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Design of a Dynamic Weighing System and AI-Based Sorting Process for Egg Sorting Machines

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ABSTRACT

Eggs are one of the world's most significant food sources since they include numerous critical nutrients such as protein, vitamins, minerals, and omega-3 fatty acids. Egg production and consumption have expanded dramatically in the previous two decades because of population growth and industrialization. To fulfill rising demand, automating of egg production facilities has become necessary. To distribute eggs to consumers and maintain quality requirements, eggs must be divided into weight categories. Due to production capacity, this process must be carried out using machines. High production volumes necessitate a rapid weighing process; hence eggs are weighed dynamically in machines. The weighing signal obtained from the load cell is filtered to determine the stable weight, which is then used to calculate the egg's weight class. In this paper, instead of performing all of these processes using classical approaches, a Stacked Autoencoder (SAE) based classification system is developed that will predict the egg's class using only raw weight data. To assess the effectiveness of the suggested method, classification performance was compared using support vector machines (SVM), k-nearest neighbors (kNN), and decision trees (DT). The suggested approach determines the weight class of the egg in roughly 0.084 sec with 100% accuracy. Given the increasing egg demand, the proposed technology allows for a considerably faster egg categorization procedure, boosting production speed and lowering production costs.

Keywords: Stacked Autoencoder, Classification, Dynamic Weighing, Egg

1. Introduction

Egg production is critical for both health and economic sustainability. They are considered a significant part of a healthy diet because they include a variety of nutrients that the human body need, including protein, vitamins (particularly B12 and D), minerals, and omega-3 fatty acids. Because of these characteristics, they are produced and consumed as a commercially significant foodstuff. Eggs are utilized in a variety of applications, particularly in the preparation of pastries, breakfasts, sauces, cakes, and sweets. As a result, they are mass-produced in commercial farms across the globe.

Eggs should be gathered from coops on producing farms daily. Because of the enormous production capacity, all these procedures must be carried out by machines. The collected eggs are subjected to a variety of processes, including weight classification, dirt and crack detection, and automated packaging. The primary reasons for separating eggs into weight classes are to provide consumers with a consistent and high-quality product, to facilitate packaging and shipping, and to control costs. Because of its large production capacity, dynamic weighing machines are used to separate eggs into different weight classes. In applications that need fast weighing speeds, dynamic weighing systems can enhance the number of products weighed per unit time. However, as the weighing system moves, mechanical vibrations increase, distorting the measurement signal (Yamazaki et al. 2002; Boschetti et al. 2013). To meet the necessary speed requirement in dynamic weighing systems, the weight of the weighted product must be established fast. As a result, the approaches used must produce quick results. FIR filters are commonly used to remove generated noise from measurement signals, but it has been suggested that this filtering method may be insufficient in terms of speed for some applications. As a result, various ways have been created. Several filtering techniques have been developed, including the Adaptive Shaper-Based Filter (Richiedei 2022), a time-varying filter (Piskorowski & Barcinski 2008; Pietrzak et al. 2014), a system identification-based approach (Y. Zhang & Fu 2010), and artificial neural network-based filtering (Bahar & Horrocks 1998; Yasin & White 1999; Yumurtacı & Yabanova 2017).

Autoencoders (AE) are unsupervised neural networks that compress input data in the encoder layer and then rebuild it in the decoder layer. It has three essential components: encoder, coding, and decoder layers. The AE's primary goal is to create the same output as the input while reducing data loss to a minimum. AEs have been utilized successfully in a wide range of applications, including medical, engineering, and agriculture. Gokhale et al. (2022) proposed a stacked AE-based framework for gene selection and cancer classification. Singh et al. (2023) proposed combination of convolutional neural networks (CNNs) based Denoising AEs and CNN-based classification model to classify atrial fibrillation. Kummerow et al. (2022) presents a robust disturbance classification procedure incorporating de-noising recurrent AEs within a novel two-stage training approach. In the field of agriculture, fruit image restoration methods based on a convolutional AE (Chen et al. 2022), a novel tracking algorithm for honey peach young fruit targets based on a convolutional AE (T. Zhang et al. 2024), a method for inferring the bee colony state using a sensitive contrastive AE and an anomaly detection model (Cejrowski & Szymański 2022), and an anomaly detection method proposed based on the joint learning of an AE and a self-supervised classifier for quality defects of strawberries (Liu et al. 2022) can be given as examples of studies.

In this study, we have developed a dynamic weighing system consisting of electronic and mechanical components for weighing round shaped products. In this way, the weight of the eggs rolling over the weighing platform can be measured. The electronic card developed to read the dynamic weighing signal from the load cell and transfer it to the computer consists of Delta Sigma Analog to digital converter (ADC) and dsPIC digital signal controllers. Thus, the determination of the weight class of the egg using the measured weight signal was carried out automatically, without the need for human intervention. To determine the weight class using classical methods, the measurement signal must be filtered, the stable weight of the egg determined from the filtered signal, and the class determined from this stable weight. All these operations were carried out in one step and in a shorter time with the developed model. A SAE and Softmax based model was developed to separate eggs into standard weight classes. With each AE utilized in the model, the data size was gradually lowered while the classification performance was improved by feature extraction. To compare the performance of the suggested model, the classification procedure was carried out using the machine learning algorithms SVM, kNN, and DT. According to the comparison results, the proposed approach divided the eggs into weight classes more accurately.

