A NEW LOW-COST DETECTION DEVICE FOR EARLY DISCRIMINATION OF EGGS FERTILITY USING ADVANCED STATISTICAL CLASSIFIERS

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ABSTRACT

Detecting fertility methods of hatching eggs is getting an importance with the increase in poultry breeding facilities size to remove the non-hatchable eggs which consume time, space and cost without benefits. Early detection of the infertile eggs is a vital economic issue. Fertility detection methods are expensive to be applied widely, hence this investigation aimed to study the possibility of using a low-cost device as light dependent resistor sensors in detecting the fertility of hatching eggs with high efficient at candling process. Mathematical formulas were developed in this study to discriminate the fertile and infertile eggs by the light dependent resistor sensor and interfaced with a personal computer programmed by LabView software package to execute a certain control decision (is a hatchable egg or not?) via these formulas. Different statistical classifiers have been used to classify eggs into fertile and infertile eggs like linear, quadratic and partial least squares discriminant analyses and support vector machine. According to literature three different times were appointed at earlier times of egg incubation process for fertility identification investigation of 6th, 9th and 12th day. For more identification precision, sensor position for light intensity measuring was investigated at three different measuring orientation lines against the investigated eggs at vertical, inclined 45˚ and horizontal orientation line. Classification mathematical models were developed using the previous classifiers. Principal component and partial least squares regression were used to develop multiple linear regression models for each incubation period. determination

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It was found by the Principal Component Analysis, that the sensor orientation line position for light intensity measuring gives different measured values of the same investigated egg, but all these measurement values have an entirely correlation relationship with the classification efficiency. The highest identification rate of 97% obtained by the classifier of linear discriminant analysis at the 6th day of the incubation period by the light dependent resistor sensor, which confirms the efficient use of this simple low-cost sensor in discrimination at earlier times of incubation period closing to the other sophisticated devices. The developed mathematical model can easily be implemented with Fuzzy logic controller; further research will be needed to accomplish the fully automated system.

Keywords: *discrimination analysis, mathematical model, hatchability determination*

NOMENCLATURE

LDR	Light-Dependent Resistor	PCA	Principal Component Analysis
LDA	Linear Discriminant Analysis	PCR	Principal Component Regression
QDA	Quadratic Discriminant Analysis	PLS-R	Partial Least Squares Regression
PLS-DA	Partial Least Squares Discriminant Analysis	DAQ R^2	Data Acquisition card Coefficient of determination
SVM	Support Vector Machine	LIFA	LabView Interface for Arduino
I_1, I_2 and I_3	Light intensity measured from MOL positions 1, 2 and 3 respectively, lux		
F_1 and F_2	First and second Principal component, respectively	MOL	Measuring Orientation Line
		SD	Standard Deviation

INTRODUCTION

The biggest problem encounters the egg incubation industry is early fertility detection. The fertility detection requires higher sophisticated devices for that discrimination process. Infertile eggs can cause a bio-contamination if they were not removed before the setting into the artificial incubator or hatchers, in addition, taking time, space and costs **(Smith *et al*., 2008; Zhu and Ma, 2011; Liu and Ngadi, 2013; Hai-ling *et al*., 2016 and Önler *et al.*, 2017)**. As the egg fertility can be detected as possible at earlier times of the incubation duration gives a huge advantage to avoid the consequence problems. There is no devices till now can detect the egg fertility prior to the incubation process because, there is no physiological features of chick embryo can be clearly distinguished inside (**Zhu and Ma, 2011**). Most of egg incubation plants were tending to use destructive and candling analysis methods for egg fertility detection at 7 to 12 days of incubation investigated and developed by **Cain *et al*. (1967); Howe *et al*. (1995); Akiyama *et al*. (1999); Tazawa *et al.* (1999); Moriya *et al*. (1999, 2000); Kato *et al*. (2002); Zhu and Ma (2011) and Liang *et al*. (2011)** which is a difficult problem due to human faults and chick embryo handling effects. Hence, using those methods not are obtainable and reducing the hatching rates to be below the optimum rates of 86-95% according to **USDA (2006)**. To overcome the problems associated to the destructive and candling analysis methods by human factor, there are many trials of automated non-destructive discrimination analysis methods for egg fertility detection at earlier times of incubation with advanced costly instruments such as machine vision **(Zhu and Ma, 2011)**, Magnetic Resonance Imaging (MRI) **(Klein *et al*., 2002; and Bain *et al*., 2007)**, acoustic resonant frequency **(Coucke *et al*., 1997)**, acoustic impulse and supervised recognition **(Lin *et al*., 2009)**, hyper spectral imaging **(Jones *et al*., 2005; and Liu and Ngadi, 2013)**. Such those methods are complicated and expensive in general. Therefore, investigating the feasibility of using low-cost methods would be helpful for developing low-cost detecting fertility instruments. The need to a comprehensive detection method for picking out the infertile eggs one by one is an important issue that the present study dealt with. Egyptian traditional hatcheries, candling process is the most widely followed procedure for identifying fertility of hatching eggs in the early periods of egg incubation. Hatchery workers are using the Candler to observe egg content. Also they are placing egg in their eye socket to judge if it reached the proper temperature or not **(FAO, 2009)**. Definitely, such those methods are not objective for judging hatchability of eggs because they depend on human experience. Hence, the research work is aiming to investigate the ability of using low-cost sensors such as Light-Dependent Resistor (LDR) to discriminate the eggs according to their fertility using different advanced statistical classifiers at earlier different ages of chick embryo to determine the highest percent of identification rate could be achieved by the classifier. The advanced classifiers are be used to develop a suitable mathematical model to allocate the eggs into a fertile or infertile group. There are many different statistical classifiers can be used for fertility detection of hatching eggs such as Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Partial Least Squares Discriminant Analysis (PLS-DA) and Support Vector Machine (SVM). SVM classifier was used before to classify the hatching eggs into fertile and infertile group and establishing a mathematical model by **(Bhuvaneshwari and Scholar, 2015; Zhihui *et al*., 2015 and Nurdiyah and Muwakhid, 2016)**. **(Deng *et al*., 2010; Zhao *et al*., 2010 and Sun *et al*., 2017)** also use SVM for eggshell cracks detection and identifying egg freshness and variety. Mathematical models generated by LDA, QDA and PLS-DA – are very useful to be included in low-cost detection devices of hatching eggs. LDA and PLS-DA have been used by **Yongwei *et al*. (2009) and Zhao *et al*. (2010)** in identifying eggs quality attributes. Therefore the present investigation aims to investigate the following assignments:

1. Studying the feasibility of using low-cost sensors, such as LDR, to discriminate fertile and infertile eggs before hatching;
2. Determining the suitable statistical classifier method which gives the highest identification rate at earlier ages of chick embryo during incubation period; and
3. Developing a mathematical model could be used for automated system to determine if a new hatching egg is fertile or not.

MATERIALS AND METHODS

Egg Samples and Physical Properties

Egg samples of Hubbard broiler aging between 42-46 weeks old. Egg physical analysis was accomplished at the Faculty of Agriculture, Poultry Production Department, Ain Shams University by measuring external and internal dimensions of egg and yolk, mean shell thickness (of the three positions: at blunt, sharp ends and equator), weights of whole egg, albumen, yolk and wet and dry shell and the strength of eggshell. The instruments used for weighing are an electronic balance with a precision of 0.01g and for eggshell thickness and breaking strength is a Vernier Caliper. All measurements and sampling were done at Tarek Diab Hatchery Plant, Nashil village, Qotour district, Gharbia Governorate, Egypt during the summer season of 2017. The freshly laid eggs were incubated in a Smart™ incubator (Pas Reform Hatchery Technologies, Zeddam, the Netherlands) at 37.6ºC and 54% relative humidity, and were turned every one hour. On days of 6th, 9th and 12th of incubation, eggs were taken out from the incubator to be candled. Candling process does not take more than two minutes to return eggs tray into the incubator immediately for chick embryos bio-security. Sampling was run at the periods of candling process at 6th, 9th and 12th days of the incubation age. Total samples of 110 eggs are including 55 fertile and other of 55 infertile eggs.

