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Research Article

A New Non-Destructive Multidimensional Yield Determination Method Approach for Walnut Crop

Remzi Gürfidan[1a], Enes Açıkgözoğlu[2b], Mevlüt Ersoy[3c]
[1] Computer Programming Department, Yalvaç Technical Sciences Vocational School, Isparta University of Applied Science, Isparta, Türkiye
[2] Computer Programming Department, Keçiborlu Technical Sciences Vocational School, Isparta University of Applied Science, Isparta, Türkiye
[3] Computer Engineering, Faculty Of Engineering and Natural Sciences, Süleyman Demirel University, Isparta, Türkiye

remzigurfidan@isparta.edu.tr

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ORCID: [a]0000-0002-4899-2219; [b]0000-0001-7293-883X; [c]0000-0003-2963-7729.

Abstract : Walnut has an important place in agricultural production and research on it covers various fields. In this study, machine learning algorithms were used for non-destructive estimation of walnut productivity. The researchers developed a setup using audio recordings and images to determine the fullness and void status of walnuts. These data were processed with various machine learning algorithms and the results were evaluated. The algorithms used in the study include RESNET50, DenseNET121, VGG16 and CNN. However, when the results obtained are analyzed, it is seen that the VGG16 algorithm gives the most successful results with 99.79% accuracy and 91.42% val_accuracy values using imagenet weights. These results were found to be quite successful compared to similar studies in the literature. In future studies, it is aimed to expand the obtained dataset and increase the val_accuracy value even more. In addition, similar methods are planned to be applied on other nuts such as hazelnuts and almonds. This could be an important step to increase productivity in agricultural production. In conclusion, this study on walnut yield estimation using non-destructive methods offers a new and effective approach in agricultural applications. The use of machine learning algorithms offers potential in various areas such as increasing productivity in walnut production and detecting diseases.

Keywords : Machine learning, non-destructive yield determination, nut non-destructive yield calculation, walnut yield determination.

1 Introduction

Walnut is a kind of nut with a very high nutritional value that is frequently consumed all over the world [1]. Walnuts contain important nutrients for human metabolism such as Omega-3 fatty acids, antioxidants, protein and fiber content, minerals, and vitamins. Many people consume walnuts in their daily diet routine due to different diseases or for balanced and regular nutrition. People's consumption habits may vary. Walnuts can be consumed raw, that is, fresh, roasted, in flour or milk form. The commonly preferred way of consuming walnuts is to consume them by separating them from the shell after drying. Since walnut food is a hard-shelled food, producers and consumers try to make maximum use of this product [2]. In addition to the edible inner part of the walnut, the inedible hard shells are used as firewood. Walnut shells are used as biomass fuel just like wood, providing secondary gain.

Determining the quality of walnuts, which are widely consumed globally, is based on different criteria. These quality criteria include shell quality, colour, inner walnut, taste and aroma and oil content. Among all these criteria, it is the walnut content that consumers pay the most attention to. Because this parameter constitutes the most important part of the price paid for walnuts. In this food, which is a shelled food and there are limited ways to get an idea about the inside without breaking it, situations such as internal rot, shrivelling and drying of the inner walnut occur. To overcome these handicaps, the inside of the nut must be visualized. Processes such as x-ray technology and ultrasound, which can perform this process, are encountered with radioactive radiation (radiation). Consumption of foods that have undergone these processes carries very unfavourable risks. To overcome these risks, methods such as appearance criteria, weight measurement, shell colour and texture, and flash tests can be tried. However, the reliability of none of these methods can be guaranteed.

The aim of this study is to introduce a reliable, fast, and healthy methodology that will enable the estimation of the inner walnut portion of walnut, which is a nut food, with an innovative approach without breaking the shell and without being exposed to radiation. With the proposed method, it will be possible to estimate how many grams of inner walnut and how many grams of shell can be obtained from the tested walnut in its current state without any crushing. The importance of realizing this process is to show the transparent yield of the walnuts purchased by the users. In addition to this, the producer and the state or the merchant who makes bulk purchases are to determine the financial values by keeping the correct yield value in the purchase and sale. We aim to minimize the amount of loss called waste, which is taken into account in the trade of this business. For this purpose, we offer an approach that guarantees that the product remains completely healthy, free from any chemical testing or radiological measurements. In the study, walnuts will be placed in the data collection device and 5-second collision sound recordings will be taken. These sound recordings will then be processed and converted first into a signal and then into a histogram graph. As a second step, the walnut will be cracked, and the shell and the inner part will be weighed separately on a precision balance to create a data set. At the end of the proposed methodology, the inner and shell weights of the uncracked walnut will be estimated from the images. At the end of the training, validation accuracy values of 0.9142%, 0.9004%, 0.8455% and 0.4452% were obtained from VGG16, CNN, DenseNet121 and ResNet50 algorithms, respectively. As can be seen from the values, the best performance was achieved by using the VGG16 algorithm using imagenet weights.

In the second part of the study, methods and techniques used in crop yield, yield and quality calculations will be reviewed. In the third section, the technical infrastructure of the methodology proposed in this study will be presented by explaining the findings obtained. In the fourth section, a comparison of the proposed methodology with similar studies will be made and the findings will be discussed. In the last section, the conclusions and future goals of the study will be shared.