2. Material and Methods

2.1. Dynamic weighing system

The dynamic weighing system is intended to weigh eggs as they roll across the weighing platform. The system is divided into three primary sections: electronics, mechanics, and data collection software. These parts are explained further in the sections that follow.

2.1.1. Electronic system

The electronic part of the dynamic weighing system consists of a load cell and an electronic card designed to receive the weighing data. The electronic card has a DSPIC microprocessor and a 24-bit Sigma-Delta ADC. The Sigma-delta ADC amplifies the load cell measurement signal, which is then transformed to a digital signal using a differential ΔΣ modulator. The Sigma-Delta ADC's configuration settings are made via SPI with the microcontroller, and weight data is received at the specified frequencies and delivered to the computer via the CAN bus. Figure 1 shows the block diagram of the electronic system. The electronic system used in this study consists of a part of the electronic system developed for the egg sorting machine.

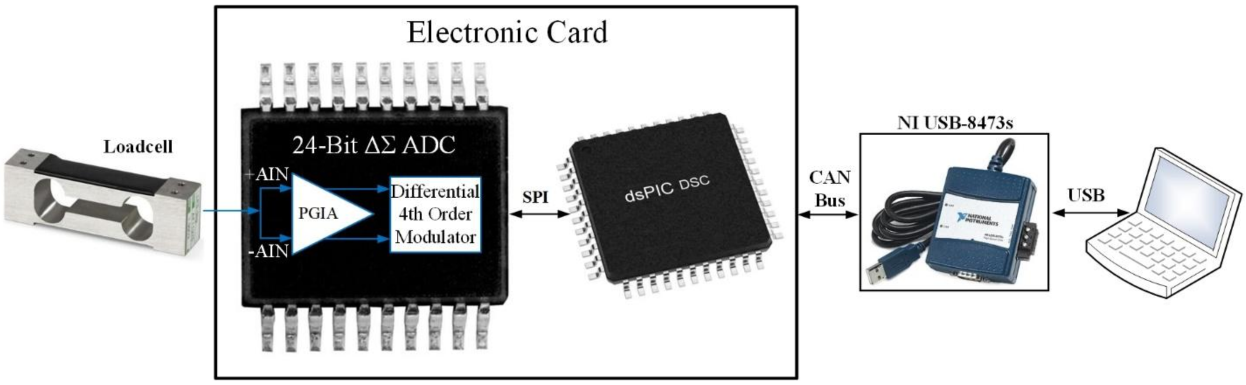

Figure 1- Block diagram of the electronic system

2.1.2. Mechanical system

To accomplish dynamic weighing of eggs, a mechanical device was developed that allows them to roll and pass over the load cell platform. Eggs emerge from an angled surface supported by carrier bars. When eggs land on the load cell platform, they are separated from the carrier bars because it is not inclined. Dynamic weighing is carried out at this moment. When they pass through the platform, carrier bars from behind remove the egg. The mechanical system is shown in Figure 2.