Experimental Setup

To investigate the effectiveness of LDR in detecting fertility of hatching eggs and thus discriminate the fertile and infertile eggs, it needs an appropriate Candler which allows an easy and fast measuring of light intensity that is traveling from the light source to the sensor transmitting through the investigated eggs. A local-made Candler is consists of 70 × 40 × 30cm container was manufactured from 3mm mild steel sheets and furnished to be like a trolley for ease movement. The Candler was manufactured in a workshop located at Gharbia Governorate, **Figure 1**. At the predetermined investigated ages (6th, 9th and 12th days), the eggs tray was carried from the incubator and positioned on the Candler for light intensity measurements of light spectrum emitted from eggs during candling. Light source used for candling was a Light Emitting Diode (LED) lamp of 40W and 250lm. Twelve lamps were uniformly distributed at the bottom of the container and were matched to be in three rows transversely and four columns longitudinally as depicted in **Figure 1**. Distance between lamps' top edges and eggs trays was of 8cm. For measuring light intensity, LDR sensor positioning was investigated at three different measuring orientation lines in space for giving the highest classification percent. The first, second and third sensor measuring orientation line was expressed as an angle, the angle between the sensor axis and egg axis of Zero, 45 and 90 degrees, respectively. LDR sensor was located in a transparent polyethylene container formed a shape of incomplete cone. The distance between the sensor and the container top is 1cm, **Figure 2**. For data acquiring from the LDR sensor, the microcontroller Arduino-Uno board was programmed as an interface Data Acquisition card (DAQ) module between the Personal Computer (PC) and LDR sensor. Arduino is a single-board microcontroller, can be used for reading data from sensors and also can use these data to control the overall system. So the Arduino-Uno board provides analog and digital Inputs and Outputs (I/O ports) to read data obtained from the sensor or giving orders for controlling. LabView software was used to program the Arduino microcontroller to be a DAQ card. LabView is graphical programming software. The interfacing between Arduino microcontroller and LabView is an innovative research tool due to the integration work between the open source microcontroller and PCs which gives higher potential tool for all biosystems monitoring and control operations. Data acquired by DAQ is processed, analyzed and presented graphically by LabView installed on the PC and this makes the programming modifications is available for any required duty. So LabView Interface for Arduino (LIFA) toolkit was used.

LDR connection to Arduino DAQ

Light intensity measurement was performed by a GL12528 12mm LDR sensor. LDR is an inexpensive cadmium sulfide photoconductive cell **(Maranhão *et al*., 2015)**. Using resistance as a function of illumination, with the increase of illumination on the cell, resistance is going to decrease. Hence sensor output voltage is linearly proportional to illumination. The measurement range of illumination was provided by the manufacturer is from 0 to 10000lux with resistance range varying linearly from 1000kΩ to 100Ω, respectively. The LDR sensor has two terminals; the first terminal is connected to power supply terminal (5Volt V_{cc}) and the second one is output terminal (V_{out}) that gives the output voltage corresponding to the sensed illumination as shown in **Figure 3**.

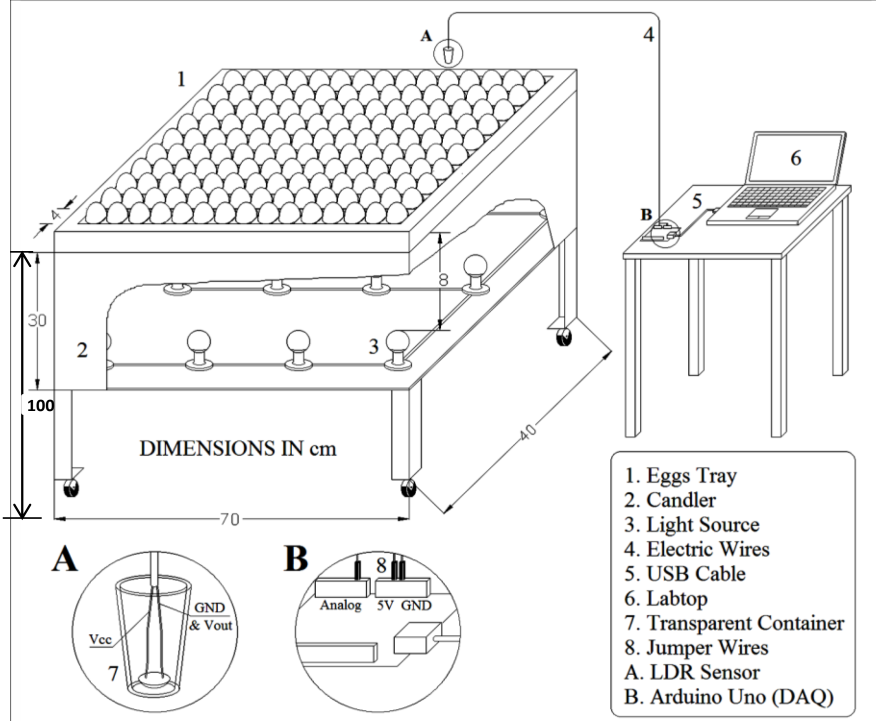

Figure 1. Schematic drawing of experimental setup used for investigating LDR efficiency in detecting fertility of hatching eggs

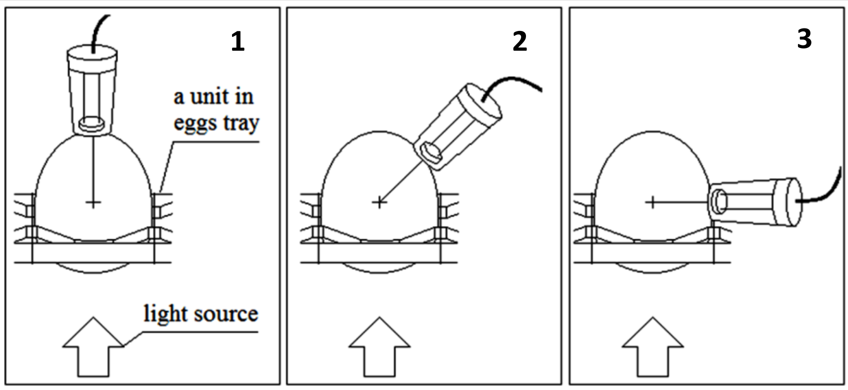

Figure 2. Schematic drawing of the three different positions that light intensity was measured from; **(1)** Zero degree, **(2)** 45 degrees and **(3)** 90 degrees

Modeling and Simulation of Light Intensity Measuring System

LabView 2013 software was used in the present investigation with NI-VISA 5.0.3 software. LIFA toolkit was downloaded and installed from

JKI VI Package Manager. So the microcontroller Arduino can be programmed and operated directly by LabView for any system controlling and data acquiring processes. For programming the DAQ (microcontroller Arduino) to acquire the data from LDR sensor, the front panel and block diagram of LabView software were used. In front panel, the indicators and controls for the programmer are appearing. Block diagram is containing the graphical source code. Hence any object on the front panel appears as a terminal on the block diagram **(Johnson and Jennings, 2006)**. The programmed graphical code designed for this experiment was depicted in **Figure 4**. VISA resource was defined to use the COM4 of the PC for data communication and transfer via USB/Serial to the Arduino board; the baud rate was adjusted at 115200baud/second for initialization. Analog input port ofA0 was chosen for data readings from the LDR sensor as shown in **Figure 3**. The while loop for the system continuous operation was timed at 1000ms to take one reading every second, **Figure 4**. After coding the system, front panel would be as shown in **Figure 5**. Analog input was chosen from the front panel to be A0 and by running the system it would be able to measure light intensity emitted from eggshell in lux as depicted in **Figure 5**. LIFA toolkit has already been used in agricultural engineering applications by **Faris and Mahmood (2014); and Pradeep *et al.* (2014)**.

