Conventional and Deep Feature Oriented Quality Inspection of Internal Defected Eggs Using Infrared Imaging

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ABSTRACT

Automatic separation of defective eggs from qualified ones would lead to a great reduction on the graders visual stress as well as to an improvement on the quality control process. Due to the increasing incidence, Infrared Imaging Technology provides an important window for eggs sorting especially when the defects are not visible externally. In this paper, we have investigated the role of infrared imaging for classification of internal defective eggs from the fresh eggs. For our work, a new infrared image dataset of fresh and defective eggs (i.e. internal defective) has been designed by maintaining standard acquisition protocol. The study also includes investigation of conventional and deep features for accurate separation of defective eggs from qualified ones. Experimental results shows that DeepFS outer performs the remaining three feature sets (i.e. AComFS, SSigFS and ASigFS) with an average accuracy of 96.26% for all the used classifiers and hence able to effectively separate the fresh and defective eggs.

CSS CONCEPTS

Computing methodologies → Machine learning → Machine learning algorithms → Feature selection

KEYWORDS

Egg; Defect; Infrared Imaging; Feature Extraction; Asymmetric Analysis; Feature Selection; Classification

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1. Introduction

Egg is one of the major source of food because it's nutritional value and grading plays a vital role in controlling its quality. Due to a high demand of eggs by the consumers, the egg production industry has become one of among large industries in India and many countries. This high demand comes with a high expectation and requirements in having good quality of eggs. In the production and selling of the commercial eggs, egg grading is one of the important processes that need to be done in order to control the quality of eggs produced [1]. In fact, the performance of egg grading is affected by the eggs internal and external quality [2]. The brief description of the various causes of interior and exterior defects of eggs are summarized in Table 1. It has been found that most of the production companies cope up with the external defects of eggs (i.e. crack, dirt, etc.) by not only producing well shaped eggs but also with extra nutrients. Owing to the physical properties of eggs, there is a high risk of human error in

Table 1. Exterior and Interior Defects of Eggs

	Quality Factor (s)	Causes of Defects
Exterior Causes	Thickness	- May show Pronounced thin shots
	Ridges	- May show Slight/ Pronounced ridges
	Stain	- May show traces of processing oils - May show small specks, stains or cage - 1/32 of shell scattered
	Dirt	- Adhering dirt or foreign material
	Shape	- Approximately the usual elliptical shape - Unusual or decidedly misshapen
	Texture	- May have small calcium deposit - Extremely rough areas that may be faulty in soundness or strength.
Interior Causes	Air Cell	- 3/16 inch or less in depth
	White Albumen	- May be weak and watery - May be reasonably firm
	Yolks	- Outline are not well defined - May have large calcium deposit and Pale Yolks
	Blood or Meat Spots	- May show pronounced thin spots - May have strained layers producing tinted

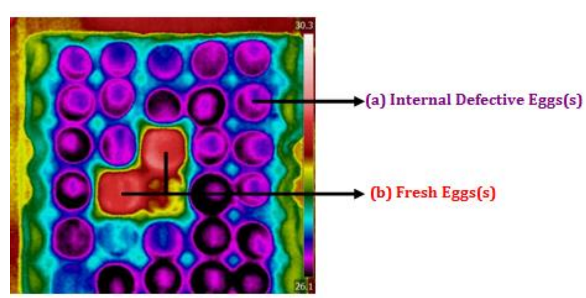

Fig. 1. Infrared Imaging (Top View) of Bunch of Eggs Kept in Trays: (a) Internal Defective Eggs; (b) Fresh Eggs

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Table 2. Methodological Review of Different Techniques for Quality Inspection of Eggs

Author/ Year	Method Used	Type of Image/ Camera Model	Number of Collected Samples	Observation	Accuracy/ Result
P. Malewadkar et.al./ 2017 [7]	RGB color model, Threshold value	Visual Imaging/ Android phone of 16 Mega pixel	150	Distinguish fertile, non-fertile, rotten eggs based on image processing and RGB color model.	Not Provided
M. Hashemzadeh et.al./ 2016 [10]	LS-SVM algorithm, Histogram Equalization (CLAHE), Adaptive Histogram Equalization, Gaussian Smoothing	Visual Imaging/ CCD Camera (DSCWX7)	4800	Distinguish fertile eggs from infertile ones based on SVM Gaussian Smoothing & histogram equalization analysis result.	Not Provided
L.H. ling et.al./ 2016 [3]	Temperature based analysis, Sobel operator, GLCM eigen values	Thermal Imaging/ FLIR A615	288	Detect unfertilized eggs used thermal difference and eigenvalues	96% classification accuracy
K. Kiratiratanapruk et.al./ 2014 [8]	K-means clustering algorithm, Otsu threshold method.	Visual Imaging/ Not Provided	60	Detection and classification three different types of egg (silkworm) including shells, defect eggs and unhatched eggs used k-means clustering.	Not Provided
S.Arivazhagan et.al./ 2013 [5]	YIQ color space, Morphological operator, Subtraction operator, median filter	Visual Imaging/ 12 Mega pixel High resolution NIKON digital camera	200	Detect internal and external egg defects applying different image processing techniques	85.66% classification accuracy
W. Syahirir et.al./ 2007 [9]	Median filter, Threshold value	Visual Imaging/ Not Provided	40	Abnormalities (bloodspot) detection in eggs use image processing approach.	83% classification accuracy
M.C.G. Alegre et.al./ 2000 [6]	Threshold value, Statistical Analysis	Visual Imaging/ Video Camera Recorder (SONY DXC-950 P and MITSUBISHI 300 E)	100	Classification of defective eggs from clean ones in critical time based on statistical analysis.	Not Provided
M.C.G. Alegre et.al./ 1997 [4]	High pass filter, Laplacian operator, Sobel filter	Visual Imaging/ video Camera Recoder (Hitachi VM-H80E)	Not Provided	Detection of all defects related to changes on the eggs-shell standard geometry, texture and color	Not Provided