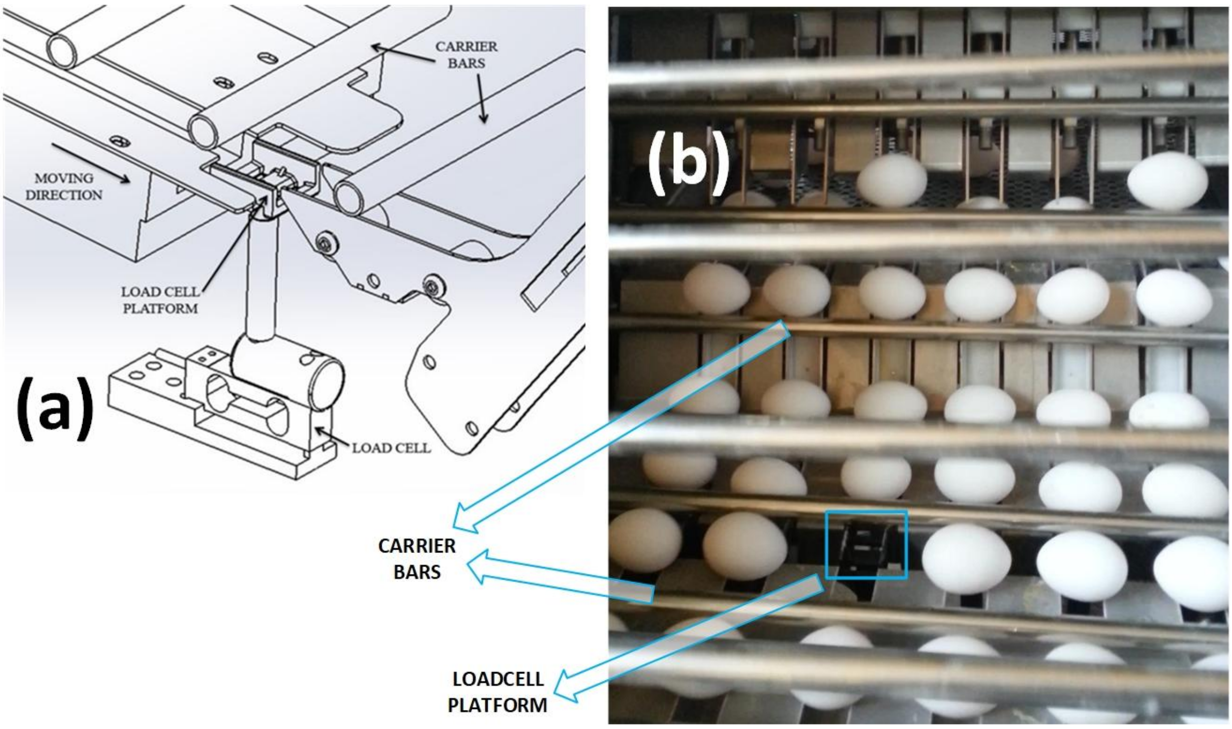

Figure 2- Technical drawing (a) and real image (b) of the mechanical system

2.1.3. Data acquisition program

A Labview-based program was created to capture and save dynamic weight data. The program transmits the data that the microcontroller sent to the CAN network via the NI USB-CAN interface to the computer. These results can be viewed graphically or saved as a text file for later examination. Figure 3 shows front panel and Figure 4 shows block diagram of the developed program.