The effect of the measuring orientation line and PCA

To study the effect of the measuring orientation line on discrimination precision; an adequate method was determined after a series of experiments to study the correlations between light intensity data and eggs fertility. Hence PCA technique was applied for this purpose. In PCA, light intensity measurements from both fertile and infertile eggs samples are presented by “loadings plots”. Measured values of samples that are positively correlated to each other are close to each other. So it is expected that the infertile samples are going to be close to each other and the same for fertile samples, while loadings that are negatively correlated are going to be positioned opposite of each other. Hence it is expected that the infertile samples are going to be positioned opposite of the fertile ones. The three different measuring orientation lines and the measured values are going to be represented in “score plots”.

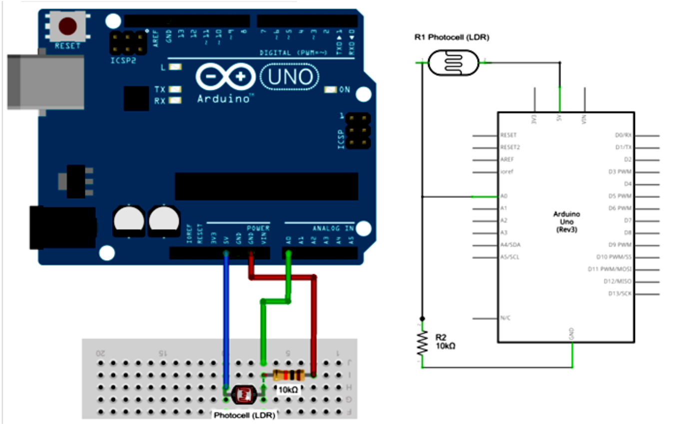

Figure 3. Schematic drawing of LDR circuit diagram and hardware system used for interfacing LDR sensor to Arduino for measuring light intensity

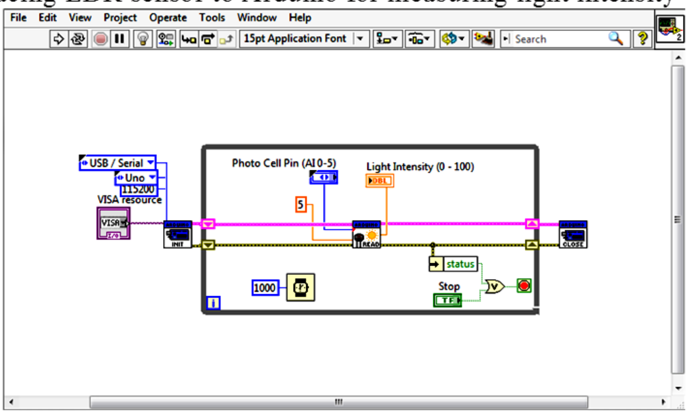

Figure 4. Block diagram of light intensity measurement code

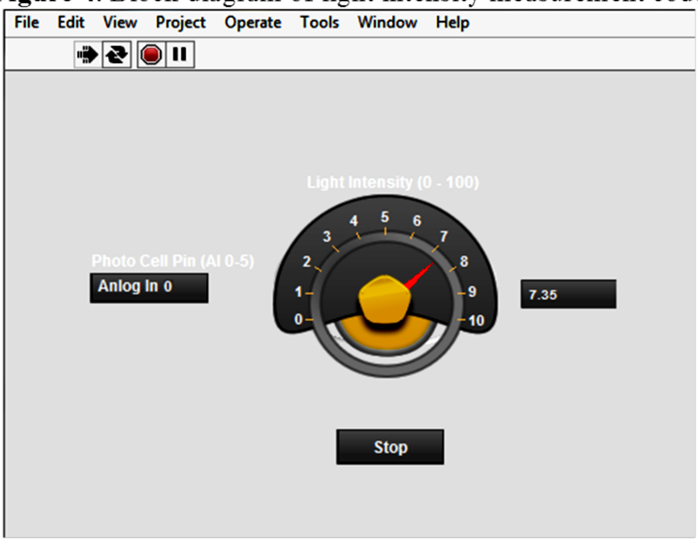

Figure 5. Front panel of light intensity measurement

If there is a similarity in light intensity between any two measuring orientation lines, i.e., they are positively correlated, their scores are going to be close to each other. While if there are some kind of dissimilarity, i.e., they are negatively correlated, their scores are going to be positioned opposite to each other **(Hopfer *et al*., 2014)**. PCA is obtaining to study if there are any differences between these orientation line positions of the sensor. XLSTAT 2017 software was used for PCA running.

Classifiers and Classification Models

To ensure if the data obtained from LDR sensor has the discrimination potential between fertile and infertile egg, different classifiers have been used for determining which one gave the highest percent of correctly classified samples. In addition, to make these data practical and applicable to be inserted in automated system for detecting fertility of hatching eggs. Classification models could be developed from these data in which two models are developed. One for fertile egg and the other for infertile and by substituting with light intensity value measured from the egg, fertility are going to be determined according to the model that gave the highest value between these two models. The statistical classifiers like LDA, QDA and PLS-DA were used for developing linear, multiple regression, second-order polynomial and interactive second-order polynomial models for predicting fertility. Also classifiers like SVM was used in the present study for finding support vectors and bias that could be used to find a boundary takes different shapes which could be used to differentiate between fertile and infertile eggs. LDA, QDA, PLS-DA and SVM have been used before in food science and engineering **(Cen and He, 2007; Cocchi *et al*., 2006 and Elmessery and Abdallah, 2014)**. Also PCR and PLS-R were used for developing a classification model could be used via substituting in that model and then the sign of resulted value determine its fertility. For running this test, hundred samples was used as a training set; fifty fertile and the other fifty infertile and for validation set ten eggs was selected; five fertile and the other fives was infertile. Light intensity measured from infertile eggs was given a value of -1 and for fertile ones was given a value of +1 as a quantified value of its fertility.

RESULTS AND DISCUSSION

From physical analysis results obtained and indicated at **Table 1**, there is no abnormal characteristics can influence hatchability and adequate production (**Narushin and Romanov, 2002**).