2 Related Works

Scholars have conducted investigations on a wide range of walnut-related topics. These research focus on the productivity of walnuts, the isolation of walnut species, and the separation of shell and kernel. Scholars have investigated several approaches and procedures for the detachment of the walnut's shell and kernel components. An et al. collected 1200 spectra of three different types of walnut materials after the shells were shattered using near infrared (NIR) spectroscopy. NIR spectroscopy was used to assess the walnut shell and kernel discriminating accuracy. Based on SVM and ELM, a shell-kernel classification model was constructed. The effects of various preprocessing techniques on the accuracy of model recognition are compared. Overall, the SVM and ELM-based shell kernel classification model created for this study demonstrated 97.11% and 97.78% accuracy for the validation set [3]. In order to address common issues with current airflow screening, such as incomplete shell-inner kernel discrimination, high costs, and low efficiency of manually assisted screening, Zhang et al. propose a YOLOX deep learning-based walnut shell-inner kernel detection method [4]. This method makes use of machine vision and deep learning technologies. In order to automatically segment the images and detect natural foreign objects of various sizes (such as fleshy leaf debris, dried leaf debris, and gravel dust) as well as man-made foreign objects (such as paper scraps, packaging material, plastic scraps, and metal parts), they apply two different convolutional neural network structures to walnut images in this study. In 101 test photos, the suggested technique can accurately segment 99.5% of the object regions, and in 277 validation images, it can correctly categorize 95% of the foreign items [5].

The detection of mold within and on the surface of walnuts has been the subject of increased investigation by certain researchers. In order to achieve the non-destructive detection of walnut mold, An et al. developed a walnut mold prediction model utilizing near-infrared spectroscopy in this article. The spectra were pre-processed using a combination of detrending and smooth, multiplicative scattering correction (MSC). The pre-processed spectra's 900–1700 nm band was used to extract features using principal component analysis (PCA), successive projection algorithm (SPA), and competitive adaptive reweighted resampling (CARS). The development of support vector machine (SVM) and extreme learning machine (ELM) models led to 100% accuracy in the identification of rotten walnuts [6]. In this study, Hu et al. assess and distinguish between moldy and normal walnuts using terahertz transmission imaging technology. To determine the filling rate of walnuts, image processing is applied to physical samples with varying internal dimensions. The overall identification accuracy of the three established qualitative discrimination models—SVM, RF and KNN-reaches 90.83%, 97.38%, and 97.87%, respectively [1].

In certain areas, scientists have made more progress in their efforts to classify and identify walnut species. These studies also address more specialized topics like yield calculation. Arndt et al. devised a technique that employs Fourier transform near-infrared (FT-NIR) spectroscopy in conjunction with chemometrics to differentiate between seven distinct geographic origins of walnuts. This analytical instrument is user-friendly, rapid, and versatile. 212 ground and freeze-dried walnut samples that were harvested over the course of three consecutive years (2017-2019) had their NIR spectra gathered. After applying and assessing 50,545 distinct preprocessing combinations, we refined the data preprocessing and used linear discriminant analysis (LDA), which was subsequently verified by nested cross-validation. Thus, this intricate approach can be applied to resolve economically significant issues, like differentiating between Chinese and European walnuts [7]. The suitability of the hyperspectral imaging (HSI) approach for precisely identifying and visualizing Chinese walnut types is examined by Jiang et al. Between 400 and 1000 nm, hyperspectral images of 400 Chinese walnuts, 200 samples of the Ningguo variety, and 200 samples of the Lin'an variety were obtained. To create classification models, three distinct modelling techniques were applied independently: support vector machines (SVM), k-nearest neighbour (KNN), and partial least squares-discriminant analysis (PLS-DDA). With correct classification rates (CCR) of 97.33%, 95.33%, and 92.00% in the calibration, cross-validation, and prediction sets, respectively, the PLS-DA model constructed from the raw full spectrum performed best, according to the results. These findings demonstrated the exceptional potential of the HSI features and their applicability as a dependable instrument for the establishment of an online identification system for Chinese walnut cultivars [8].

Using chemometric techniques, Peng et al. created a regression model for the moisture content of walnut kernels based on NIR diffuse reflectance spectroscopy. The prediction model under these conditions had a squared correlation coefficient (R2) of 0.9865 and a root mean square prediction error (RMSEP) of 0.0017. The study's findings provide a workable technique for quickly determining the moisture content of walnut kernels [9]. Zhu et al. want to quickly and accurately classify ten walnut species produced in four provinces by utilizing machine learning techniques in conjunction with Fourier transform mid-infrared spectroscopy. Three different types of models were built using five machine learning classifiers to differentiate between four geographical origins, identify varieties derived from the same origin, and categorize all ten varieties from the four origins. The spectrum was denoised and smoothed using a wavelet transform approach prior to modelling. According to the results, the classification of four distinct origins (accuracy = 96.97%) and the identification of varieties under the same origin performed the best (accuracy = 100% for some origins), while the discrimination of all 10 varieties was the least desirable (accuracy = 87.88%). Additionally, it was demonstrated that random forests (RF) yielded the worst outcomes, whereas back-propagation neural networks (BPNN) offered the highest model performance [10].