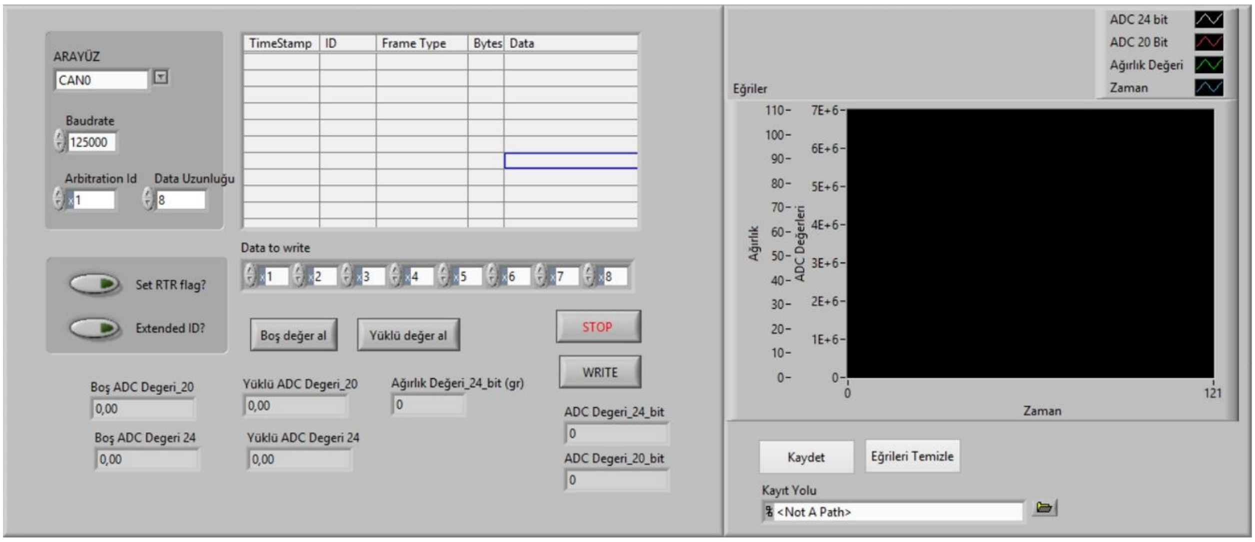

Figure 3- The developed data collection program front panel

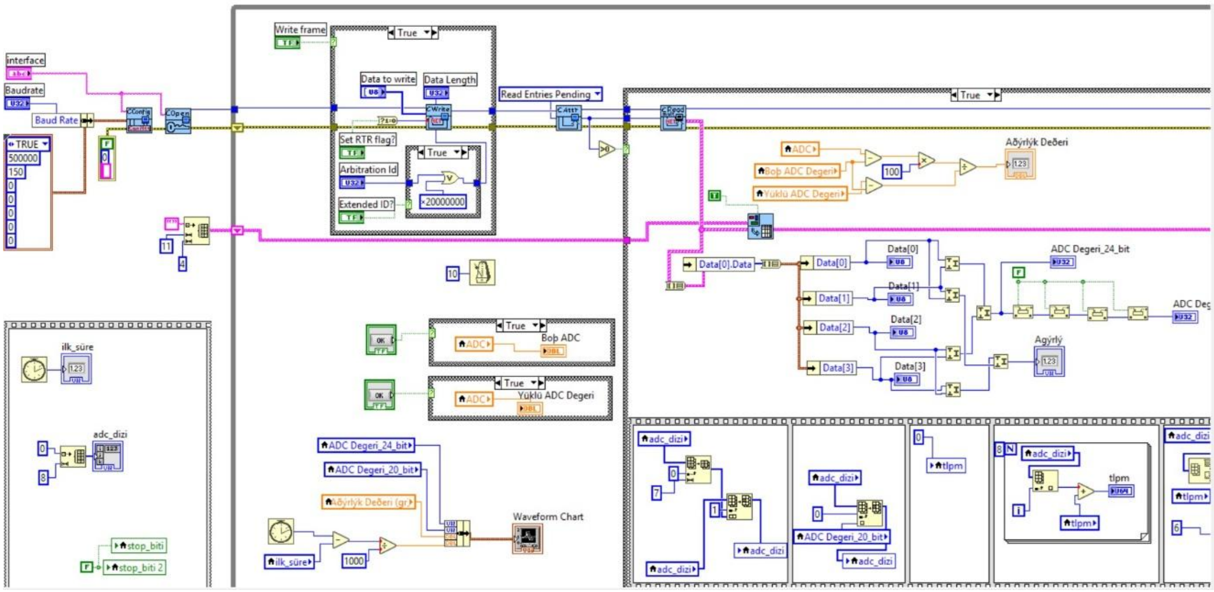

Figure 4- The developed data collection program block diagram

2.2. Egg samples

In order to produce the data set for the application, a local egg production farm was employed, with an egg sorting machine situated utilizing the designed electronic and mechanical weighing system. While the eggs were being weighed dynamically, the raw weight data was transferred to a computer via the designed electronic system and recorded for future investigations. In the egg sorting machine that uses the created technology, 6 eggs are dynamically weighed at the same time, and 36,000 eggs are sorted based on their weight every hour. The eggs' dynamic weighing data ranged from 28 gr to 102 gr, covering all weight classes. The dynamic weighing signal was recorded at a sampling frequency of 100 Hz. In this manner, weight data for over 500 eggs were collected and recorded. The data set was produced for the classification process by picking the weight signals of 240 eggs, 60 of which came from four different weight classes. 192 data points from this dataset were used for training, while the remaining 48 were used for testing. Weight classifications for chicken eggs vary by country/region. According to the Turkish Food Codex Egg Communiqué of the Ministry of Food, Agriculture, and Livestock, eggs are classified into four weight classes (Turkish food Codex Notification No. 2014/55 on egg.). Table 1 classifies eggs based on their weights.

Table 1- Weight classes of eggs

Classes	*Small (S)*	*Medium (M)*	*Large (L)*	*Extra Large (XL)*
Weight	< 53 g	≥53 – <63 g	≥63 – <73 g	≥73 g

The dimensions of the weight data vary according to the weight of the eggs and their condition as they pass through the load cell. When comparing the sample data shown in Figure 5, the weight data size received for an egg during passing through the load cell ranges between 27 and 47 data points. The data acquired from the load cell varies according on the form of the egg and the vibration it causes in the load cell during transit.

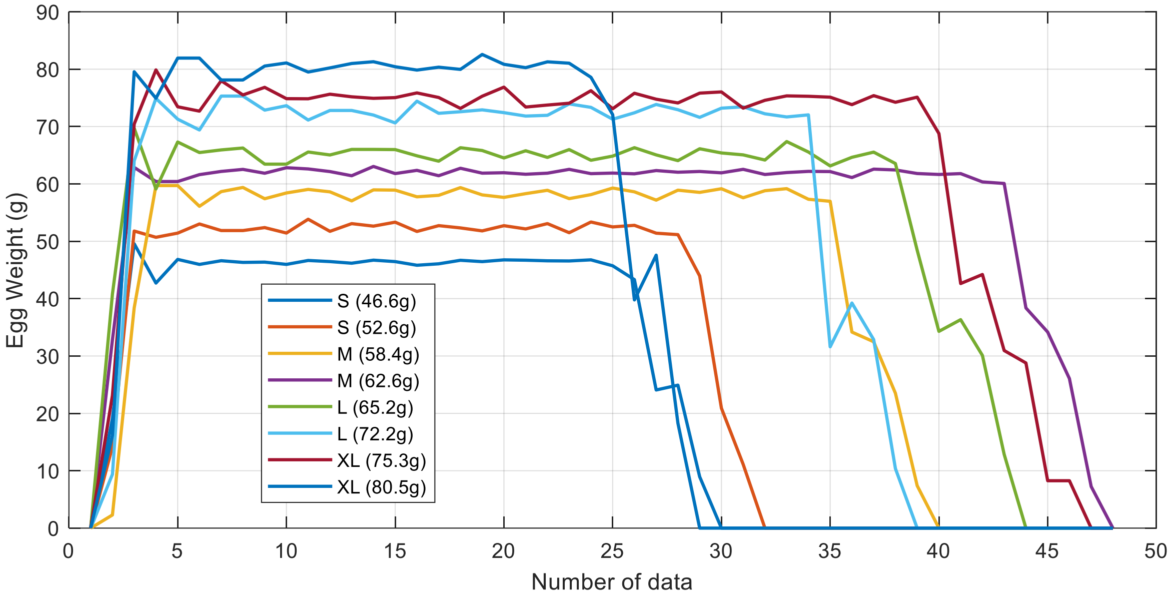

Figure 5- Weight data of eggs in different weight classes

2.3. Classification algorithms and evaluation metrics

In this study, stacked AE, SVM, kNN, and DT were used to classify eggs into specific weight classes, and a brief description of each classifier was provided. The performance and classification time of each classifier were assessed.

2.3.1. Autoencoders and Softmax

AEs are neural networks utilized in artificial intelligence and machine learning. Its primary goal is to generate data in the input layer for use in the output layer. AEs normally have two primary components: the encoder and the decoder. The encoder reduces the input data to a lower-dimensional representation. The decoder turns the representation data back to the original data. AEs are used for a variety of applications, including data compression, de-noising, and feature extraction. AEs learn by attempting to reduce the difference between the input and output data during training. In this way, they require the network to encode and decode the incoming data. This phase guarantees that the learned representation accurately reflects the supplied data. Figure 6 shows a simple AE model.