Table 1. Physical Properties of the investigated eggs

Item	Mean±SD	Item	Mean±SD
Egg weight, g	65.75±3.42	Albumen height, mm	9.87±2.27
Length, mm	56.82 ± 2.1	Yolk diameter, mm	41.21 ±1.03
Width, mm	46.4 ± 2.11	Yolk weight, g	19.9±0.96
Shell breaking strength, N/cm^2	24±5.90	Shell wet-weight, g	7.74±0.51
		Shell dry-weight, g	5.68±0.19
Yolk height, mm	17.31±1.25	Shell thickness, mm	0.36 ±0.05

Discrimination analysis by PCA method

The main purpose of running Principal Component Analysis (PCA) is to find if there are any differences between the three different positions of Measuring Orientation Line (MOL) for light intensity measurements, **Figure 2**, and to find the correlation between fertility state and MOL positions. From PCA correlation matrix between light intensity value and the MOL positions of 1, 2 and 3 as reported in **Table 2** for each investigated age of eggs, it is evident from these results that the fertility has a high negative correlation between light intensity measured from MOL position 1 in each case of incubation period and the coefficient of correlation was of -0.791, -0.840 and -0.898 for the 6th, 9th and 12th day of the incubation period, respectively. Also from PCA, the score plots are showing differences between light intensity values obtained from the three MOL positions. It is evident that MOL position 1 has a positive correlation with MOL position 2 according to the first component analysis because they were closely positioned at the quarter. This positive correlation between the two MOL positions 1 and 2 raises as incubation period increases as shown in **Figure 6-C** due to the increase of chick embryo size, this result has an important approach issue for chick embryo aging determination. Series of experiments will be required to deliver a scientific tool for embryo age measuring. Overall differences among light intensities measured at the three MOL positions which represent 56.20, 74.87 and 50.02% for chick embryo at the 6th, 9th and 12th day of incubation period, respectively as shown in **Figure 6**. The highest percent of 74.87% obtained at the 9th day of the incubation period illustrates that there are high differences among light intensities measured from the three different MOL positions, **Figure 6-B**. Light intensity values measured from MOL positions 1 and 2 are very close to each other. For loading plots, it is evident there are differences between fertile and infertile eggs. The observations from 1 to 50 (Obs1 to Obs50) and from 51 to 100 (Obs51 to Obs100) were infertile and fertile eggs, respectively.

Table 2. Correlation matrixes between light intensity measured from the three different MOL positions and fertility for each investigated incubation period

	Variables	Position 1	Position 2	Position 3	Fertility
6 days of incubation period	Position 1	**1.000**	0.460	0.200	-0.791
	Position 2	0.460	**1.000**	0.353	-0.432
	Position 3	0.200	0.353	**1.000**	-0.093
	Fertility	-0.791	-0.432	-0.093	**1.000**
9 days of incubation period	Variables	Position 1	Position 2	Position 3	Fertility
	Position 1	**1.000**	0.857	0.391	-0.840
	Position 2	0.857	**1.000**	0.590	-0.640
	Position 3	0.391	0.590	**1.000**	-0.068
	Fertility	-0.840	-0.640	-0.068	**1.000**
12 days of incubation period	Variables	Position 1	Position 2	Position 3	Fertility
	Position 1	**1.000**	0.452	0.129	-0.898
	Position 2	0.452	**1.000**	0.092	-0.507
	Position 3	0.129	0.092	**1.000**	-0.114
	Fertility	-0.898	-0.507	-0.114	**1.000**

Regression analysis by PCR and PLS-R methods

PCR and PLS-R were used to develop a linear equation fitting the data obtained from the three MOL positions of the fertility eggs, **Equation 1**. By substituting light intensity values in this equation; if the result value is negative the egg be infertile, otherwise be fertile. The model constants for **Equation 1** have been listed in **Table 3** for both PCR and PLS-R methods.

$$Fertility = a + b\,I_1 + c\,I_2 + d\,I_3 \qquad \text{Eqn 1}$$

Where I_1, I_2 and I_3 are light intensity measured from positions 1, 2 and 3, respectively. It was noticed that with the increase in chick embryo age the model fitness is increased. The mathematical model developed by PCR has higher coefficient of determination than PLS-R at all incubation ages and the highest value obtained of the coefficient of determination obtained is 0.819 at age of 12 days.

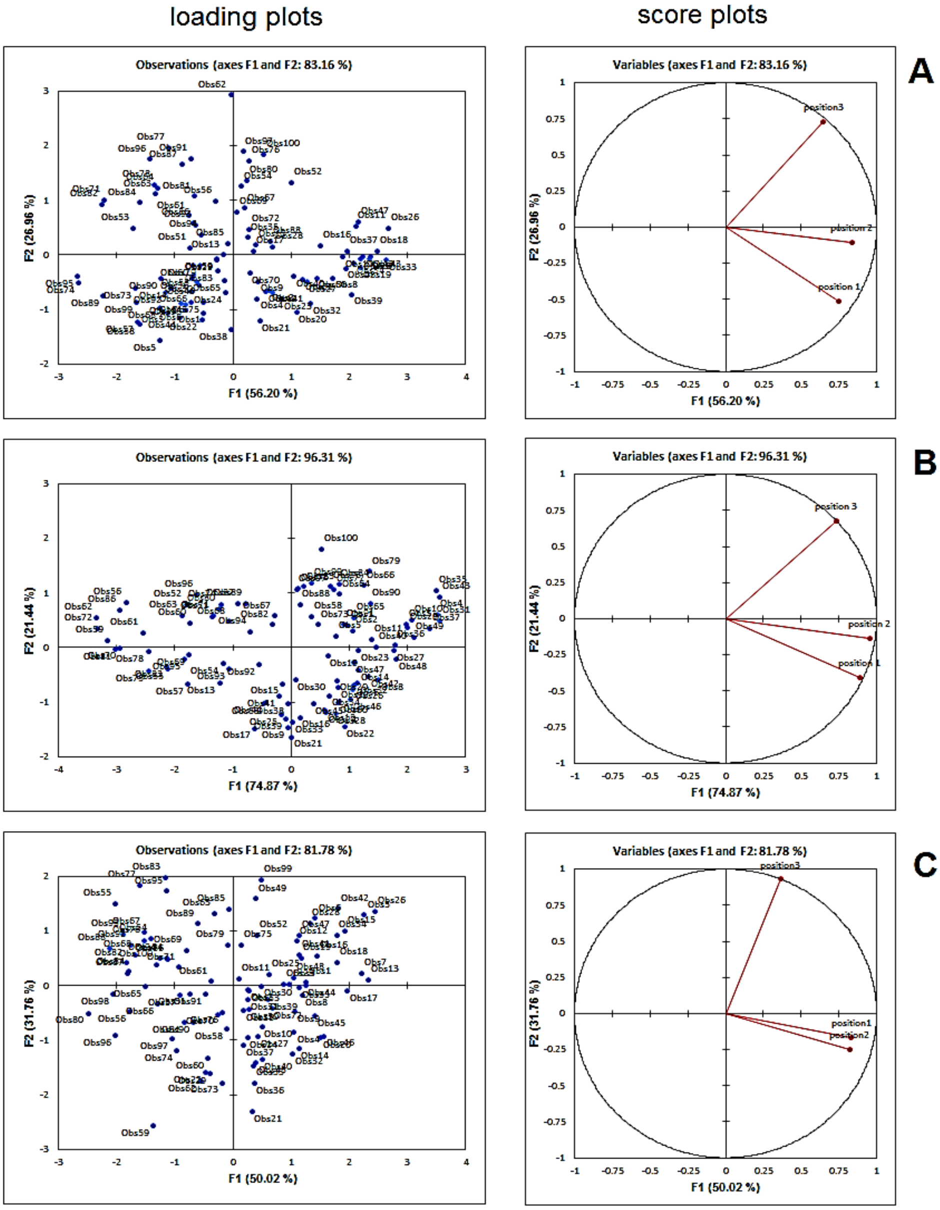

Figure 6. Loading plots and score plots of PCA results for each age of chick embryo at (A) 6, (B) 9 and (C) 12 days old