In order to assess the quality and quantity of the interior of walnuts and other nuts whose shells are opaque to the naked eye, researchers have experimented with both destructive and non-destructive methods. An optimization model for EU processing planning that a walnut exporter faces was given by Brunner-Parra et al. Detailed information from the fruit, including its size, colour, and flaws, was incorporated into our model. Our model became a decision assistance system when it was integrated into a web application. We were able to improve earnings by 9.8% in our computational studies, and in certain circumstances, producers were able to increase their profits by 34% [11]. Qui et al.'s work introduces a novel non-destructive technique that uses radiomics and Low Field Magnetic Resonance Imaging (LF-MRI) to evaluate the quality of walnut kernels. The hard shell of walnuts makes it challenging to judge their quality. Radiomics approaches were employed to extract, select, and reduce the dimensionality of features from MRI pictures by analysing the features of the walnut kernel Low Field Nuclear Magnetic Resonance (LF-NMR) relaxation curve and LF-MRI imaging. Using six optimal classification algorithms, ten significant features that are significantly linked to walnut kernel souring were found, and machine learning models were constructed. With a 93.52% test accuracy, 92.78% test recall score, and 96.81% test F1 score, Random Forest (RF) models demonstrated excellent performance [12]. Gao et al. suggested combining machine learning with X-ray imaging and image processing technologies to address the issue of low accuracy in walnut mass identification caused by relatively unchanging density. Following the extraction of the form and texture of the walnut characteristic parameters and the kernel shape characteristic parameters, mass prediction models may be constructed by applying image processing technology to separate the kernels from the background of the walnut X-ray picture. Using RBF, an R2 value of 0.889% was found [13].

An adaptive neuro-fuzzy interface system (ANFIS) was employed by Rezaei et al. to forecast the percentage and quality of walnut kernels. Fuzzy and artificial neural network (ANN) learning methods are used in ANFIS. As model inputs, 100 genotypes of walnuts from the Iranian province of Golestan were analyzed for a total of 14 morphological features. ANFIS was able to estimate the percentage of walnut kernels with a coefficient of determination (R2) of 99%, according to data modelling. Additionally, kernel quality detection had a 99% accuracy rate. These findings demonstrated that the most beneficial approach for creating the ANFIS model is to combine the fuzzy c-means (FCM) method with a hybrid training algorithm [14]. The improved whale optimization algorithm (IWOA) was proposed by Zhang et al. as a new feature selection technique for walnut kernel protein inversion from hyperspectral images. The model that combined spectral and textural information performed better and produced the best prediction results when compared to models that only used spectral information. The R2 and RMSE for the calibration group were 0.9047 and 11.1382 g/kg, respectively. The validation group's RMSE was 18.9288 g/kg and R2 was 0.8537. The findings demonstrated that it is possible to accurately estimate the protein content of walnuts by combining specific wavelengths with textural characteristics using IWOA [15]. A novel technique for non-destructively identifying shriveled kernels in in-shell walnuts was presented by Zhai et al. The technique relies on machine learning combined with weight and picture data. First, an industrial charge-coupled device camera and an electronic scale were used to gather weight and picture data for walnut samples. Then, in order to distinguish between the walnuts with wrinkled kernels, three different types of models were developed: a support vector machine (SVM), a back-propagation particle swarm optimization technique (PSO-BP), and partial least squares-linear discriminant analysis. All of the approaches' classification efficiencies were thoroughly compared in order to identify the best one. With an accuracy rate of 97%, the SVM algorithm produced the best results [2].

The discovery of specific disorders linked to walnuts is another area in which the experts have expanded their investigation. The goal of Anagnostis's and his team's study is to develop a quick and accurate object detection system that can identify walnut tree leaves afflicted with anthracnose in order to be used in actual agricultural situations. By comparing the expert classifications with the system's anticipated classes, 279 of the 379 trees in the orchard were utilized to examine the efficacy and resilience of the object detector [16]. Of these, 100 trees were chosen at random to train the detector.

In order to determine and develop the ideal conditions for walnut farming and harvesting, researchers have expanded their investigations. Yang and colleagues employed a hybrid approach of artificial neural network (ANN) and genetic algorithm

(GA) to derive a model of the drying-assisted walnut cracking process along with the ideal parameters for execution. Using air compression technology, walnuts were dried to various moisture contents (10%, 15%, 20%, and 25%) at various infrared temperatures (40, 45, 50, and 55 degrees Celsius) and air velocities (1, 2, 3, and 4 m/s). Subsequently, the dehydrated walnuts were split into three loading directions: longitudinal, vertical, and suture. With coefficients of determination of 0.996, 0.998, 0.990, 0.991, and 0.993 for DT, SEC, HR, WR, and SR, respectively, the ANN model has a good capacity for prediction [17]. Huang et al. used walnut in Wensu County, Aksu District, Xinjiang as the research object in order to address the issues of low accuracy of crop evapotranspiration (ETc) estimation in arid places and optimize ETc for precision irrigation in agriculture. However, Deep learning sequence models including LSTM, GRU, and BiLSTM were used to forecast crop evapotranspiration (ETc) of walnut in arid regions under various micro-irrigation strategies based on multivariate time series data of walnut production [18].

Studies of this kind are being conducted on other nuts, like walnuts. An effective methodology for categorizing hazelnut variants was presented by Taner et al. The dataset with pictures of 17 different types of hazelnuts was used to train the suggested model. It was discovered that the suggested model has an accuracy rate of 98.63%. Other nut dataset's classification performance can be enhanced by adapting the CNN model shown in this paper. The collection consists of 250 photos per image class, with a total of 17 classes [19]. In order to categorize cashew kernels into five groups based on the butts and fragments of first-class fancy whole cashew kernels, Vidyarthi et al. recommended using deep convolutional neural networks (DCNNs) in conjunction with image processing. Model evaluators like sensitivity, specificity, precision, accuracy, and F1-score were used to compare the performance of four DCNN models—Inception-V3, ResNet50, VGG-16, and a custom model—that were implemented [20].