classification of internal defect eggs from fresh eggs where the parameters cannot be well detected by visual inspection. The Food and Drug Administration (FDA) has approved eggs which are resistant to internal defects could have unknown risks to human health. However detection of internal defects (i.e. blood spots in albumen, etc.) in eggs is a challenging task because of the hard shell surface.

Infrared Imaging Technology (IIT) have proven to be valuable educational research tools that provides non-invasive, non-contact and radiation free imaging modality for assessment of abnormal infrared radiation from objects. The infrared detectors absorb the infrared energy emitted by the object and convert it into an electrical impulse. The electrical impulse is sent to the signal processing unit which translates the information into thermal image. Most of the thermal imaging devices scan at a rate of 30 times per second and can sense temperature ranging from −20 to 1,500°C. It has been observed (as shown in Fig.1) that the eggs under normal circumstances or when incubated have high temperature as compared to the defected eggs. Up to 95% of internal defects of eggs were detected using infrared imaging by discriminating surface temperature between defect and non-defect tissues [3].

Recognizing the importance of infrared imaging in the community of food inspection, the main contributions of this paper are:

1. The paper provides the research community with an infrared image dataset of fresh and internal defective eggs (i.e. chicken and duck eggs) so that one can utilize this dataset for inspection of defective eggs where the quality of eggs to be defect are not well detected by visual perspective.
2. The paper also provides conventional feature based asymmetric analysis of fresh and defect eggs for accurate selection of discriminative features that can effectively classify between these two categories of eggs.
3. It provides a comparison of seven most widely classifiers for classification between fresh and defective eggs and thus helps to identify the liability of discriminative feature selection for accurate sorting of fresh group from the defective ones.
4. Moreover the paper also investigates the application of deep learning based features extracted from the images for accurate classification of defective groups from fresh ones so as to identify the remaining challenges in order to provide focus for future research.

The whole paper is organized as; Section 2 describes the literature survey on the computer aided techniques for detection of defect in eggs. Section 3 elaborately describes the procedure for dataset acquisition of fresh and defective eggs. In Section 4, methodology for extraction of conventional and deep learning based features from infrared images has been illustrated. Section 5 describes the asymmetric analysis of conventional features extracted from fresh and defective eggs for discriminative feature selection. In section 6, comparison of seven most widely used classifiers to illustrate the importance of feature selection for sorting of fresh eggs from internal defective eggs has been reported. And finally, section 7 concludes the paper.

2. Previous Work

Detection of mechanical defects in eggs plays a crucial role for quality inspection systems. Various techniques including optical, mechanical, electrical and acoustical have been proposed by the several researchers for classification and/or sorting of defected eggs. The brief summary of these techniques are summarized in Table 2. In [4], M.C.G. Alegre et.al. proposed a machine vision system to detect defects in eggs. The algorithmic process consist of detecting the egg shape to fix the region of interest. Color processing is then performed only on the egg shell to obtain an image segmentation that allows the discrimination of defectives eggs from clean ones in critical time. They used a sample of 64 eggs and forty of them corresponding to defected eggs. In [5], S. Arivazhagan et.al. developed an image processing technique to detect internal and external egg defects. From the analysis of the obtained results it is observed that the clean eggs and eggs with dirt's and cracks were detected easier and in case of blood spot detection the median filter is used to remove "shot" noise. In [6], M.C.G. Alegre et.al. proposed focused on designing and implementation of an artificial vision system for automatic classification of eggs at the farm/ grader manufacturing industry. They developed a well-fitted algorithms for capable of enhancing and detecting any kind of in homogeneous patter on a regular egg shell background under controlled illumination condition. To demonstrate the performance of the proposed algorithms, a sample of hundred eggs i.e. 50 defective and 50 fresh eggs were used. In [7], P. Malewadkar et.al. designed an android based application to differentiate between consumable and non-consumable eggs. They classified the eggs into three categories: fertilized, non-fertilized and rotten eggs. The application calculates the RGB values of the input image and compare it with the threshold values stored in the database. The dataset consists of about 150 eggs in different category i.e. fertilized, non-fertilized, rotten eggs. Android phone of 16 mega pixel was used to capture the image of the eggs. In [8], K. Kiratiratanapruk et.al. proposed an image analysis technique for silk worm egg quality inspection. They demonstrate how to detect silk worm egg objects and classify them into three different egg types including shell egg, defect egg and unhatched egg. They used many techniques in this work such as an ellipse fitting, Hough Circle Transform, Morphology, K-means clustering and watershed algorithm. The performance was evaluated on 60 sample images and shown satisfier accuracy in many cases. In [9], W. Syahirir et.al. used image processing techniques to detect the abnormalities(blood spot) in the eggs image. In this study they follow four steps in pre-processing techniques and these are RGB enhancement, Convert to gray scale, filter image and threshold image. The result shows that the system meets its objectives where 83% of the egg with blood spot images is correctly being detected. In [10], M. Hashemzadeh et.al. developed an economical machine vision system for detecting the fertility of hatching eggs. The fertility detection accuracy of the system on the provided dataset reached 47.13% at day 1 of incubation, 81.41% of day 2, 93.08% at day 3, 97.73% at day 4 and 98.25 at day 5. Comparing with existing approaches show that the proposed method achieved noticeable performance. In [3], L.H. ling et.al. used thermal imaging technology to determine fertilized eggs and un fertilized eggs. Analyzing the cooling curve and the cooling area and region growing, ellipse fitting, morphological processing, the methods were used to extract eggs region of interest and entire ROI area was seen as characteristic parameters and the decision threshold was set according to minimum error rate Bayes rule. The non-fertilized eggs in incubating 4 days was 89.6% overall recognition and the dead embryo eggs in incubating 16 days was 96.3% overall recognition. After a rigorous survey, it has been found that most of the research work have concentrated on using visual imaging for quality inspection of eggs but very few work has been investigated on the infrared imaging based detection of defective eggs. So in our work, we have investigated the role of infrared imaging for sorting of fresh and defective eggs especially when the eggs are defected internally.