Table 3. Fertility predicting mathematical model constants for PCR and PLS-R methods

Classification method	Incubation period, days	Model constants				R^2
		a	b	c	d	
PCR	6	5.784	-0.102	-0.028	0.027	0.640
	9	1.280	-0.147	0.001	0.082	0.786
	12	4.648	-0.084	-0.017	0.001	0.819
PLS-R	6	11.087	-0.074	-0.070	-0.018	0.565
	9	8.942	-0.067	-0.058	-0.010	0.587
	12	7.061	-0.063	-0.048	-0.015	0.760

Identification Rates of PLS-DA, QDA, LDA and SVM Classifiers

The feasibility of using LDR sensor to achieve high percentage of identification rate in which eggs samples were classified correctly into fertile and infertile eggs. The percentages of correctly classified observations were listed, for all classifiers used in the present study, in **Table 4**. According to LDA classifier the data measured from each individual MOL position have higher identification rate than by QDA, where the MOL position 1 achieves the highest identification rate by LDA at chick embryo age of 6 days old of 95% for training set. But, for MOL positions 2 and 3, the identification rates were lower. In case of using the three MOL positions in the training set, classification at age of 6 days old was correctly classified of 97% by LDA and 95% by QDA. The validation set was 100% correctly classified by both classifiers LDA and QDA. For an early fertility detection of hatching egg, light intensity should be measured from MOL positions of 1, 2 and 3 and data obtained should be classified according to LDA. For simple or quick detection, light intensity can be measured at MOL position 1, and age of 12 days old of chick embryo. Using QDA classifier it is of course an advanced level of chick embryo development, so it is not recommended. PLS-DA classifier gave the lowest percentage of correct classification of eggs at each chick embryo age among other statistical classifiers at the three MOL positions, **Table 5**. To compare Radial Basis Function, RBF-SVM classifier results obtained by this study and the other done by **Zhu and Ma (2011)**; RBF kernel classifier achieves the percent of 92% at training set among the other three types of kernel classifier of SVM at the age of 6 days old of chick embryo, but the validation set present of the three types of kernels was 100%. However the investigation done by **Zhu and Ma (2011)** obtains higher identification rate of 95.8% for training set by linear kernel with the machine vision for eggs were investigated in the period from7th to 12th day of the incubation and 99.1% by RBF kernel. But on the other hand in this study, the classifiers of LDA, QDA and PLS-DA with LDR sensor achieve the percent of 97, 95, and 85% of training set at 6th day for the three MOL positions, respectively, **Table 5**. This confirms that the simple low-cost LDR sensor can classify eggs according to their fertility as well as machine vision system does.

Classification Mathematical Models

The main purpose of using classifiers is to find a suitable mathematical model could be used for fertility predicting of an egg by substituting the value of light intensity in two models, i.e., a model for fertile eggs and the other for infertile ones. In comparison between the result values of the two models, the highest result value obtained determines its fertility. Hence the mathematical models have been developed by those classifiers studied above that can be included in any automated control system such as Fuzzy logic control system for sorting eggs according to their fertility. **Table 6** shows the overall model constant values for all measured values of light intensity obtained from the three MOL positions together. On the other hand, **Table 7** illustrates the constant values of the simple model which depends only on one position of MOL to measure light intensity of the egg. After that **Equations 2 and 4** would be used for discrimination process. These equations were generated using LDA and QDA. In case of using three MOL positions, **Equations 3 and 5** would be used including multiple linear regression model and interactive second-order polynomial model. The previously mentioned models were developed also for each age of incubation period and by them any automated system could detect the hatching egg fertility. Because of the shortage of time and space, list of SVM for RBF kernel was reported only because its highest performance in discriminating the eggs at 6 days old of chick embryo, **Table 8**. The list of SVM and their bias for each age of chick embryo to make a boundary separates between measured values of light intensity from fertile and infertile eggs could be used in classifying eggs according to its fertility and for further research on it in the future.

Table 4. Identification rate of LDA and QDA classifiers according to chick embryo age and one identical MOL position on the egg

Measuring Position	Incubation period, days	Correctly classified observations by different classifiers, %											
		Linear Discriminant Analysis						Quadratic Discriminant Analysis					
		Training set			Validation set			Training set			Validation set		
		Fertile	Infertile	Total	Fertile	Infertile	Total	Fertile	Infertile	Total	Fertile	Infertile	Total
Position 1	6	94.00	96.00	**95.00**	100.00	100.00	**100.00**	98.00	90.00	**94.00**	100.00	100.00	**100.00**
	9	88.00	98.00	**93.00**	100.00	100.00	**100.00**	94.00	96.00	**95.00**	100.00	100.00	**100.00**
	12	100.00	96.00	**98.00**	100.00	100.00	**100.00**	100.00	100.00	**100.00**	100.00	100.00	**100.00**
Position 2	6	60.00	64.00	**62.00**	60.00	60.00	**60.00**	58.00	68.00	**63.00**	60.00	80.00	**70.00**
	9	68.00	86.00	**77.00**	80.00	100.00	**90.00**	66.00	86.00	**76.00**	80.00	100.00	**90.00**
	12	62.00	80.00	**71.00**	80.00	100.00	**90.00**	62.00	86.00	**74.00**	80.00	100.00	**90.00**
Position 3	6	54.00	52.00	**53.00**	40.00	40.00	**40.00**	38.00	68.00	**53.00**	20.00	40.00	**30.00**
	9	54.00	48.00	**51.00**	100.00	40.00	**70.00**	54.00	50.00	**52.00**	100.00	40.00	**70.00**
	12	52.00	54.00	**53.00**	80.00	20.00	**50.00**	70.00	42.00	**56.00**	80.00	20.00	**50.00**

Table 5. Identification rate of each classifier according to chick embryo age and the whole three MOL positions on the egg

Measuring Position	Incubation period, day	Correctly classified observations by different classifiers, %											
		Linear Discriminant Analysis						Quadratic Discriminant Analysis					
		Training set			Validation set			Training set			Validation set		
		Fertile	Infertile	Total	Fertile	Infertile	Total	Fertile	Infertile	Total	Fertile	Infertile	Total
Whole MOL Positions of 1, 2 and 3	6	96.00	98.00	**97.00**	100.00	100.00	**100.00**	92.00	98.00	**95.00**	100.00	100.00	**100.00**
	9	90.00	98.00	**94.00**	100.00	100.00	**100.00**	98.00	96.00	**97.00**	100.00	100.00	**100.00**
	12	100.00	100.00	**100.00**	100.00	100.00	**100.00**	100.00	100.00	**100.00**	100.00	100.00	**100.00**
		Partial Least Squares Discriminant Analysis						Support Vector Machine **(**Linear kernel)					
		Training set			Validation set			Training set			Validation set		
		Fertile	Infertile	Total	Fertile	Infertile	Total	Fertile	Infertile	Total	Fertile	Infertile	Total
	6	94.00	76.00	**85.00**	100.00	80.00	**90.00**	98.00	80.00	**89.00**	100.00	100.00	**100.00**
	9	76.00	98.00	**87.00**	100.00	100.00	**100.00**	94.00	98.00	**96.00**	100.00	100.00	**100.00**
	12	96.00	96.00	**96.00**	100.00	100.00	**100.00**	100.00	98.00	**99.00**	100.00	100.00	**100.00**
		Support Vector Machine **(**Power kernel)						Support Vector Machine **(**RBF kernel)					
		Training set			Validation set			Training set			Validation set		
		Fertile	Infertile	Total	Fertile	Infertile	Total	Fertile	Infertile	Total	Fertile	Infertile	Total
	6	98.00	80.00	**89.00**	100.00	100.00	**100.00**	100.00	84.00	**92.00**	100.00	100.00	**100.00**
	9	94.00	98.00	**96.00**	100.00	100.00	**100.00**	94.00	96.00	**95.00**	100.00	100.00	**100.00**
	12	100.00	98.00	**99.00**	100.00	100.00	**100.00**	100.00	98.00	**99.00**	100.00	100.00	**100.00**