In this study, the physical parameters of walnut kernels, walnut oil and DF from nine different varieties were analyzed. In addition, the effect of genotype, crop year and the interaction between the two on the color parameters of walnut oil and DF was studied [21]. Hakimi et al. evaluated 31 quantitative and qualitative characteristics of seven superior walnut genotypes comparable to 'Jamal', 'Lara' and 'Serr' varieties [22]. There are also comprehensive reviews of walnut nuts in the literature. The aim of the existing reviews is to provide an overview of the bioactive compounds present in the different structural parts of walnut by-products and elderberry fruits, which offer a specific or common activity relevant to human health and the conservation of agricultural products in the context of sustainable development [23].

3 Material and Method

In this section, you will find a title with detailed and technical information about the dataset. Then the machine learning methods performed with the dataset will be explained.

3.1 Dataset Collection

The walnuts used in the data collection phase belonged to the same species of walnuts, called Chandler, from one region. In the system shown in Figure 1, a walnut is first placed in a chamber containing a sensitive microphone. Considering that the placed walnuts can be of different sizes, it is ensured that the placed walnuts are always at the same height through the laser distance sensor before hitting the walnut with the moving rod. Until the laser distance sensor detects the placed walnut, the platform is pushed upwards by means of a rotating shaft connected to the stepper motor end. If the sensor detected the walnut in the first placement, the platform is first pulled down and then the platform is pushed upwards until the distance sensor detects the walnut again. After the height of the nut is adjusted, the nut is tapped with the help of a rod connected to the end of the servo motor. The tapping process is achieved by the servo motor lifting the rod up 45 degrees and lowering it again. In order to ensure that the servo motor can easily hit the walnut, the required height was created with a fixed platform.

The sound waves produced by hitting the walnut were recorded to the computer in mp3 file format by means of a microphone. A computer and an Arduino Uno control card connected to the computer were used for all these operations. The sound files recorded through the computer were numbered separately for each nut. The recorded sounds were converted from mp3 file format to wav format.

Audio files in Wav format are converted into a graph in frequency space so that they can be processed as images. In this way, audio files are converted into a form that machine learning algorithms can learn. Examples of frequency images obtained from walnuts are shown in Table 1. After the image conversion process was completed, the walnuts were crushed and separated into shell and kernel walnuts. Each walnut was weighed separately with a precision balance and clustered by the ratio of the total weight to the weight of the inner walnut. This clustering was used to determine the class to which the related walnut image would belong.

The obtained numerical values and examples of class identification are shown in Table 2. A total of 1457 walnuts were used to create the dataset.

As seen in Table 2, the percentage value obtained from the ratio of the total weight of the walnut and the amount of walnut kernel obtained was used to determine the class to which the walnuts belonged. Class values vary between 1-9. While 1 is the least productive walnut class, 9 is the most productive walnut class.

Table 1: Examples of frequency domain images obtained from walnuts.

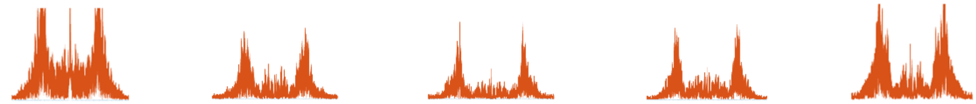
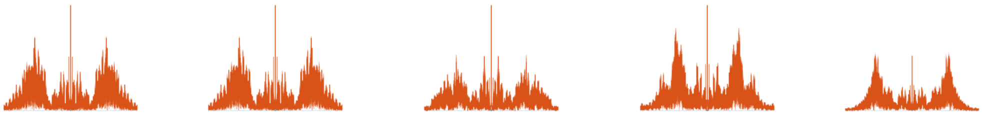
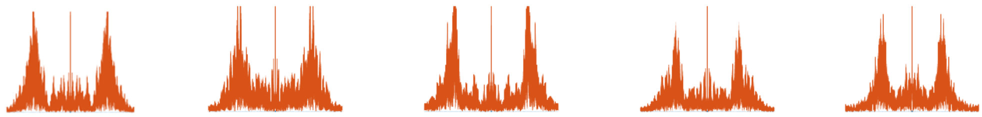
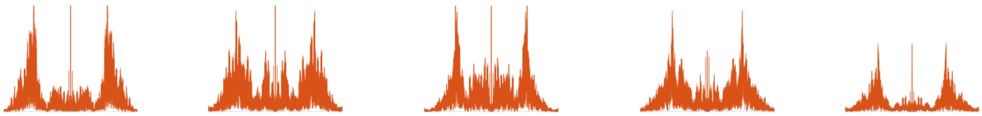
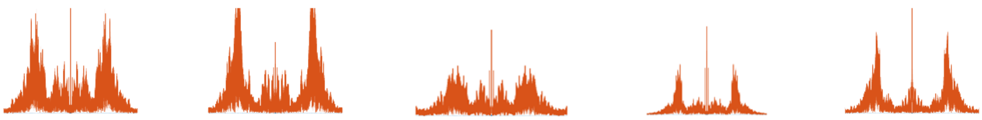
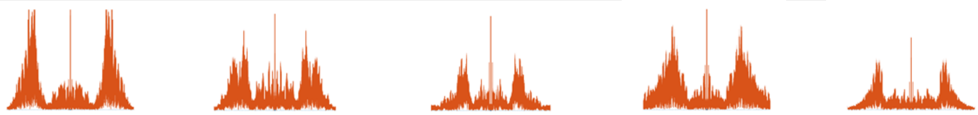
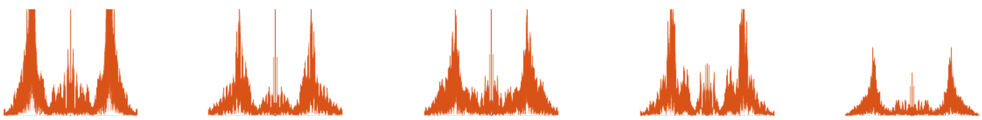
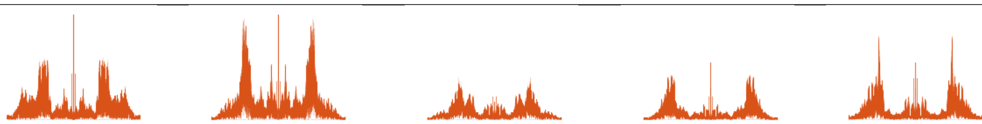
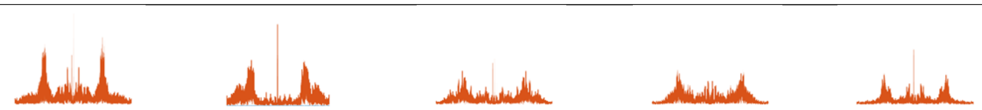
Class	Frequency Graph Examples
1	
2	
3	
4	
5	
6	
7	
8	
9	

