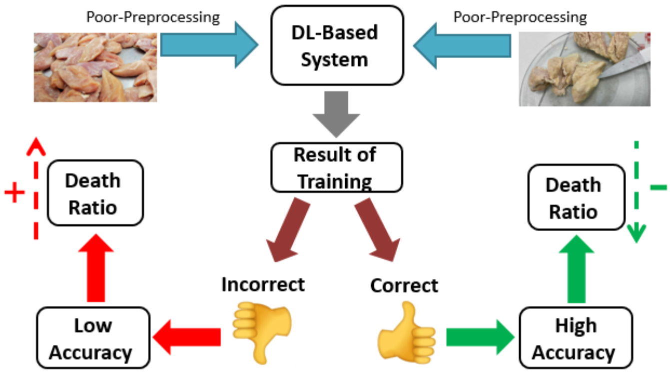

Fig -1: Problem in terms of low accuracy.

As shown in Figure 1, the correct prediction leads to high accuracy of prediction, which in turn leads to decrease the death ratio. On opposite, poor prediction leads to increase the death ratio.

1.2 Research Question

The corresponding research question that is linked to the problem stated above is: how to increase detection of Salmonella contamination through providing effective technique of pre-processing linked with intelligent DL system. This research question can be solved by using histogram equalization technique to enhance the quality of images (Chicken Breast Contamination with Salmonella Bacteria), even if there is unseen amount of contamination by naked eyes, before training the intelligent system.

2. Literature Review (Past Studies)

This section presents an overview of some related works that used artificial intelligence for detection of Salmonella contamination, as described below.

First study: Authors of work [5] used Hyperspectral imaging (HSI) with CNN (ResNet) to enhance the accuracy of detection. The system is feed and trained on spectral signatures of Salmonella colonies. One of the key contribution of this work is to reduce the detection time to be within the range of 24 hours.

Second study: Authors of work [6] used transfer learning to train the intelligent system based on microscopic images. The key idea behind this work is to employ colony morphology to extract signatures of Salmonella growth over time. This leads to real time detection.

Third study: Authors of work [7] used YOLOv5 CNN based methodology to detect existing of Salmonella, where detection based on analysing the colours affected by the amount of concentration of Salmonella. The colour analysing method used is related to analysing the RGB colour system and generation of other colours from basic ones.

Forth study: Authors of work [8] provided an intelligent alarming system based on pH\temperature indicators to provide proper recommendation related to classify chicken meat as healthy or not, They used CNN technique, where data is captured using Internet of Things (IoT) sensors.

Table 1 summarizes the reviewed works in terms of achieved accuracy, used technique and drawbacks.

Table -1: Summarization of reviewed works.

Work	Used Technique	Accuracy	Drawback
[5]	(HSI) + CNN	90%	Requires expensive HSI equipment
[6]	ResNet+Transfer Learning	94%	Needs high-resolution microscopy
[7]	YOLOv5 +CNN	91%	Sensitivity affected by lighting
[8]	pH/temperature + CNN + IoT	88%	Requires farm-wide sensor deployment

As noticed in Table 1, all drawbacks are related to poor pre-processing stage, which forms the research gap addressed in this work.

3. Methodology

The methodology consists of six stages, as shown in Figure 2.

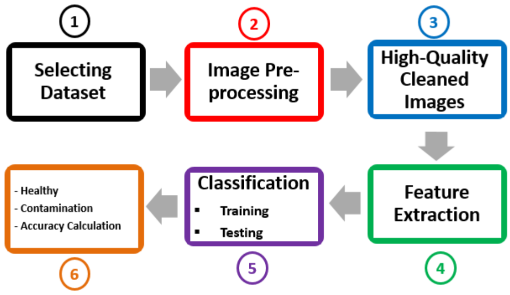

Fig -2: Stages of proposed methodology.

3.1 Data set Selection

The data set used to develop the intelligent system (classifier) is called Chicken Salmonella, which available online [9] for usage by researchers. The data set contains 2391 images of breast chicken. All images are coloured ones with a size of 640x640 resolution. Figure 3 shows samples taken from the dataset.