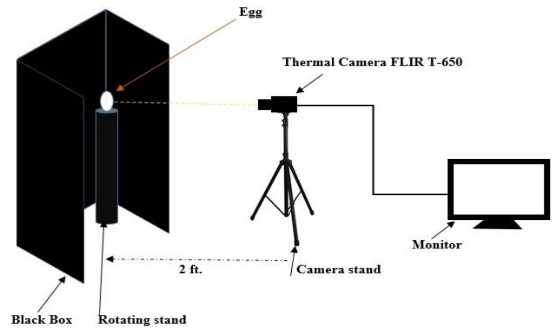


Fig. 2. Diagrammatic Representation of Overall Acquisition Setup

3. Dataset Acquisition

Due to the sensitivity of Infrared Imaging Technology (IIT) to the environmental conditions, it is necessary to maintain a standard and strict protocol suite during data acquisition. However in the absence of any universal acquisition protocol, an extensive study has been made on the various factors that can influence the analysis and evaluation of infrared images. Practically it is difficult to control all the factors but being conscious about these factors is essential in many context. The overall acquisition setup for dataset acquisition is shown in Fig.2. The details description of acquisition setup and overall statistics of the created dataset is described below.

3.1 Acquisition Setup for Dataset Capturing

Analysis of infrared images involves many factors related to an acquisition that can provide negative impact in analysis. The factors that affects the acquisition of the infrared images are:

- **Specification of Infrared Camera:** The quality of infrared images for analysis relies on the specification of thermal camera which is based on resolution and sensitivity. For accurate analysis, dataset are captured using FLIR T650sc infrared camera. The camera is highly sensitive and that allows obtaining temperature differences as small as 0.02°C at 30°C with ± 1°C or ± 1% accuracy of the reading. The spatial resolution of this camera is 640×480 pixel with a spectral range of 7.5-14.0 µm that help to reduce measurement errors by providing clear image with fine details.
- **Position of Infrared Imaging System and Objects:** The position of the infrared camera with respect to the object is

Table 3. Overall Statistics of Created Dataset under Fresh and Defective Condition of Eggs

Image Type	Camera Model	Types of Egg	Egg Conditions		Total Samples
			Fresh	Defective	
Infrared Images	FLIR T650 Sc	Chicken Egg	40	32	72
		Duck Egg	35	28	63
Total Number of Samples			**75**	**60**	**135**

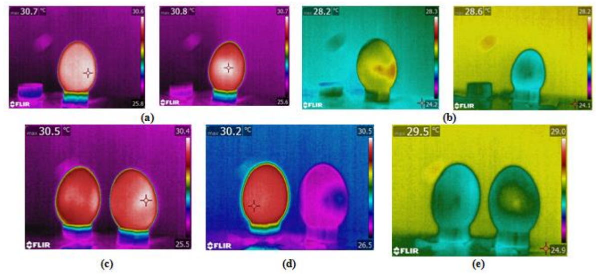


Fig. 3 Sample Images of Created Dataset (a) Fresh Eggs; (b) Defective Eggs; (c) Two Fresh Eggs; (d) One Fresh and One Defective Egg; (e) Two Defective Eggs

also a key factor to be considered while dataset acquisition. In our study the camera has been mounted on a tripod stand with an alignment of 90° in between the camera and the object. The distance between the thermal camera and object has been kept within 2 feet (ft) distance.

- **Environmental Condition:** As the environmental factors may affect the quality of infrared images, it is necessary to reduce the impact of environment on analysis. To eliminate external infrared energy emitted from sources such as electric wires, pipes, outlets, etc., we have made a black cubicle which has been fixed behind the object. The size of the background has been positioned based on the Field of View (FOV) of the infrared camera and distance between the object and the camera. The other two environmental factors are relative humidity and room temperature. In our study the room temperature and humidity are fixed to 22°C-25°C and 40%-60% respectively.

3.2 Dataset Description

Considering the above mentioned protocol suite, we have acquired the infrared images of fresh eggs and defective eggs that are almost defect inside but are not visible externally as per instruction of the vendors. The images are captured by placing them in the rotating stand. The overall statistics of the created dataset is shown in Table 3. The dataset contains chicken and duck eggs. In this dataset, there are total 75 fresh eggs (i.e. 40 chicken eggs and 35 duck eggs) and 60 defective eggs (i.e. 32 chicken eggs and 28 duck eggs). Some of the captured sample images are shown in Fig. 3.