Table 2: Numerical data obtained from walnuts and classification criteria.

Walnut No	Total Weight	Shell Weight	Kernel Weight	Internal Yield Rate	Class Type
...	...	...	...	...	...
22	8	4	4	50.00	6
23	8	5	3	37.50	4
...	...	...	...	...	...
124	7	4	3	42.86	5
125	7	3	4	57.14	8
...	...	...	...	...	...
420	10	7	3	30.00	2
421	10	4	6	60.00	8
...	...	...	...	...	...
890	6	3	3	50.00	6
891	6	3	3	50.00	6
...	...	...	...	...	...
1456	9	5	4	44.44	5
1457	9	5	4	44.44	5

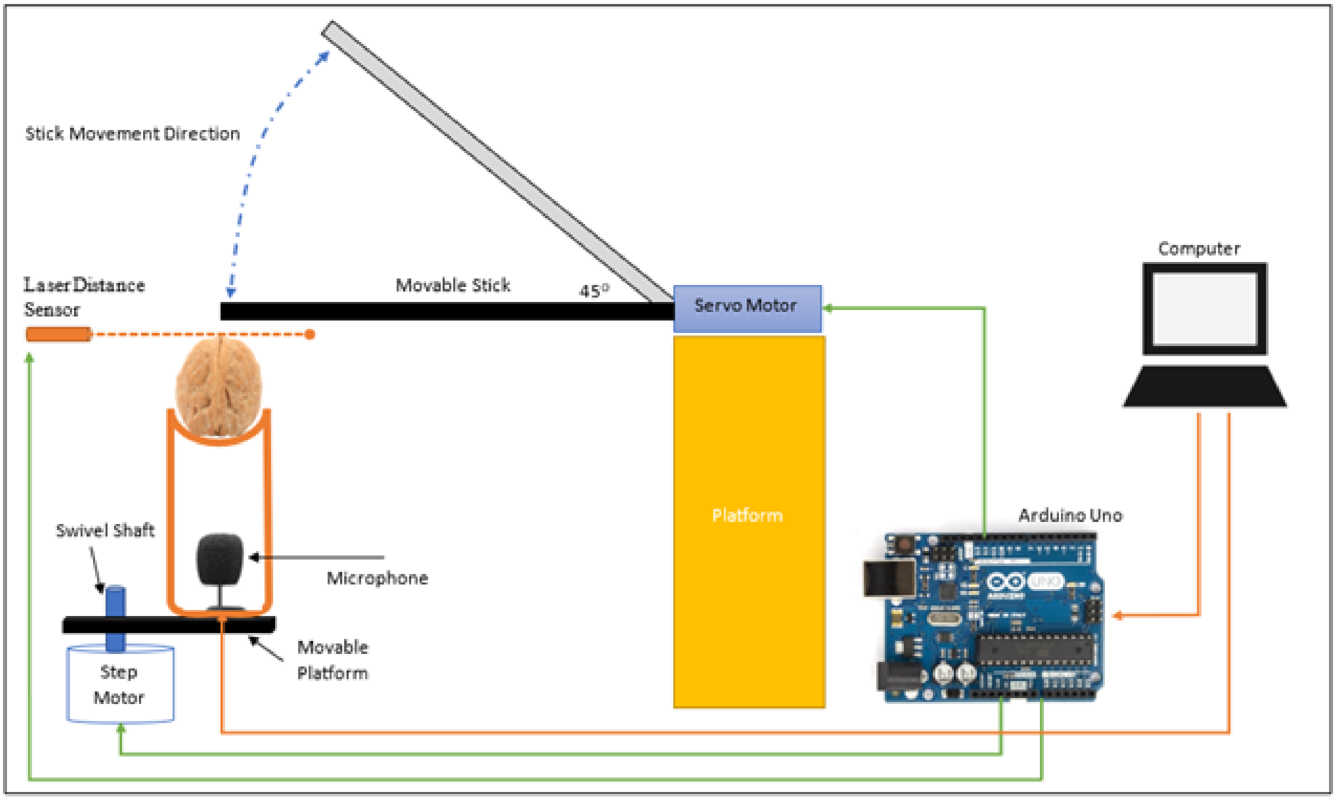


Figure 1: Architecture of the data collection setup

Table 3: Architectural Variable Values of Algorithms.