CONCLUSIONS

In the present study the discrimination efficiency of a low-cost device for fertility early detection of hatching eggs has been investigated. Mathematical models to discriminate the fertile eggs were developed using different advanced statistical classifiers. Based on the research work described here, it is possible to release the following conclusions:

1. By using PCA the differences between light intensity values obtained from the first two measuring orientation line positions on the egg fertility discrimination which are going to decrease with the increase of chick embryo age.
2. The mathematical models developed by the classifier of LDA, QDA and PLS-DA can successfully early discriminate the fertile eggs at 6^{th} day of the incubation process based on the whole data obtained from the three MOL positions together was 97, 95 and 85% for the training set, respectively.
3. SVM classifier which was widely used for egg fertility discrimination with machine visions can discriminate egg fertility in the present study with LDR sensor according to its fertility with an identification rate of training set 89, 89 and 92% for 6 days of incubation for three types of the sub classifiers of linear, power and RBF kernel, respectively the validation set identification rate reached 100% for each method of SVM.
4. Simple sensors like LDR are efficient to detect fertility of hatching eggs using Candlers and could be used for Fuzzy logic automated system using the mathematical formulas developed in the present study.
5. Mathematical models (Equations 3 and 5) developed by LDA and QDA classifiers can precisely discriminate the fertile eggs using the constants which are indicated at Table 6. By substituting the light intensities obtained by low-cost Light-Dependent Resistor (LDR) in the developed equation of fertile part of equation 3 or 5, if the result is +1 means that the egg is fertile and as the same by substituting the light intensities in the infertile part of equation 3 or 5, if the result is -1 indicates that the egg is infertile.

Table 6. Developed general form of classification models used for eggs discrimination according to their fertility

Model type in case of measuring from:			
MOL position 1		MOL positions of 1, 2 and 3	
Linear regression		Multiple linear regression	
$f = a + b\,I_1$ $n = a + b\,I_1$	} Eqn 2	$f = a + b\,I_1 + c\,I_2 + d\,I_3$ *(fertile part)* $n = a + b\,I_1 + c\,I_2 + d\,I_3$ *(infertile part)*	} Eqn 3
Second-order polynomial		Interactive second-order polynomial	
$f = a + b\,I_1 + c\,I_1^2$ $n = a + b\,I_1 + c\,I_1^2$	} Eqn 4	$f = a + b\,I_1 + c\,I_2 + d\,I_3 + e\,I_1^2 + f\,I_1\,I_2 + g\,I_1\,I_3 + h\,I_2^2 + i\,I_2\,I_3 + j\,I_3^2$ $n = a + b\,I_1 + c\,I_2 + d\,I_3 + e\,I_1^2 + f\,I_1\,I_2 + g\,I_1\,I_3 + h\,I_2^2 + i\,I_2\,I_3 + j\,I_3^2$	} Eqn 5

Table 7.Classification mathematical models constants of higher identification rate classifier

Predicting models need to measure light intensity from positions 1, 2 and 3															
Classifier	Classification model (Eqn 3) constants	Incubation period, days						Classifier	Classification model (Eqn 5) constants	Incubation period, days					
		6		9		12				6		9		12	
		f	***n***	***f***	***n***	***f***	***n***			***f***	***n***	***f***	***n***	***f***	***n***
LDA	a	-355.392	-386.903	-260.297	-272.022	-176.625	-226.982	QDA	a	-504.602	-352.868	-306.324	-433.351	-234.444	-215.179
	b	1.210	1.767	0.458	1.808	1.557	2.468		b	3.228	-1.600	0.303	4.886	2.742	1.707
	c	2.835	2.988	-0.494	-0.503	1.370	1.557		c	4.412	1.857	-2.897	5.631	1.282	2.896
	d	5.092	4.943	6.223	5.469	2.648	2.635		d	5.874	7.610	9.290	1.382	3.507	1.624
PLS-DA	a	6.043	-5.043	4.971	-3.971	4.031	-3.031		e	-0.020	-0.080	-0.065	-0.187	-0.031	-0.023
	b	-0.037	0.037	-0.034	0.034	-0.032	0.032		f	-0.007	0.117	0.072	0.168	-0.002	0.000
	c	-0.035	0.035	-0.029	0.029	-0.024	0.024		g	-0.006	0.037	0.016	0.064	-0.006	0.007
	d	-0.009	0.009	-0.005	0.005	-0.007	0.007		h	-0.028	-0.165	-0.062	-0.151	-0.008	-0.031
									i	0.001	0.178	0.093	0.085	-0.003	0.015
									j	-0.032	-0.135	-0.098	-0.070	-0.019	-0.018
Predicting models need to measure light intensity from position 1															
Classifier	Classification model (Eqn 2) constants	Incubation period, days						Classifier	Classification model (Eqn 4) constants	Incubation period, days					
		6		9		12				6		9		12	
		f	***n***	***f***	***n***	***f***	***n***			***f***	***n***	***f***	***n***	***f***	***n***
LDA	a	-69.817	-103.187	-103.480	-152.161	-30.495	-69.818	QDA	a	-58.967	-133.509	-68.349	-340.914	-37.881	-61.484
	b	2.570	3.130	3.998	4.853	1.736	2.643		b	2.107	4.013	2.573	10.873	2.084	2.264
									c	-0.020	-0.031	-0.025	-0.087	-0.030	-0.022

Table 8. List of support vectors and bias for each incubation period using RBF kernel