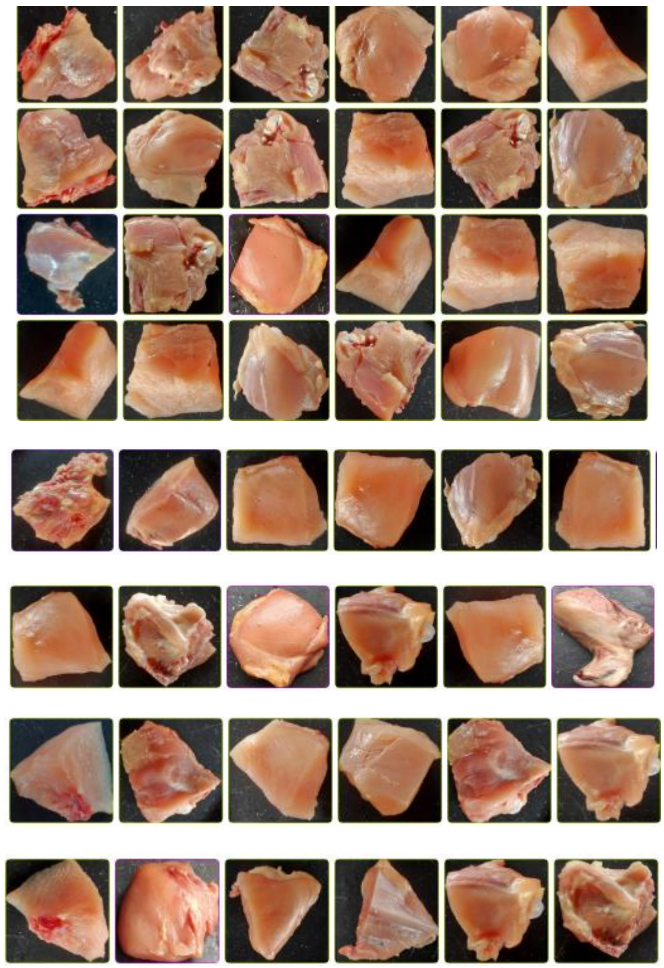

Fig -3: Samples taken from the dataset.

3.2 Image Pre-processing

As the images are colored, they firstly converted into gray images to facilitate further processing. Then histogram equalization technique [10] is applied to enhance the quality. This in turn will enable extracting good features for the purpose of training. The following steps summarizes the image pre-processing stage:

1- Define region of interest by cropping method.
2- Converting colored region into gray images.
3- Applying histogram equalization technique.

However, applying histogram equalization leads to some blurring, which negatively affect the process of extracting good features. To enable extracting good features that may be unseen by naked eyes, CLAHE method [11] is applied followed by intensity inversion. Figure 4 shows the result of image pre-processing.

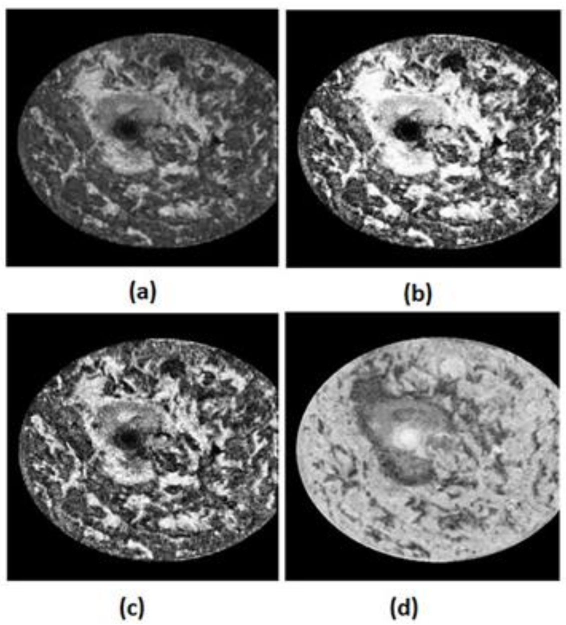

Fig -4: Pre-processing stage with Histogram Equalization Technique.

As shown in Figure 4, (a) represents the original region of interest that contain Salmonella contamination. (b) represents the region after applying histogram equalization. (c) represents region after applying CLAHE method. (d) represents the region after intensity inversion. It is clear that the parts affected by Salmonella contamination are highlighted even if they are not seen by naked eyes. Now, the images are ready to enter feature extraction stage.

3.3 Features Extraction

This work employs Convolutional Neural Network (CNN), which is a common Deep Learning technique used to deal with images effectively. With the help of the Scale-Invariant Feature Transform (SIFT) method [12] to extract good features. The good property of SIFT is that it filters the pixels that affect negatively of features, while saving the good ones based on the pre-processed images. Figure 5, illustrates the operation of the CNN while features extraction, where the filter scans the image in a convolutional manner and a pooling process is performed to collect the final features.