Model Architecture Variables	VGG16	CNN	DenseNet121	ResNet50
Weights	imagenet	-	imagenet	imagenet
Activation Function	softmax	reLU, softmax	softmax	reLU, softmax
Loss	Categorical crossentropy	Categorical crossentropy	Categorical crossentropy	Categorical crossentropy
Optimizer	adam	adam	adam	adam
Epochs	20	20	20	20
Validation Split	0.2	0.2	0.2	0.2

3.2 Machine Learning Models and Hyperparameters

Machine Learning models include algorithms used in fields such as data analysis and pattern recognition. These algorithms are used to identify patterns in data sets and predict future data. Commonly used algorithms such as VGG16, DenseNet121, CNN, and ResNet50. VGG16 is a convolutional neural network containing 16 layers. In this model, weights are learnable parameters and are removed from the data set during training. Activation functions determine the outputs of neurons in each layer and influence the learning capacity of the model. Generally, ReLU (Rectified Linear Unit) and Softmax function are preferred. The loss function measures the difference between the model's actual labels and its predictions. Mean Squared Error or cross entropy are frequently used loss functions. The optimizer algorithm is used to update the model's weights during training. Methods such as Stochastic Gradient Descent and Adam optimizer are frequently preferred. Epochs indicate how many times the data set is processed by the model during the training process. This can increase the model's ability to recognize more patterns and generalize. Validation split allows a portion of the data set to be reserved for validation during training. This helps prevent overfitting of the model and increases its generalization ability. These variables are important factors that affect the performance of Machine Learning models. Architecture values of the machine learning models used in this study are shown in Table 3.

In this section, since the accuracy values obtained from the ResNet50 algorithm were found to be quite low, re-trials were carried out by increasing the learning number. However, it was clearly seen in the following chapters that it could not reach the

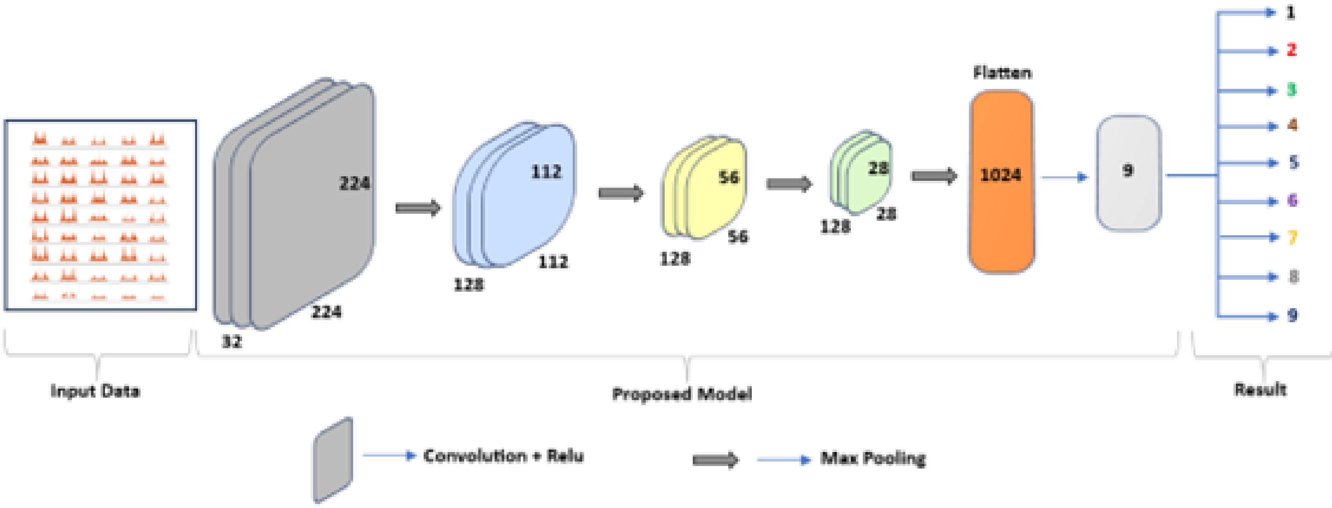


Figure 2: CNN architecture used for model training

Table 4: Accuracy, loss, sharpness and sensitivity values as a result of training machine learning algorithms.

Metrics/Algorithms	VGG16	CNN	DenseNet121	RESNET50
Accuracy	0.9979	0.9990	0.9474	0.5227
Loss	0.0199	0.0031	0.2710	1.3054
Recall_m	0.9979	0.9990	0.8708	0.2487
Precision_m	0.9989	0.9990	0.9928	0.8093
F1_m	0.9983	0.9990	0.9269	0.3655
Val_Accuracy	0.9142	0.9004	0.8455	0.4452
Val_Loss	0.4290	0.6611	0.5421	1.3789
Val_Recall	0.9068	0.8963	0.7357	0.2500
Val_Precision_m	0.9435	0.9103	0.8867	0.8217
Val_F1_m	0.9225	0.9029	0.8023	0.3643

desired level of success, and the reasons for this were discussed.

Figure 2 shows the CNN architecture prepared for model training. The highest accuracy value in the training results was obtained from the CNN architecture. However, it ranks second among all models in terms of validation accuracy value. It also shows the same degrees in F1 score metric values. For this reason, the numerical results prove that the CNN architecture prepared is successful.