3.3 Naming Convention

Accurate segmentation of cervical cancer cells in microscopic images is a significant task to detect the abnormality of cells in the pre-cancerous stage. Cells mainly consist of two components: Nucleus and Cytoplasm. After capturing, naming of the infrared images has been done for the ease of understanding the category of the dataset during analysis. To make the naming convention meaningful, different codes have been assigned for different samples, different categories and also for the type of each thermogram. With all these codes, the name of a thermogram is like **Sample-Type_Sample-Category_Sample-ID.jpg**. Using the

Table 4. Codes Used for Naming the Dataset Images

Sample-Type		Sample-Category		Sample-ID	
Type	**Codes**	**Category**	**Codes**	**ID**	**Codes**
Chicken Egg	C	Fresh	F	Sample 1	1
Duck Egg	D	Defective	D	Sample 2	2
				...	...
				Sample n	n

above naming convention, every image in the database acquires a distinctive identity. All the assigned codes for each component of the name are illustrated in Table IV. Based on the codes provided in Table 4, the image name "**D_F_01.jpg**" indicates that the infrared image with a sample with ID 01 is the fresh category of egg (F) and it is duck egg (D).

4. Methodology for Feature Extraction from Infrared Images

In this section, detailed description of the proposed methodology for feature extraction towards accurate selection of discriminative features and classification of defective and fresh eggs is presented. The overall flow diagram of the proposed methodology is shown in Fig. 4.

4.1 Pre-processing of the Infrared Images

The pre-processing of the infrared images are generally carried out to reduce the computational complexity of an automated system. The original captured infrared images contains pixel based temperature information of the captured area and additionally it contains colour bar, company logo and maximum and minimum temperature range of image. In case of eggs, low temperature distribution indicates the presence of internal defects. So in the pre-processing stage, the infrared images are cropped manually to a standard resolution of 200×200 pixels from the original images. Then these cropped images are converted into gray scale image for further analysis.

4.2 Region of Interest (ROI) Extraction

After pre-processing, the output consists of temperature based pixel information present in the infrared images along with background region. To enhance the accuracy of reliable feature extraction and classification, the removal of background region is established by automated generation of binary mask using Expectation Maximization (EM) method [11]. In some of the infrared images, pixel values of foreground regions are almost similar to the background region and in this case use of EM method may consider some portion of foreground region as background region and vice versa. To cope up with such problem, sobel edge detection method [12] has been applied on the output of EM segmentation and the detected edges are finally convolved with the output binary mask of EM method and region fill [13] is applied over the convolution result. In the final step of background subtraction, the output mask generated from post processing of EM method is multiplied with the pre-processed RGB palette infrared images. Thus the background pixel intensities of the RGB palette images are converted to zero without affecting the foreground region (i.e. egg region).

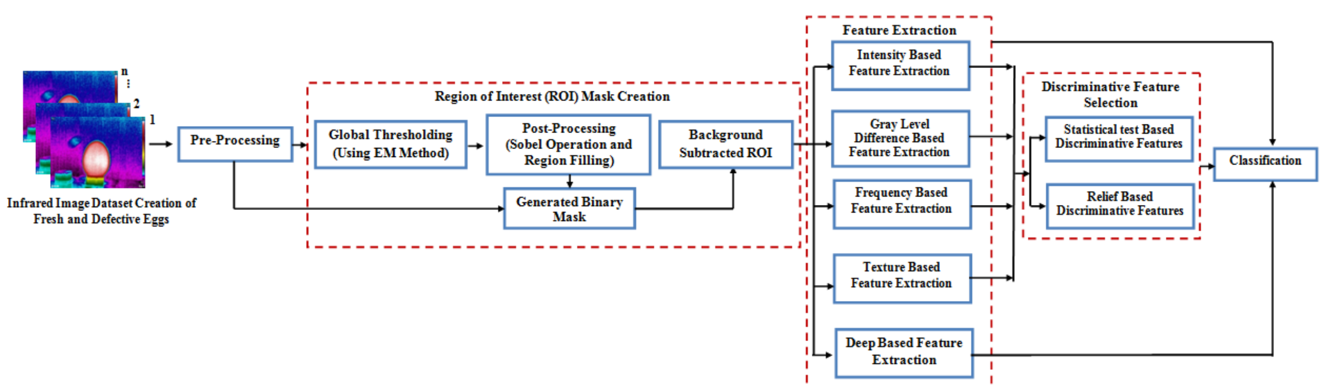
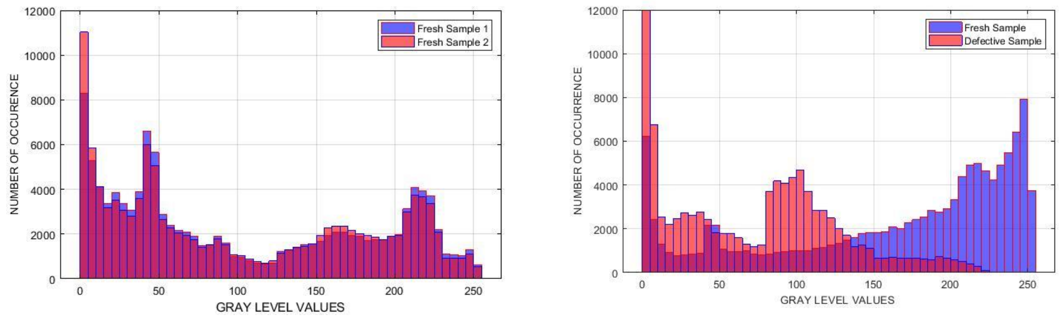