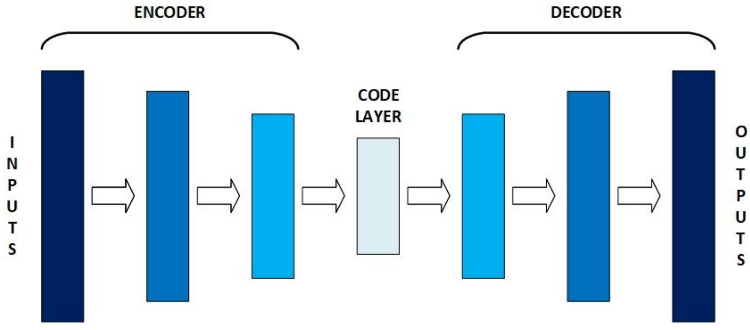

Figure 6- A simple autoencoder model

The Softmax layer is a probability-based sequential classification algorithm that computes the input's probability distribution across n dimensions. It only employs the most significant feature to improve classification accuracy (Mohana & Subashini 2023). Softmax regression is derived from logistic regression for multiple categorization tasks. Because it is simple to build, it is extensively utilized in real applications such as MNIST step classification (Jiang et al. 2018).

2.3.2. K-nearest neighbors

The kNN method is theoretically mature and one of the most basic machine learning algorithms (Li et al. 2021). kNN computes the distances between an unknown sample and the predefined training set. The number of closest samples (k) to the unknown sample is set manually. The unknown sample's category is defined by the categories of the k closest samples in the training set.

Determining k is critical for kNN (Qiu et al. 2018). kNN excels in solving multi-class simultaneous problems (Balabin et al. 2011).

2.3.3. Support vector machine

SVM is a relatively new computational learning method based on statistical learning theory that can be used to expert systems (Widodo & Yang, 2007). SVM is a supervised machine learning method that works well with linear and nonlinear data for classification and regression (Feng et al. 2018). SVM is a generalized linear classifier that uses supervised learning to classify data into binary categories. The decision boundary is the greatest margin hyperplane for learning instances (Li et al. 2021).

2.3.4. Decision tree

A DT logical model is built by dividing and recombining training data based on similarity. Each node in a DT has logical expressions that assist determine if a data point is consistently placed on its neighboring node to the left or right of that node. The DT begins with the root node, and subsequent splits are referred to as branches. Leaves are terminal nodes, signifying that there is no more data. Using a trained DT for prediction, the input data is routed through the root node, then through branches based on the logical expression, and finally terminates at the leaf node. A DT produces the average of the linear regression of the training data points collected from the leaf node. Training datasets influence the shape and properties of a DT (Vidyarthi et al. 2020).

When evaluating a classifier's performance, it is common to focus on prediction accuracy. The rate at which the classifier assigns untrained input to the proper class is commonly used as a performance statistic. Furthermore, classification performance is evaluated using scalar values in several measures such as accuracy, sensitivity, and specificity (Tharwat 2021). A confusion matrix is a table that summarizes the classification problem's prediction results and can be used to calculate a variety of scalar performance measurements. The matrix's cells reflect four types of cases: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). TPs are instances in which the classifier properly identifies a positive class, whereas TNs occur when the classifier correctly predicts a negative class. FPs are instances when a positive class is mistakenly predicted, whereas FNs are instances where a negative class is incorrectly anticipated and categorized as positive. According to (Hadimani & Garg 2021), the scalar performance measurements extracted from the confusion matrix are as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$F1-Score = \frac{2TP}{2TP+FP+FN} \tag{4}$$

The parameter variations vary from 0 to 1, and for the classifier to perform properly, the parameter values must be very close to 1. Aside from this, the classifier detection time was considered when evaluating the classifier's performance.

3. Proposed Model

AE is a combination of encoder and decoder. The encoder converts high-dimensional input data into a lower-dimensional feature vector, and the decoder uses this feature vector to recreate the original data with minimal error (Qian et al. 2022). Figure 7 shows that the AE is essentially a basic artificial neural network structure with three layers: input, hidden, and output. The concealed layer has fewer neurons than the prior layer.

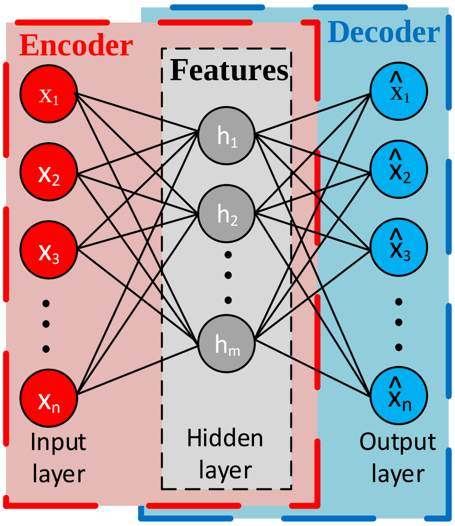

Figure 7- Structure of the autoencoder

In the encoder segment, equation (5) is utilized to generate the m-dimensional feature vector h from the n-dimensional input data x. Notably, the dimensionality of n surpasses that of m. Subsequently, within the decoder, equation (6) facilitates the reconstruction of the input data from the derived feature vector h in the hidden layer.