4 Result and Discussion

In this section, accuracy, loss and other metric values obtained from machine learning algorithms will be presented. The performances of the trained algorithms will be compared with each other. Recall, precision, accuracy, f1_m and loss values will be given together with validation measurements so that the results obtained are as clear as possible for the readers and the success of the trained model can be clearly seen. Four different machine learning methods were tried to train the data set. These algorithms are VGG16, CNN, DenseNet121 and Resnet50. We believe that the best efficiency that can be obtained from training with the data set will be obtained by observing the results of these four algorithms.

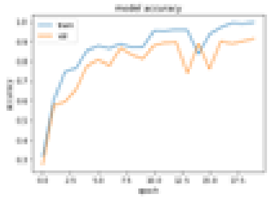
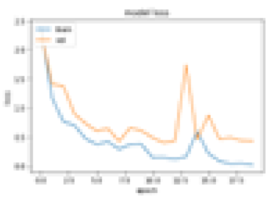
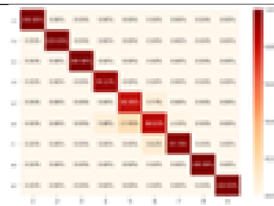
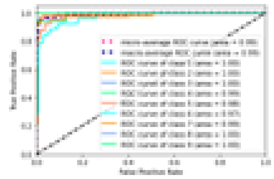
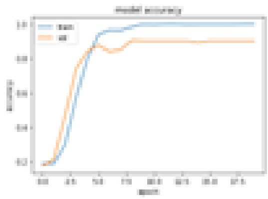
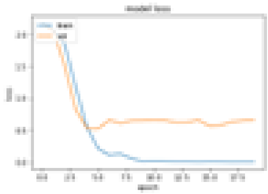
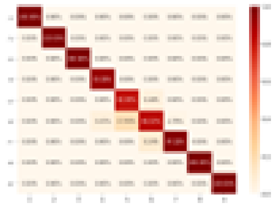
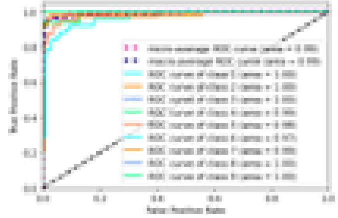
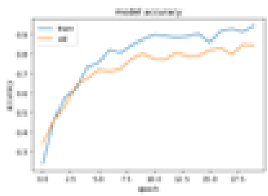
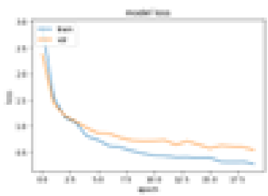
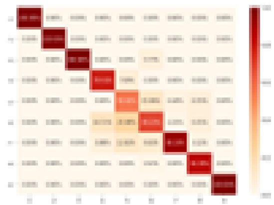
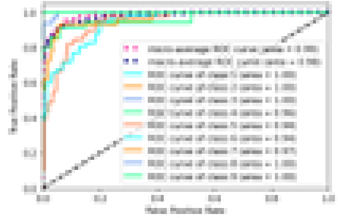
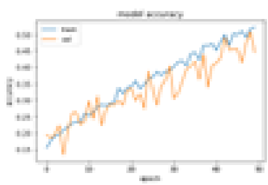
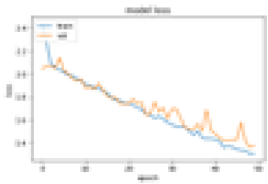
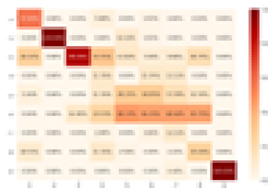
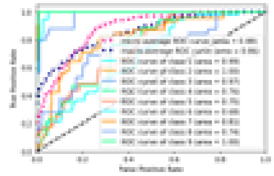
In machine learning, precision and recall are metrics used to evaluate the performance of classification models. In addition to these metrics, the terms val_precision and val_recall refer to the precision and recall values calculated on the validation set. Precision indicates how many of the instances that a classification model predicts as positive are actually positive. Precision measures how few false positives (instances predicted as positive by the model that are actually negative) are made. A high precision value indicates the reliability of the model by showing that most of the samples that your model predicts as positive are actually positive. The presicion value can be calculated as in Equation 1. TP: True Positives, FP: False Positives;

$$Precision = TP/(TP + FP) \tag{1}$$

Recall shows how many true positives (instances that the model correctly predicts as positive) are captured. Sensitivity is important to minimize the cases where your model misses true positives (false negatives). A high recall value indicates that your model captures most of the true positives. FN: False Negatives, the Recall value can be calculated as in Equation 2.

$$Recall = TP/(TP + FN) \tag{2}$$

Table 5: Success, loss complexity metric and ROC Curve graphs of machine learning algorithms.

	Model Accuracy	Model Loss	Confusion Matrix	ROC
VGG16				
CNN				
DenseNet121				
ResNet50				

val_precision is the precision value calculated on the validation set. It indicates how many of the samples that the model predicts as positive in the validation set are actually positive. val_recall is the sensitivity value calculated on the validation set. It shows how much of the true positives are captured in the validation set. Table 5 shows the accuracy, loss graphs, complexity matrix and ROC curve graphs obtained from the machine learning algorithms.