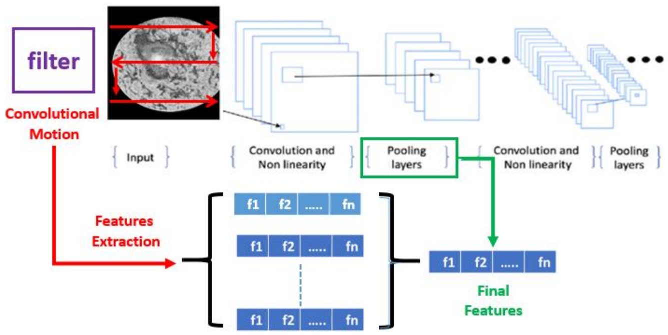

Fig -5: Features extraction using CNN with SIIFT techniques.

3.4 Classification (Training and Testing)

This stage requires dividing the cleaned \ enhanced dataset into training and testing parts. In this context, the Holdout method is used to divide the enhanced dataset into training (with 2000 images) and testing (with 391 images). Figure 6 illustrates the division process in terms of percentages.

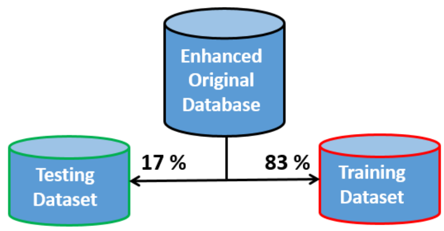

Fig -6: Holdout division process.

For training, the CNN is used. Practically, ResNet version is used to perform convolutional and pooling process with standard parameters. ResNet is combined with the SIFT method to extract features as explained in features extraction stage. The architecture of the ResNet consists of 5-based convolutional layers with 4-based pooling layers, where max-pooling function is employed to group the advanced features from abstract ones. The classification layer uses the Softmax function to generate outputs (i.e., predictions if the food is healthy or Salmonella contamination). Figure 7 illustrates the operation of the Softmax function from mathematical point of view to generate predictions.

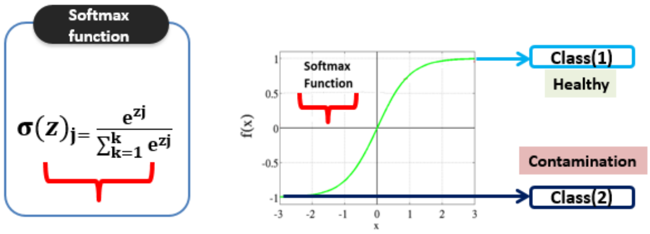

Fig -7: Softmax function used for prediction outputs.

As shown in Figure 7, there are two classes of prediction. Class 1 refers to healthy food represented by +1 value of Softmax function, while class 2 refers to Salmonella contamination represented by -1 value of Softmax function.

As for testing, it is related to calculate the accuracy degree based on the conducted experiments, as described below.

4. Experiments and Results Discussion

The experiments related to dividing the cleaned dataset, training, testing, and measuring accuracy are conducted in AIML Lab [13] at college of computing in Fahad Bin Sultan University (FBSU). The reason behind conducting experiments in such Lab is that handling images requires GPUs to facilitate scanning images, applying enhancement methods, and training and testing stages. Matlab programming language is employed to implement the code of the classifier.

4.1 Used Metrics

Two main DL-based metrics are used to evaluate the proposed classifier. They are inferred from the confusion matrix [14] shown below.

Table -2: Confusion matrix.

Actual class (Predicted class)	**Confusion matrix**		
	Img1	***¬ Img1***	***Total***
Img1	True Positives (TP)	False Negatives (FN)	TP + FN = P
¬ Img1	False Positives (FP)	True Negatives (TN)	FP + TN = N

- True positives (TP): positive images that are correctly labelled by the classifier.
- True negatives (TN): negative images that are correctly labelled by the classifier.
- False positives (FP): negative images that are incorrectly labelled as positive.
- False negatives (FN): positive images that are mislabeled as negative.

Accuracy is the percentage of the chicken breast images included in the testing data set that are correctly classified (as healthy or Salmonella contamination). The accuracy is defined as:

$$Acc = \frac{(TP+TN)}{number\ of\ all\ images\ in\ enhanced\ dataset} \quad (1)$$

Sensitivity refers to the true positive recognition rate. It is given by:

$$Sen = \frac{TP}{P} \quad (2)$$

The proposed classifier \ system (ResNet-HE) is compared to the results of second study (ResNet-TR) presented in the literature review section as it offers the highest accuracy among the reviewed works.

4.2 Results and Discussion

Frist Experiment: In this experiment, the proposed system is evaluated under the original division of the cleaned dataset (83% for training and 17% for testing). Table 3 summarizes the values of used metrics achieved by the proposed system.