S.N.	Support vectors (RBF kernel)														
	Incubation period, day														
	6 (Bias = -0.743)					9 (Bias = 0.094)					12 (Bias = -0.464)				
	Fertility	alpha	Light intensity, lux			Fertility	alpha	Light intensity, lux			Fertility	alpha	Light intensity, lux		
			Position 1	Position 2	Position 3			Position 1	Position 2	Position 3			Position 1	Position 2	Position 3
1	-1	1.000	0.693	0.506	0.237	-1	1.000	0.626	0.850	0.614	-1	1.000	0.708	0.551	0.573
2	-1	1.000	0.699	0.272	0.211	-1	1.000	0.732	0.776	0.629	-1	1.000	0.570	0.593	0.611
3	-1	1.000	0.654	0.840	0.329	-1	1.000	0.740	0.682	0.586	-1	1.000	0.664	0.754	0.809
4	-1	1.000	0.667	0.383	0.053	-1	0.854	0.886	0.916	0.814	-1	1.000	0.542	0.605	0.237
5	-1	1.000	0.595	0.519	0.184	-1	1.000	0.821	0.822	0.643	-1	1.000	0.691	0.647	0.656
6	-1	1.000	0.719	0.679	0.447	-1	1.000	0.528	0.393	0.129	-1	1.000	0.586	0.778	0.427
7	-1	1.000	0.810	0.938	0.842	-1	1.000	0.715	0.561	0.271	-1	1.000	0.586	0.599	0.237
8	-1	1.000	0.588	0.469	0.211	-1	1.000	0.715	0.561	0.014	-1	0.791	0.708	0.611	0.603
9	-1	1.000	0.575	0.556	0.474	-1	1.000	0.846	0.579	0.514	-1	1.000	0.641	0.623	0.542
10	-1	1.000	0.614	0.309	0.289	-1	1.000	0.789	0.822	0.557	-1	0.270	0.713	0.904	0.878
11	-1	1.000	0.706	0.531	0.618	-1	1.000	0.740	0.598	0.314	-1	1.000	0.686	0.641	0.374
12	-1	0.339	0.771	0.852	0.697	-1	1.000	0.911	0.925	1.000	-1	1.000	0.564	0.677	0.504
13	-1	1.000	0.647	0.630	0.553	-1	0.807	0.732	0.654	0.186	-1	1.000	0.537	0.802	0.573
14	-1	1.000	0.660	0.568	0.184	-1	1.000	0.797	0.907	0.600	-1	1.000	0.636	0.491	0.908
15	-1	1.000	0.752	0.481	0.382	-1	1.000	0.707	0.598	0.200	-1	1.000	0.702	0.593	0.504
16	-1	1.000	0.673	0.691	0.605	-1	1.000	0.951	0.925	0.986	1	1.000	0.426	0.485	0.504
17	-1	1.000	0.686	0.383	0.500	-1	1.000	0.683	0.570	0.143	1	1.000	0.443	0.766	0.588
18	-1	1.000	0.588	0.481	0.329	1	1.000	0.537	0.738	0.086	1	0.935	0.432	0.204	0.366
19	-1	1.000	0.601	0.605	0.592	1	1.000	0.569	0.290	0.243	1	1.000	0.388	0.467	0.489
20	-1	1.000	0.595	0.432	0.342	1	1.000	0.463	0.280	0.057	1	1.000	0.421	0.737	0.427
21	-1	1.000	0.732	0.691	0.197	1	1.000	0.634	0.579	0.614	1	1.000	0.448	0.665	0.298
22	-1	1.000	0.627	0.469	0.158	1	1.000	0.626	0.682	0.757	1	1.000	0.454	0.551	0.573
23	-1	1.000	0.562	0.568	0.211	1	1.000	0.707	0.766	0.686	1	1.000	0.355	0.743	0.214
24	-1	1.000	0.588	0.506	0.316	1	1.000	0.618	0.813	0.829	1	1.000	0.421	0.341	0.427
25	-1	1.000	0.765	1.000	0.842	1	1.000	0.528	0.785	0.543	1	1.000	0.393	0.952	0.557

To be continued Table 8

S.N.	Support vectors (RBF kernel)														
	Incubation period, day														
	6 (Bias = -0.743)					9 (Bias = 0.094)					12 (Bias = -0.464)				
	Fertility	alpha	Light intensity, lux			Fertility	alpha	Light intensity, lux			Fertility	alpha	Light intensity, lux		
			Position 1	Position 2	Position 3			Position 1	Position 2	Position 3			Position 1	Position 2	Position 3
26	1	1.000	0.536	0.370	0.461	1	0.388	0.301	0.178	0.014	1	0.262	0.322	0.880	0.237
27	1	1.000	0.503	0.790	0.842	1	0.273	0.496	0.785	0.729	1	0.830	0.327	0.743	0.748
28	1	1.000	0.510	0.543	0.316	1	1.000	0.561	0.860	0.886	1	0.035	0.393	0.186	0.885
29	1	1.000	0.477	0.432	0.026	1	1.000	0.488	0.551	0.471	1	1.000	0.404	0.557	0.855
30	1	1.000	0.542	0.358	0.053	1	1.000	0.528	0.757	0.771	1	1.000	0.377	0.605	0.527
31	1	1.000	0.575	0.531	0.447	1	1.000	0.642	0.888	0.757	1	1.000	0.388	0.683	1.000
32	1	1.000	0.418	0.630	0.316	1	1.000	0.667	0.776	0.629					
33	1	1.000	0.536	0.728	0.329	1	1.000	0.488	0.617	0.257					
34	1	1.000	0.516	0.593	0.237	1	1.000	0.537	0.383	0.214					
35	1	1.000	0.490	0.494	0.118	1	1.000	0.577	0.654	0.771					
36	1	1.000	0.458	0.630	0.632										
37	1	1.000	0.556	0.827	0.395										
38	1	1.000	0.477	0.753	0.566										
39	1	1.000	0.569	0.148	0.237										
40	1	1.000	0.497	0.741	0.184										
41	1	1.000	0.588	0.309	0.961										
42	1	1.000	0.582	0.444	0.408										
43	1	1.000	0.536	0.642	0.368										
44	1	0.722	0.386	0.802	0.434										
45	1	1.000	0.575	0.235	0.605										
46	1	1.000	0.529	0.864	0.553										
47	1	1.000	0.536	0.025	0.158										
48	1	0.617	0.588	0.235	1.000										
49	1	1.000	0.595	0.494	0.211										
50	1	1.000	0.451	0.383	0.105										

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الملخص العربي

جهاز كشف جديد منخفض التكلفة للتمييز المبكر لخصوبة البيض باستخدام مصنفات إحصائية متقدمة

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تعتبر عملية إستبعاد البيض غير القابل للفقس قبل عملية التحضين من أعقد العمليات نتيجة لعدم وجود ملامح فسيولوجية داخل البيضة تميز البيض المخصب عن غيره من غير المخصب. لذا لجأ العديد من الباحثين إلي دراسة إمكانية الكشف المبكر للبيض كلما أمكن ذلك في مراحل التحضين الأولى لتعظيم الإستفادة من الفراغات المتاحة داخل الحضان والإستفادة منه كبيض مائدة وكذلك تقليل التلوث الحادث من البيض غير المخصب والذي يفسد داخل الحضان. إن الطرق المستخدمة فى كشف خصوبة بيض التفريخ تزداد أهمية مع زيادة حجم منشآت إنتاج الدواجن لإزالة البيض غير القابل للتفريخ والذي يستهلك الوقت والمساحة وأيضاً التكلفة. هذه الطرق ذات تكلفة عالية لكى يتم تطبيقها بشكل واسع، ومن ثم فقد تم إجراء بحث عن إمكانية إستخدام طرق ذات تكلفة منخفضة مثل حساس الضوء من نوع (GL12528 ١٢مم) فى كشف خصوبة بيض التفريخ. وأيضاً إنشاء وتطوير معادلات رياضية تستخدم للتمييز بين البيض المخصب وغير المخصب، وبواسطة هذه المعادلات يمكن توصيل حساس الضوء بنظم تحكم مثل نظم التحكم المنطقية الضبابية Fuzzy Logic Control Systems لفرز البيض من خلالها. تم أخذ عينات البيض من أمهات نوع (Hubbard Breed) بعد إجراء الفحوصات عليها للتأكد من عدم وجود مظاهر غير طبيعية بداخل أو خارج البيضة، وقد تم إجراء هذه الفحوصات بقسم إنتاج الدواجن بكلية الزراعة بجامعة عين شمس. وتم إجراء جميع القياسات بمعمل طارق دياب للتفريخ بقرية نشيل،مركز قطور، محافظة الغربية خلال عام ٢٠١٧م. تم أخذ البيض المنتج حديثاً ووضعه في حضانات من نوع:

Smart™ (Pas Reform Hatchery Technologies, Zeddam, the Netherlands)

وتم ضبطها عند درجة حرارة ٩٩,٧° فهرنهيت (٣٧,٦°م) و ٥٤٪ رطوبة نسبية، وقد تم تقليب البيض كل ساعة. تم إختيار ثلاث توقيتات مختلفة لفحص البيض مبكراً كلما أمكن ذلك وهم اليوم السادس والتاسع والثاني عشر من بداية عملية التحضين.