When the accuracy and loss graph obtained after training the ResNet50 algorithm is examined, it is seen that the train and validation lines progress in a zigzag manner. There may be several reasons for this situation. In such cases, if the data set is small or the diversity of your data set is insufficient, your model may tend to overfit the data. In this case, your model may fluctuate during training. In addition, if the model is too complex or has too many parameters, it may be more difficult for the model to learn during training, which may cause fluctuations. Considering these reasons, it is seen that the ResNet50 algorithm is not successful on the existing dataset and is inadequate. As can be seen from the confusion matrix and ROC graph, the model performs a very unsuccessful classification. It has been determined that the other algorithms are close to each other both graphically and in terms of their classification success. Of these three algorithms, it is clearly seen that VGG16 and CNN algorithms are very close to each other and show more successful results than the results of the other two algorithms.

When the studies on similar topics in the literature are examined, it is seen that the success rate obtained is quite promising. The success rates and the metrics shown in the study provide more detailed information than other studies. Although many studies complete the study by giving only Accuracy value, in this study, Accuracy and Val_accuracy values are given together and model learning is transparently revealed. Table 6 shows the year, methodology, technique, dataset, study purpose, and success status of similar studies. In addition, the precision and recall values shown in Table 4 clearly show the precision and accuracy of the model.

The novelty and perspective positions that this study brings to the literature can be explained as follows;

• The study introduces a non-destructive method for estimating walnut yield using machine learning algorithms. This contributes to the existing literature by providing an innovative approach that does not require physical destruction of walnuts for evaluation.

• The study introduces a new method of data collection using voice recordings to assess the fullness and void status of walnuts. This extends existing techniques for collecting data in agricultural studies and potentially inspires similar approaches in other crop yield prediction research.

Table 6: Comparison table of studies similar to this study according to different criteria

Ref.	Year	Dataset	Technique	Aim	Metrics
An et.al. [3]	2022	1200 spectrum image	SVM, ELM, GA+ELM	Classification of walnut shell, kernel and Diaphragma juglandis Fructus (DJF) structures	Accuracy: 97.11%
Taner et.al. [19]	2021	4250 images	CNN	Classification of hazelnut species by image	Accuracy: 98.63%
Jiang et.al. [8]	2021	400 images	PLS-DA, KNN, SVM	Correctly identifying Chinese walnut varieties	Accuracy: 97,33%
Peng et.al. [9]	2021	136	MLR, PCR, PLS, SVR	Estimation of moisture content in walnut kernels	R^2 : 98.65%
Rong et.al. [5]	2019	378 images	CNN	Detection of foreign substances inside the walnut	Accuracy: 95%
Anagnostis et.al. [16]	2021	379 images	VGG16, YOLO, RESNET50	Detecting infected leaves on walnut trees on the tree	Accuracy: 87%
Qiu et.al. [12]	2024	Approximately 1000 walnuts	SVM, SGD, KNN, RF, LightGBM, XGBoost	Walnut internal quality was evaluated with LF-MRI technology.	Accuracy: 93.52%
Gao et.al. [13]	2022	-	RBF	Estimation of walnut internal mass by X-Ray technology	R^2 : 88.9%
Rezaei et.al. [14]	2022	100 walnuts	Anfis	Estimating walnut kernel percentage and kernel quality	R^2 : 99%
Zhang et.al. [4]	2023	185 walnuts, 2753 images	YOLOx, YOLOv3, Faster-RCNN, SSD	Realization of walnut shell and kernel separation	Accuracy: 96.3%
Zhang et.al. [15]	2022	30 walnuts	SVM, RF, BPNN	Walnut kernel protein inversion from hyperspectral image	R^2 : 85%
Hu et.al. [1]	2022	2445 walnuts	SVM, RF, KNN	Identify and analyze normal walnuts and moldy walnuts	Accuracy: 97.8%
Zhai et.al. [2]	2020	-	SVM, PSO-BP	Detecting shriveled kernels from walnut image and weight information	Accuracy: 97%
This Work	2024	1457 walnuts and images	VGG16, CNN, RESNET50, DENSENET121	Yield estimation from walnut sound frequency plane images	Val_Accuracy: 91.42 %

- The study mentions plans to apply similar processing techniques to different nuts such as hazelnuts and almonds. This extension of the methodology broadens the applicability of the findings beyond walnuts, demonstrating their potential generalizability across a variety of nuts.

5 Conclusion

In this study, machine learning algorithms were trained to non-destructively predict the yield of walnuts. With the help of a mechanism prepared for the realization of the study, audio recordings were taken, which we thought would allow us to obtain the occupancy and vacancy status of all walnuts under equal conditions. These records were taken in the frequency plane and their images were recorded so that the image algorithms could process them. To classify the images, the value obtained from the ratio of the whole weight of the walnut to the inner walnut was recorded as the class label. When the accuracy and loss results obtained from different machine learning algorithms were evaluated, the most successful VGG16 algorithm was using imagenet weights to obtain Accuracy of 99.79% and Val_accuracy of 91.42%. When the results obtained are compared with similar studies in the literature, it can be seen that successful results have been achieved. In future studies, it is aimed to further increase the Val_accuracy value by increasing the amount of data. In addition, similar processing processes are planned to be applied to different nuts such as hazelnuts and almonds.

Authors' Contributions

RG: training of machine learning algorithms, interpretation of results, literature and conclusion section author. EA: design of the data collection system and creation of the data set, author of the introduction and literature section. ME: author of the training of machine learning algorithms, interpretation of results and discussion section.

Competing Interests

The authors declare that they have no conflict of interest.

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