Fig. 4 Overall Flow Diagram of Asymmetric Analysis and Classification



(a) **(b)**

Fig. 5 (a) Histogram of two Fresh Eggs and (b) Histogram of a Fresh and a Defective Egg

4.3 Feature Extraction

The characteristics of an image is often determined by the way the gray levels are distributed in the region. It describes an image looks by fine or coarse, smooth or irregular, homogeneous or inhomogeneous etc. Thus, features are described to specify some quantifiable property and significant characteristics of an image by utilizing space relations underlying the distribution of a given image. The features can be either low-level features or high level features. Extraction and selection of appropriate features is a crucial task in analysis of infrared images. In an intensity histogram as shown in Fig. 5 (where X-axis represents the gray level values of the image and the Y-axis represents the probability of occurrences of each pixel value), it can be observed that there is a large difference in the intensity distributions of fresh and defective eggs and hence describes the presence of the thermal asymmetry between this two categories of eggs. So in our study, we have extracted two categories of features: **Conventional Features** (i.e. First order statistical features, Gray level difference features, Frequency level features and Texture Features) and **Deep Based Features**. A brief description of each feature used in our study is provided below.

4.3.1 First Order Statistical Feature Extraction

The first order statistical features are also known as the Gray Level Histogram Based Features because they are directly calculated from the probability of pixel occurrence.

In an intensity histogram as shown in Fig. 5 (where X-axis represents the gray level values of the image and the Y-axis represents the probability of occurrences of each pixel value), it can be observed that there is a large difference in the intensity distributions of fresh and defective eggs and hence describes the presence of the thermal asymmetry between this two categories of eggs. The histogram based features that are extracted from the intensity histogram are [14][15]: Mean (F_1), Variance (F_2), Standard Deviation (F_3), Skewness (F_4), Kurtosis (F_5), Entropy (F_6), Maximum Temperature (F_7), Median Temperature (F_8), Modal Temperature (F_9).

4.3.2 Gray level Difference Based Feature Extraction

The features that are computed from generated from the first-order statistics provide information about the distribution of gray levels but does not provide any information about the positions of gray levels in an image. The Gray level difference features are calculated from Gray Level Co-occurrence Matrix (GLCM) that deals with the gray-level configuration in an image. A GLCM is a square matrix G(i, j, d, ɵ) where each variable represents the frequency of occurrence of a pixel i at the position (x,y) with a certain pixel j at the position (x + dx, y + dy) with a distance d and direction ɵ. The gray level difference based features that are computed in our study are [16][17]: Contrast (F_{10}), Correlation (F_{11}), Energy (F_{12}), Entropy (F_{13}), Homogeneity (F_{14}).

4.3.3 Frequency Level Feature Extraction

Fourier power spectrum analysis can be used for Coarse and fine texture analysis of ROI. To use the Fourier power spectrum (FPS) features, one must first compute the sample power spectrum and is mathematically represented as [17]:

$$\Phi(u,v) \equiv \mathrm{F}(u,v)\mathrm{F}^*(u,v) = \left|\mathrm{F}(u,v)\right|^2 \tag{1}$$

Here, Φ denotes sample power spectrum; F denotes Fourier transform of an image and $*$ denotes complex conjugate. Generally the coarse structure have higher values of $|F|^2$ concentrated towards the origin whereas in case of fine texture the values will be more scattered from the origin. The FPS features that are computed in our study are [19]: Radial sum (F_{15}), Angular sum (F_{16}).

4.3.4 Texture based Feature Extraction

Texture is a set of connected that occur repeatedly in an image. It provides the information about the variation in the intensity of a surface. To describe texture features, the most widely accepted model is gray level run length matrix (GLRLM) [18]. Each of the element (i,j) of run length matrix represents number of times an image contains a run of length j lying in gray level range i. A gray level run is a set of repeated and collinear pixel elements having the same gray level value. For a given image, we have computed seven GLRLM based texture features for runs [18]: Short Run Emphasis (F_{17}), Long Run Emphasis (F_{18}), Gray Level Non-Uniformity (F_{19}), Run Percentage (F_{20}), Run Length Non-Uniformity (F_{21}), Low Gray Level Run Emphasis (F_{22}), High Gray Level Run Emphasis (F_{23}).