١- أستاذ هندسة التصنيع الزراعي المساعد – قسم الهندسة الزراعية – كلية الزراعة – جامعة كفرالشيخ
٢- طالب ماجستير - قسم الهندسة الزراعية – كلية الزراعة – جامعة كفرالشيخ

تم إستخراج البيض من الحضانات لإجراء عملية الفحص الضوئي للبيض Candling من خلال نقل صواني البيض بالكامل إلى وحدة مصممة لهذا الغرض وتم قياس شدة الإضاءة المنبعثة من كل بيضة بواسطة حساس الضوء لكل مرحلة من مراحل التحضين سابقة الذكر، وفى ثلاثة مواضع مختلفة للقياس موضع ١ و ٢ و٣ وهى التى تصنع مع محور البيضة زاوية صفر°(رأسية) و٤٥°(مائلة) و٩٠° (أفقية)على سطح البيضة بالترتيب. وفي كل مرحلة تم دراسة ١١٠ بيضة منهم ٥٥ بيضة مخضبة و٥٥ أخرى غير مخصبة. كانت عملية القياس لكل البيض لا تتجاوز الدقيقتين للحفاظ على حياة الأجنة داخل البيض.

تم إدخال البيانات المتحصل عليها لبرنامج XLSTAT 2017 للتعرف على كفاءة حساس الضوء باستخدام عدة مصنفات إحصائية متقدمة ومنها التحليل التمييزي الخطي والتربيعي ولأقل فرق مربعات الجزئي وأيضاً إنحدار العنصر الرئيسي وإنحدار فرق المربعات الجزئي، حيث يمكن إستخدام النماذج الرياضية المتحصل عليها فيما بعد للكشف عن الخصوبة من خلال التعويض بقيم شدة الضوء المقاسة للبيضة في برامج تحكم متطورة مثل Fuzzy Logic Control System. سيتم إجراء مزيد من الدراسة على هذا التطبيق في المستقبل لاستخدامه كأداة بحثية متطورة. تم إستخدام تحليل العنصر الرئيسي لتحديد ما إذا كانت هناك فروق في القراءات ما بين المواضع التى تم أخذ القياسات بواسطة حساس الضوء LDR منها، وأيضاً إذا كان هناك علاقة إرتباط بينها وبين كفاءة الفرز لتحديد أفضل المواضع التى يمكن أخذ القياسات عندها للبيضة. تم أيضاً إستخدام المصنف الإحصائي آلة متجه الدعم Support Vector Machine في هذه الدراسة مع الحساس الضوئي رخيص الثمن LDR كواحد من المصنفات شائعة الإستخدام مع الأجهزة المتقدمة مثل آلات الرؤية Machine Visions للتمييز بين البيض المخصب وغير المخصب باستخدام الثلاثة أنواع من المصنفات لديه.

<u>وقد تم التوصل لأهم النتائج الآتية:-</u>

(١) حساسات الضوء من النوع (GL12528 ١٢مم) رخيصة الثمن مناسبةً تماماً فى كشف خصوبة بيض التفريخ.

(٢) باستخدام تحليل العنصر الرئيسي فإن الإختلافات في قياسات الكثافات الضوئية بين الوضع رقم ١ (الرأسي) ورقم ٢ (المائل) على البيضة منخفضة والتي تتقارب فيها القياسات أكثر مع التطور في زمن التحضين من ٦ أيام إلى ١٢ يوم. بينما كانت أعلى نسبة إختلافات بين القياسات المأخوذة من الثلاثة مواضع كانت في العمر التحضيني ٩ أيام بنسبة إختلاف٧٤,٨٧٪ أما بالنسبة لعلاقة الإرتباط بين دقة التمييز وشدة الإضاءة المقاسة من الموضع الرأسي فقط بحسب ما أوضحت مصفوفة الإرتباط كانت معاملات الإرتباط لفترات التحضين ٦ و٩ و١٢ يوم هو – ٠,٧٩١ و – ٠,٨٤٠ و – ٠,٨٩٨ على الترتيب.

(٣) النماذج الرياضية المطورة باستخدام التحليل الإنحداري للعنصر الرئيسي PCR ولأقل فرق مربعات جزئي PLS كانت لها أعلى معاملات تقدير عند عمر أجنة ١٢ يوم وقد كانت ٠,٨١٩ و٠,٧٦٠ على الترتيب.

(٤) أما بإستخدام المصنفات الإحصائية المتقدمة، تم التوصل إلى أعلى دقة في التمييز عن طريق التحليل التمييزى الخطي LDA والتربيعى QDA، حيث نجحت فى تمييز البيض المخصب عن غيره من غير المخصب عند عمر تحضيني ٦ أيام بنسبة ٩٧ و٩٥٪ على الترتيب، وذلك لمجموعة البيانات المستخدمة فى إجراء التصنيف (Training Set) وذلك بإستخدام الثلاثة مواضع للقياس موضع ١ و ٢ و٣ مجتمعة. ومن ثم تم الحصول على نماذج رياضية لتلك المصنفات الإحصائية السالفة الذكر لاستخدامها فى تحديد خصوبة البيض من نوع (Hubbard Breed) من خلال التعويض فيها بشدة الإضاءة المقاسة.

(٥) آلة متجه الدعم Support Vector Machine (SVM) تم إستخدامها للتمييز بين البيض بحسب الخصوبة للأنواع الثلاثة المستخدمة (Linear, Power and RBF kernel)، دقة التصنيف المتحصل عليها كانت ٨٩ و٨٩ و٩٢٪ على الترتيب، وذلك عند عمر تحضيني ٦ أيام، لذلك يعتبر حساس الضوء المستخدم رخيص الثمن له دقة تصنيف مقاربة لآلات الرؤية والتي تستخدم مصنف SVM.

النماذج الرياضية المتحصل عليها من التحليل التمييزي الخطي LDA (المعادلة رقم ٣) أو التحليل التمييزي التربيعي QDA (المعادلة رقم ٥) وباستخدام ثوابت المعادلة الموجودة بالجدول رقم ٦ يمكننا التمييز ما بين البيض المخصب وغير المخصب كالتالي:

المعادلة رقم ٣ (المعادلة الخاصة باختبار البيض المخصب):

$$f = a + b\,I_1 + c\,I_2 + d\,I_3$$

وثوابت هذه المعادلة عند اليوم السادس من عمر تحضين البيضة:

a	-355.392	b	1.210	c	2.835	d	5.092

إذا كان ناتج المعادلة يساوي +١ فإن البيضة مخصبة

المعادلة رقم ٣ (المعادلة الخاصة باختبار البيض غير المخصب):

$$n = a + b\,I_1 + c\,I_2 + d\,I_3$$

وثوابت هذه المعادلة عند اليوم السادس من عمر تحضين البيضة:

a	-386.903	b	1.767	c	2.988	d	4.943

إذا كان ناتج المعادلة يساوي -١ فإن البيضة غير مخصبة

يقوم البرنامج بتعويض قيم شدة الإضاءة في المعادلة رقم ٣ بشقيها (معادلتي البيض المخصب وغير المخصب). وبنفس الطريقة يمكننا إستخدام النموذج الرياضي الناتج من التحليل التمييزي التربيعي وكذلك للعمر المحدد للجنين.