$$h = f_e\left(w_e x + b_e\right) \tag{5}$$

$$\hat{x} = f_d\left(w_d h + b_d\right) \tag{6}$$

Where; w_e and b_e represent the weight matrix and bias for the encoder layer, respectively, while w_d and b_d denote those for the decoder. The subscript e signifies the encoder, and d indicates the decoder. Depending on the dataset, an appropriate activation function, such as Sigmoid, Tanh, or ReLU, is selected. Equation (7) is employed during the training process to adjust the parameters using the loss function, with the objective of minimizing the discrepancy between the original input data x and the reconstructed input data $\hat{x}$.

$$L\left(w,b\right) = \frac{1}{N}\sum_{n=1}^{N}(x-\hat{x})^2 \tag{7}$$

Stacked AEs are created by combining two or more AEs. High-dimensional input data is handled layer by layer (Han et al. 2020). The top layer's hidden layer vector serves as the input vector for the following AE layer, commonly known as pre-training (Yu et al. 2022). Thus, effective and distinct features are recovered from the input data, while the data quantity is minimized (Toma et al. 2021).

In this study, the data collected from the instant the egg hatches into the load cell is sent into the SAE to identify the egg weight class. The SAE, which is made up of two AEs, gradually reduces the data size to six and finally four. Without the need for preprocessing on the raw data, the input data is directly reduced, and its features are extracted with the SAE. Figure 8 shows the layered AE structure constructed in Matlab. Finally, the feature vector created from the stacked AE output is sent into the Softmax classifier. The Softmax layer is a probability-based linear classifier used when there are two or more classes (Adem et al. 2019). The weight class of the egg is calculated by running the classification process with Softmax. The suggested stacked AE's outputs show eggs in four weight groups: small, medium, large, and extra-large. The outputs vary from 0 to 1, and the one closest to 1 represents the egg's weight class.

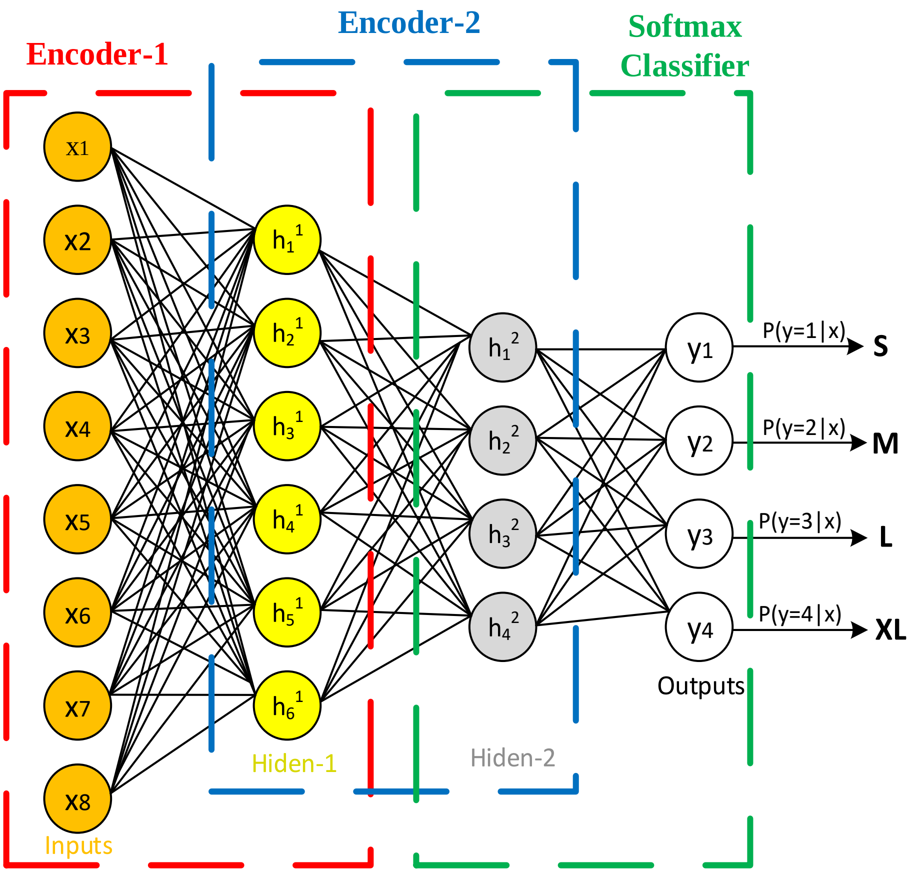

Figure 8- Recommended SAE structure

The SAE's L2WeightRegularization and SparityRegularization parameters prevent the model from overlearning during the training phase, and the SparsityProportion parameter controls the sparsity of data in the hidden neurons (Adem et al. 2019). In the softmax classifier, the loss function can be mse or croos entropy. Table 2 contains detailed information on the suggested model's parameters.