4.3.5 Deep Feature Extraction

Deep learning based approaches has gained more attention for feature extraction with higher accuracy by defining higher level features with lower level and vice versa. Comparing to other deep learning architectures, the Convolution Neural Network (CNN) gained the highest impact in the area of feature extraction. The

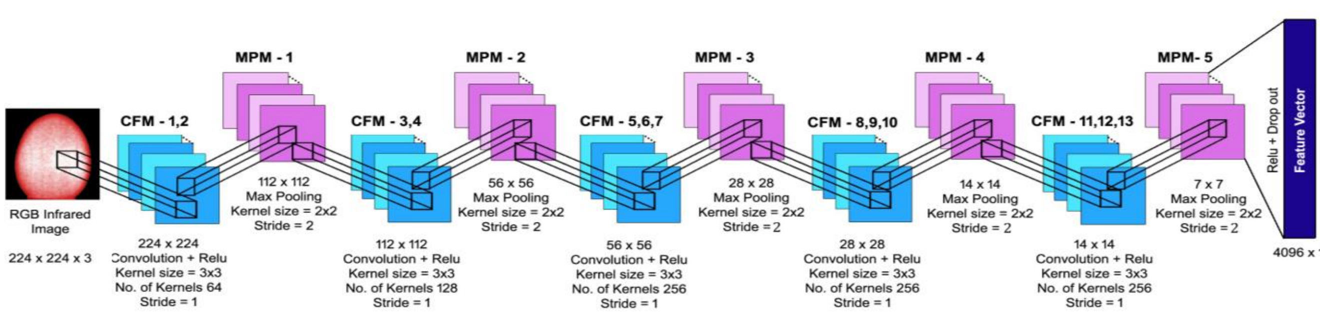


Fig. 6 CNN Architecture for Deep Feature Extraction

Table 5. Feature based Asymmetric Analysis of Fresh and Defective Eggs for Discriminative Feature Selection

Feature ID	Chicken Eggs				Duck Eggs			
	Egg Category		Significance Level Test		Egg Category		Significance Level Test	
	Fresh Eggs (25)	**Defective Eggs (25)**	**P-Value**	**P<0.00001**	**Fresh Eggs (25)**	**Defective Eggs (25)**	**P-Value**	**P<0.00001**
$F_1(\mu)$	121.205±24.076	101.026±28.147	1.5259e-04	**Significant**	128.447±23.977	98.254± 27.738	1.72e-06	**Significant**
$F_2(\sigma^2)$	2742.01±356.123	1190.491±389.565	6.1035e-05	**Significant**	2551.868± 799.22	1138.451± 388.379	1.1175e-07	**Significant**
$F_3(\sigma)$	50.992±12.162	34.062±5.695	3.0532e-04	**Significant**	49.555± 9.992	33.236±6.034	4.5638e-07	**Significant**
$F_4(S_k)$	0.383±0.679	0.341±0.554	0.7003	---	0.337± 0.546	0.314± 0.427	0.6882	---
$F_5(K_u)$	3.010±0.633	2.599±1.418	0.9794	---	3.404±0.662	2.516±0.791	0.4588	---
$F_6(H)$	7.408±0.371	6.849±0.198	3.0518e-05	**Significant**	7.521±0.280	6.775±0.176	3.9002e-03	**Significant**
$F_7(Max)$	237.375±20.410	189.00±17.849	3.0212e-05	**Significant**	235.333±19.957	195.142±16.332	3.4583e-05	**Significant**
$F_8(Med)$	119.125±29.716	98.8±32.098	0.000025	**Significant**	119.010±32.218	95.785±32.614	0.000013	**Significant**
$F_9(Mod)$	160.25±77.504	95.866±41.446	4.8828e-04	**Significant**	143.592±73.677	91.928±47.960	1.0332e-05	**Significant**
$F_{10}(Con)$	0.209±0.029	0.126±0.033	5.4327 e-07	**Significant**	0.193±0.032	0.130±0.039	2.1332e-03	**Significant**
$F_{11}(Cor)$	0.167±0.052	0.149±0.064	0.9999	---	0.156±0.055	0.151±0.053	0.7641	---
$F_{12}(E)$	0.939±0.014	0.917±0.011	1.1057e-07	**Significant**	0.937±0.016	0.921±0.011	1.1235e-9	**Significant**
$F_{13}(H_s)$	0.973±0.032	0.953±0.069	3.0518e-05	**Significant**	0.970±0.030	0.924±0.068	0.0443	---
$F_{14}(Hom)$	0.956±0.018	0.945±0.016	0.0090	---	0.958±0.013	0.941±0.020	0.00054	---
$F_{15}(RS)$	3.615±6.777	2.838±6.772	0.0017	---	3.567±6.607	2.754±6.754	0.0050	---
$F_{16}(AS)$	0.003±0.001	0.002±0.001	0.1947	---	0.038±0.125	0.034±0.099	0.2112	---
$F_{17}(SRE)$	0.539±0.036	0.518±0.059	7.6743e-19	**Significant**	0.780±0.201	0.737±0.345	5.8728e-12	**Significant**
$F_{18}(LRE)$	30.724±26.479	23.240±21.707	5.3115e-7	**Significant**	21.819±12.123	21.032±15.350	5.4852e-7	**Significant**
$F_{19}(GLN)$	1206.32±209.74	1045.643±165.875	0.1947	---	1521.172±216.267	1335.889±145.553	0.1998	---
$F_{20}(RP)$	0.349±0.056	0.333±0.059	0.0090	---	0.413±0.216	0.411±0.359	0.0266	---
$F_{21}(RLN)$	3796.822±1031.601	3770.41±1063.071	0.9723	---	4426.059±1088.419	4.3049±1031.282	0.77	---
$F_{22}(LGRE)$	0.045±0.014	0.032±0.016	4.5052 e-12	**Significant**	0.039±0.016	0.025±0.079	3.2032e-23	**Significant**
$F_{23}(HGRE)$	80.883±27.574	79.141±16.822	0.3394	---	97.464±24.216	93.925±18.435	0. 1129	---