Table -3: Accuracy and sensitivity of proposed system (ResNet-HE).

Work	Training to Testing Ratio	Accuracy	Sensitivity
Proposed classifier (ResNet-HE)	83% to 17%	97%	96%

Discussion of Frist Experiment: The results that is achieved is 97% and 96% for accuracy and sensitivity, respectively. The values are comparable as the classifier is trained on a large number of images. Actually, increasing the size of the training dataset leads to enhance the accuracy because the system is trained from more features extracted from the images during training stage.

Second Experiment (Generalization Concept): Taking into account the generalization concept, which refers to the robustness of the classifier against changing the percentage of the training dataset with a step equals to 10% (i.e, decreasing the percentage of the training dataset with 10%), Table 4 summarizes the achieved results.

Table -3: Accuracy and sensitivity of proposed system (ResNet-HE) under generalization concept.

Decreasing Step	Training to Testing Ratio	Accuracy	Sensitivity
10%	73% to 27%	≈ 96%	≈ 95.5%
20%	63% to 37%	≈ 95%	≈ 95.3%
30%	53% to 47%	≈ 94%	≈ 95%
Average		≈ 95	≈ 95.3

Discussion of Second Experiment: The results that is achieved in average is 95% and 95.3% for accuracy and sensitivity, respectively. The reason behind recording lower results compared to first experiment is that the number and quality of extracted features is less than the first experiment. However, the proposed system is still comparable and showed steady level of prediction as the accuracy decreased only by 2% and sensitivity by 0.7%. This means that the system showed good robustness in terms of generalization, where the standard value used to assess a given system is 3% decreasing.

Third Experiment: In this experiment, the proposed system is evaluated compared to the second study (Resnet-TR) in terms of accuracy. The proposed system is evaluated with and without applying Histogram Equalization (HE) technique to show its impact. The achieved accuracy of the proposed system (ResNet-HE) is taken into consideration in this experiment. The ResNet-TL is implemented (i.e., trained and tested) under the same dataset to offer fair comparison. Figure 8 below shows the comparison.

Discussion of Third Experiment: As shown in Figure 8, the proposed system (ResNet-HE) outperform the (ResNet-TL) system as it uses an enhanced method to improve the quality of the raw images, while the (ResNet-TL) does not employ any enhancement technique in the pre-processing stage. The proposed system showed less level of accuracy when ignoring the HE technique. This means that the HE technique has positive impact on the accuracy as it enables observing unseen regions that affected by Salmonella contamination. This in turn means that the extracted features after applying HE technique are better for training. The transfer learning is stronger than ResNet as it presents further processing of images in terms of knowledge transferring to form a good background for learning. For this reason, the ResNet-TL provides better accuracy level when compared to the proposed system without applying HE technique. To sum up, the ResNet-HE system outperform the ResNet-TL by 1% accuracy enhancement, while the ResNet-TL outperform the proposed system (without using HE) by 2 % accuracy enhancement.

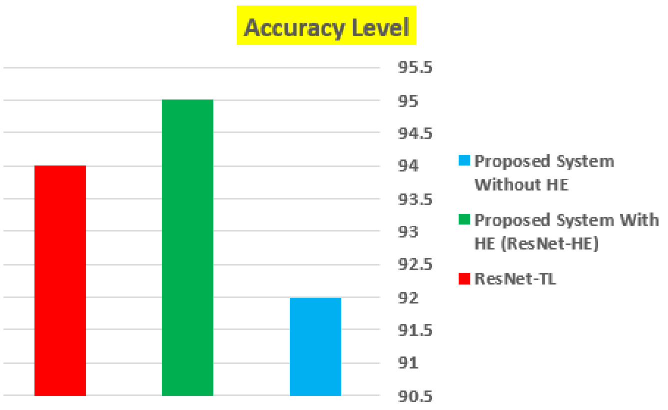

Fig -8: Accuracy based comparison.

5. Conclusion

Detection of Salmonella contamination in chicken breast meat is avital domain in food industry. Intelligent system that used deep learning technique (ResNet) is proposed. The proposed system is equipped with an enhancement method for increasing the quality of the training images, which is Histogram Equalization (HE) technique. The HE technique contributes to offer more advanced extracted features for training, where unseen region of Salmonella contamination become available to be trained on by the proposed system. The proposed system showed better accuracy of 97% and 95% with and without taking into account generalization concept, respectively. The proposed system provides enhancement of accuracy level by 1 % when compared to similar work. Employing deep learning in food science technologies can contribute to save life of people, increasing the trust of clients in food companies, and optimizing the sustainability quality attribute of developing counties, such as Syria, as well as other advanced countries.

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