Table 2- Recommended SAE with Softmax tuning parameters

Components	*Parameters*
Encoder-1	MaxEpochs = 1150
	L2WeightRegularization= 0.0001
	SparsityRegularization = 4
	SparsityProportion = 0.1
Encoder-2	MaxEpochs = 400
	L2WeightRegularization= 0.000001
	SparsityRegularization = 4
	SparsityProportion = 0.1
Softmax	MaxEpochs = 4000
	Loss Function = Cross Entropy

4. Experimental Results

To compare the performance of the created classification model, 8 eggs were chosen, the raw weight signal was filtered, the weight value at which the eggs were stable was calculated from the filtered signal, and the weight class to which they belonged was determined. Figure 9 depicts the raw and moving average filtered signals from eight randomly selected eggs. As can be seen from the original signal, each passing egg produces a distinct signal. After filtering the signal, the egg's stable weight must be calculated from it. Figure 10 shows the graph of the algorithm utilized for this procedure.

Δ: Variations of weights;
t: Measurement time;
m: Number of weights measured in a stability range (4 selected);
n: Stability range (0.5 gr selected).

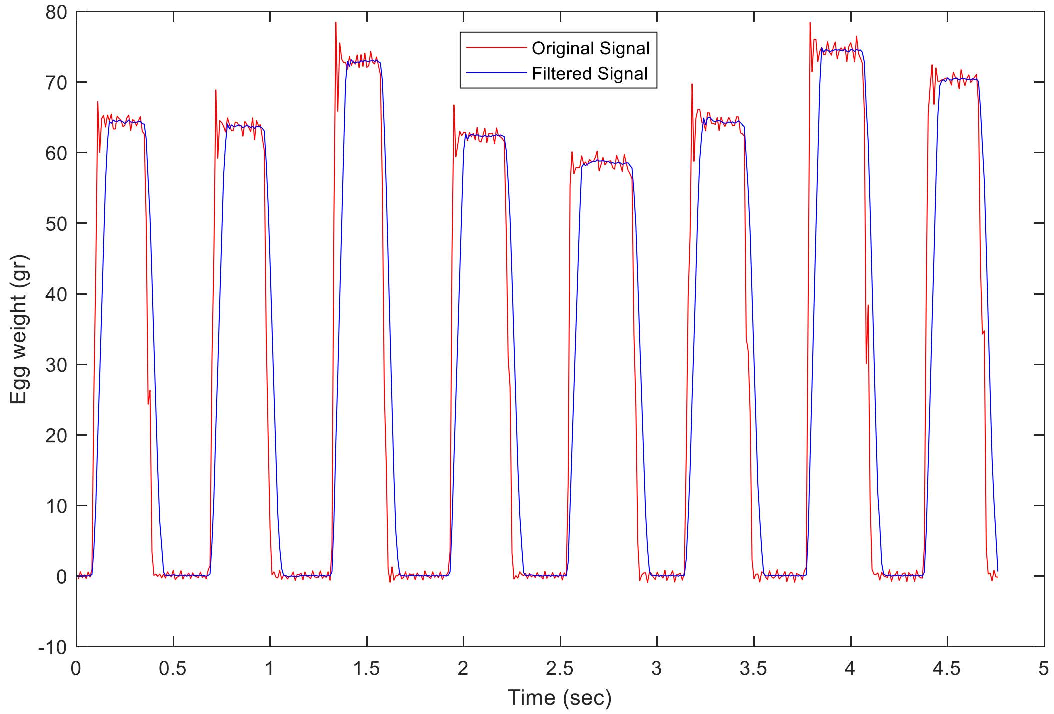

Figure 9- Filtering 8 egg weights

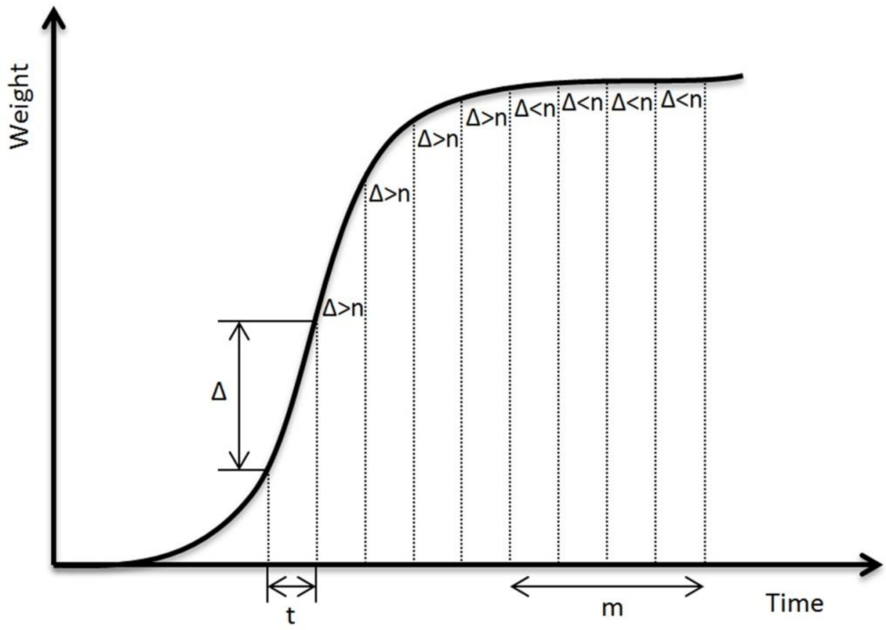

Figure 10- Algorithm used to determine stable weight

Table 3 shows the times and data counts required to determine the stable weight and class of each of the eight eggs selected. Because each egg moves across the load cell platform in a unique way, the amount of data points required to calculate each egg's stable weight differs. On average, 15-16 data points are necessary to calculate the egg's stable weight from the moment it enters the load cell platform. Even if signal filtering and other procedures are omitted, because there is a 10 ms interval between each data set, the less data required to estimate this number, the faster the egg class can be identified.