$F_1(\mu)$- Mean; $F_2(\sigma^2)$- Variance; $F_3(\sigma)$- Standard Deviation; $F_4(S_k)$- Skewness; $F_5(K_u)$- Kurtosis; $F_6(H)$- Entropy; $F_7(Max)$- Maximum Temperature; $F_8(Med)$-Median Temperature; $F_8(Mod)$- Modal Temperature; $F_{10}(Con)$- Contrast; $F_{11}(Cor)$- Correlation; $F_{12}(E)$- Energy; $F_{13}(H_s)$- Entropy; $F_{14}(Hom)$- Homogeneity; $F_{15}(RS)$- Radial Sum; $F_{16}(AS)$- Angular Sum; $F_{17}(SRE)$- Short Run Emphasis; $F_{18}(LRE)$- Long Run Emphasis; $F_{19}(GLN)$- Gray Level Non-Uniformity; $F_{20}(RP)$- Run Percentage; $F_{21}(RLN)$- Run Length Non-Uniformity; $F_{22}(LGRE)$- Low Gray Level Run Emphasis; $F_{23}(HGRE)$- High Gray Level Run Emphasis

Table 6. Classification Accuracy of Fresh and Defective Eggs based on Extracted Feature Set

Classifiers	Classification Accuracy											
	AComFS			SSigFS			ASigFS			DeepFS		
	Accuracy	Specificity	Sensitivity	Accuracy	Specificity	Sensitivity	Accuracy	Specificity	Sensitivity	Accuracy	Specificity	Sensitivity
SVM	**91.10%**	**87.50%**	**92.70%**	**93.30%**	**93.80%**	**97.41%**	**96.30%**	**95.34%**	**97.60%**	**98.03%**	**96.32%**	**97.60%**
KNN	65.85%	53.33%	73.07%	80.48%	66.67%	86.79%	82.92%	73.33%	88.46%	95.12%	93.33%	92.84%
LDA	73.17%	60.00%	80.76%	78.04%	69.02%	88.46%	80.48%	78.77%	84.61%	92.68%	86.66%	96.15%
RF	79.58%	80.00%	92.31%	82.93%	76.66%	84.62%	85.36%	80.00%	92.30%	97.56%	93.33%	95.02%
DT	79.64%	73.33%	83.15%	85.37%	73.33%	88.46%	90.24%	86.67%	96.15%	94.68%	96.15%	92.59%
NB	82.93%	71.28%	88.46%	87.80%	80.00%	92.31%	87.80%	86.66%	92.31%	96.15%	94.33%	91.28%
ANN	87.76%	78.02%	85.83%	85.36%	80.06%	89.28%	94.24%	84.61%	93.24%	95.12%	92.61%	92.31%

SVM- Support Vector Machine; KNN- K-Nearest Neighbour; LDA- Linear Discriminant Analysis; RF- Random Forest; DT- Decision Tree; NB- Naive Bayesian Classifier; ANN- Artificial Neural Network; AComFS- Combination of All COnventional Feature Set; SSigFS- Statistical Significant Feature Set; ASigFS- Automatic Selected Significant Feature Set (Using Relief Feature Selection Method); DeepFS- Deep Learning based Feature Set (Using VGG-16 Architecture)

most widely used CNN architecture are: AlexNet, VGG-16, VGG-19, etc. [19]-[20]. The VGG architecture have shown promising implications over AlexNet by replacing large kernel size in convolution [20]. As our dataset contains limited number of images so all the three architectures are fine-tuned for our use through trial and error mechanism. As the VGG-16 with fine tuning best suited for classification in our dataset, the VGG-16 architecture for feature extraction from the pre-processed RGB image dataset is used in our work. Fig. 7 sketches the CNN-architecture that we have adopted to tackle the deep feature extraction (i.e. DeepFS) consisting of multiple neurons with learnable weights. In our deep based feature extraction architecture, we have used RELU activation function for different convolution layers as the function has a much effective gradient [21] as compared to the other activation functions which results in a more dynamic and rapid optimization of the loss function. Also we have used Max Pool layers stacked with the convolution layers as shown in Fig. 6. This layer is specialized to select features which are superior and position invariant which in turn helps in faster convergence and improves generalization performance of the model. For each images, the final output after feature extraction is 4096×1 feature vector which are served as an input to different classifiers for performance evaluation.

5. Asymmetric Analysis of Fresh and Defective Eggs for Discriminative Feature Selection

After extracting these twenty three conventional feature values (i.e. Feature set (AComFS): F_1-F_{23}) from both fresh and internal defective eggs, an asymmetric analysis of the feature values are examined between fresh and defective group. The average and standard deviation of these extracted features from the fresh and the defective eggs are shown in Table 5. It has been observed that each of these extracted features of the fresh group are higher as compared to the defective group.

5.1 Statistical Significant based selection of Discriminative Features

For accurate classification and separation of fresh eggs from the internal defective ones, appropriate selection of discriminative features that can effectively differentiate between this two categories is a vital task. By excluding those irrelevant features that have less contribution to the accuracy of the system can reduce the complexity of the system. In our work, non-parametric Mann-Whitney-Wilcoxon (MWW) test [22] has been used to find the most discriminative features with significance levels p<0.00001. In order to perform this statistical test, we have considered the null hypothesis that the extracted features of internal defective group is less than the extracted features of the fresh group. The significance level of each feature value is measured against the null hypothesis and the p-value of the features which reach the significant difference of $p<0.00001$ are marked as significant. Based on the statistical test as shown in Table 5, it has been found that among these 23 features, 13 features accepted the null hypothesis and are considered as discriminative features (i.e. feature set (SSigFS): $F_1(\mu)$; $F_2(\sigma^2)$; $F_3(\sigma)$; F_6(H); F_7(Max); F_8(Med); F_8(Mod); F_{10}(Con); F_{12}(E); F_{13}(Hs); F_{17}(SRE); F_{18}(LRE); F_{22}(LGRE)).