Table 3- Determination of egg weight class by classical method and required periods

Egg No	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
Stabil Weight (g)	64.4	63.9	72.7	62.4	58.5	64.4	74.4	70.5
Number of data from which stable weight can be determined	14	16	15	14	12	17	14	17
Time required to determine stable weight (ms)	140	160	150	140	120	170	140	170

The weight class must be determined quickly and accurately before the egg comes out of the load cell. Therefore, the classifier performance and detection times according to different data numbers taken from the moment the egg comes out onto the load cell are given in Table 4.

Table 4- Classifier accuracy and detection time values according to different input data points

Data Size	*Parameters*	*DT*	*kNN*	*SVM*	*SAE*
1x20	**Accuracy**	0.9375	0.9583	0.9375	0.917
	Predict time (s)	0.0020	0.0045	0.0036	0.0044
1x15	**Accuracy**	0.9375	0.9375	0.9375	1
	Predict time (s)	0.0019	0.0043	0.0037	0.0044
1x10	**Accuracy**	0.9375	0.9166	0.9375	1
	Predict time (s)	0.0019	0.0038	0.0034	0.0043
1x8	**Accuracy**	0.9375	0.9375	0.9375	1
	Predict time (s)	0.0016	0.0034	0.0033	0.0042
1x7	**Accuracy**	0.9166	0.9166	0.9375	0.979
	Predict time (s)	0.0016	0.0033	0.0033	0.0043

Table 4 shows that when the number of input data drops, the classifier's accuracy value increases while the detection time lowers. The less data used to calculate the weight class from the moment the egg is placed on the weighing platform, the faster the data collecting will be. Because the performance of the classifiers degrades when the number of data points falls below 8, the input data value is set at 8. To establish the egg weight class, the first 8 data points from the load cell are obtained in 0.08 sec at a sampling frequency of 100 Hz.

To evaluate the uncertainty of the model and its performance in class prediction, 5-fold cross validation was applied. Therefore, the dataset was randomly divided into five equal parts. Four parts were used in the training process of the proposed model, while the remaining one part was used in the testing process of the model. Then, another part was used in the testing process, while the remaining parts were used in the training process. To assess the classification performance of the proposed deep network model, the Confusion matrix was generated using the test data. This matrix's values represent the real and predicted class output values. Table 5 displays the average accuracy, precision, recall, and F1-Score values acquired from the five-fold cross-validation process for all classifiers.

Table 5- Average evaluation parameters of the classifiers in the case of 1x8 data input

Performance Metrics	*DT*	*kNN*	*SVM*	*SAE*
Accuracy	93.3332%	94.1666%	95.0006%	100%
Precision	93.72%	94.31%	95.46%	100%
Recall	93.33%	94.17%	95%	100%
F1-Score	0.9333	0.9414	0.9492	1
Predict time (s)	0.0016	0.0034	0.0033	0.0042

When Table 5 is examined, it is clear that the time taken to determine the egg weight class by all classifiers is significantly shorter and more stable than the classical method. The DT classifier determines the egg weight class in the quickest amount of time, but has the lowest performance value. While the suggested technique achieves 100% performance, it takes longer to detect than other classifiers. The suggested technique processes the input data and determines the egg weight class in about 4 ms. Since it takes 0.08 sec to get the first 8 egg weight data from the system, the suggested approach determines the weight class of a total egg in about 0.084 sec. Thus, the egg's weight class may be established quickly before it leaves the load cell.

5. Conclusions

Eggs, which are high in protein, vitamins, and minerals, are used extensively in the food business. Eggs are essential everyday items for maintaining a healthy and balanced diet. The need for eggs is increasing day by day, both in the industrial sector and among individual consumers. The outward qualities of eggs, such as look, size, and weight, influence market prices as well as consumer preferences and decisions. Although egg weight classes vary by country/region, they are generally classified as Small, Medium, Large, and Xlarge. Although there have been studies that use image processing to assess weight, in this work, egg weight classes are estimated using data from the load cells. In this study, the first 8 data points from the load cell are used to determine the egg weight class using a stacked AE and softmax classifier, with no preprocessing. The classification process is carried out on a data set generated using SVM, kNN, and DT classifiers from machine learning methods, and the performance results are compared to the suggested method. The suggested deep network model has achieved 100% success in both the training and testing phases. While 0.08 sec is required to obtain 8 data points from the load cell, approximately 4 ms is required to process this data and determine the weight class with the proposed deep network model, and in a total of approximately 0.084 s, the weight class can be determined before the egg leaves the load cell. Manpower is limited throughout the egg processing and packaging phase, necessitating the use of machines. When compared to the classical methods used in the literature, it is obvious that this unique method determines the egg weight class swiftly, sensitively, and precisely.

Conflict of Interest Statement

The authors have declared no conflicts of interest for this article.

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