5.2 Automatic Selection of Discriminative Features

Conversely for automatic selection of most effective and discriminative features, Relief based feature selection method is used [23]. The feature selection through Relief generally calculates a feature score against each feature which can then be applied to rank and select the top scoring features as the best discriminative features. Thus the method is highly influenced by the choice of input parameters like rank and weight respectively. Due to the limitation of space provided, the accuracy analysis of the features set against different rank values are not provided in this paper. From analysis, it has been found that decrease of the rank value decreases the number of features and accuracy. Also with the increase in rank value, more features are selected. But higher the number of features decreases the accuracy of classification. Therefore rank value 12 starting from 1 (i.e. number of selected features is 12) for Relief generates highest accuracy of inter egg classification and in our work we have considered these 12 features as best discriminative features. These feature IDs are (i.e. feature set (ASigFS)): F_7(Max); F_{10}(Con); F_{13}(H); F_{12}(E); F_{11}(Cor); $F_2(\sigma)$; F_{13}(Hs); F_{18}(LRE); $F_1(\mu)$; $F_2(\sigma 2)$; F_8(Med); F_9(Mod).

6. Classification of Fresh and Defective Eggs Based on Extracted Feature Sets

In designing of a computer aided quality inspection system, classification of the infrared images as fresh and defective is necessary. For classification purpose, we have used 50 samples of fresh eggs and 50 samples of fresh eggs from our own created dataset. The four feature sets used in our study for investigation are: Combination of all Conventional Feature Set (AComFS), Statistical Significant Feature Set (SSigFS), Automatic Selected Significant Feature Set (ASigFS) and Deep Learning based Feature Set (DeepFS). The classification performance of these four feature sets has been evaluated with seven 'state-of-the-art' classification systems including: SVM, KNN, LDA, RF, DT, NB and ANN [24]-[30]. For the SVM classifier, the performance has been tested with linear kernel. In case of KNN classifier, in order to achieve the best number of neighbourhood K, the classification accuracy is performed with K=2 to 10 and found that highest accuracy is obtained for K=2. On the otherhand, no parameter tuning is performed for LDA and NB classifiers. For implementing DT, other parameters are tuned to default except maximum number of splits is set to 4 so as to attain the optimal classifier to better fit our data. RF is generally a cascade of decision trees and to obtain a reliable prediction, 20 numbers of decision trees are used to model the RF classifier. In our work, the classification accuracy for ANN is tested for the number of hidden layers varying from 1 to 10 and best prediction is achieved for ten hidden layers and used Scaled Conjugate Gradient as training function to train the network. Each of this classifiers excluding ANN are performed based on K-Fold cross validation.

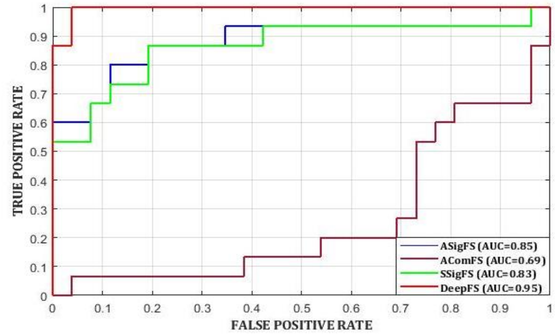


Fig. 7. ROC Curve Representing Different Category of Feature Sets for Classification of Fresh and Defective Eggs using SVM Classifier

Due to the limitation of space, the accuracy, sensitivity, specificity of these classifiers against each feature set for the best suited parameters is shown in Table 6. The observations that can be made from Table 6 are:

1. Different classifiers have shown their best performances either with AComFS, SSigFS, ASigFS or DeepFS. However in all of these four feature sets, the highest performance has been obtained for SVM classifier. Moreover, the accuracy of ASigFS through Relief method is comparatively higher as compared to SSigFS. Conversely AComFS under performs as compared to the remaining three feature set.
2. From the Receiver Operating Characteristic (ROC) curve as shown in Fig. 7 plotted against the most outer performed classifier (i.e. SVM) it has been observed that Area Under Curve (AUC) for DeepFS is 0.95 and is higher as compared to the remaining three feature sets and thus has highest prediction accuracy to sort the fresh eggs from the internal defective ones.

7. Conclusion

We have presented an infrared image dataset of fresh and defective eggs for understanding the applicability of Infrared Imaging Technology (IIT) in quality inspection and automatic separation of this two category of eggs. Furthermore, the paper emphasizes the importance of feature selection in improving the accuracy for discriminating internal defective eggs from fresh or qualified ones. From the experimental results it has been found that although classification based on discriminative selection of conventional features (i.e. SSigFS and ASigFS) provides noticeable prediction accuracy as compared to combination of all conventional features (AComFS) but deep learning based feature extraction (DeepFS) outer performs the remaining three feature sets with the area under the ROC curve (AUC) of 0.95. In future the dataset will be extended with infrared image samples of different internal and external defects in the eggs and extraction of more reliable and robust features for accurate separation of these categories.

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