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Mass estimation of citrus limetta using distance based hand crafted features and regression analysis

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ABSTRACT

Sorting and grading are qualitative operational tasks performed in food processing industries. Realization of higher accuracy in mass estimation is the key inclination of this work. In this work, an automated technique for mass estimation of citrus limetta is devised based on the geometrical features derived from pre-processed images. Dataset includes 250 data samples of citrus limetta, whose images are acquired in different orientations. Two novel handcrafted distance-based geometrical features along with four conventional geometrical features were employed for regression analysis. Predictive modeling is conducted with configuration of 150 training and 100 testing data samples and subject to regression analysis for mass estimation. Multiple linear and support vector regression models with linear, polynomial and radial basis function (RBF) kernels were employed for mass estimation with two different model configurations, conventional and conventional with handcrafted features, for which an R2 score of 0.9815, root mean squared error (RMSE) of 10.94 grams, relative averages of accuracy and error of 96.61% and 3.39% respectively is achieved for the proposed model and configuration which was validated using k-fold cross-validation. Through comparison with performance of model with conventional and conventional with handcrafted features configurations, it was established that inclusion of handcrafted features was able to increase the performance of the models.

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1. INTRODUCTION

Citrus limetta is commonly known as Mosambi or Musambi in India, it has an excellent market and is the 3rd largest fruit cultivated in India. It is cultivated in dry climatic condition and needs 60-75 cm of rainfall annually. Citrus limetta and similar citrus fruits provide excellent and unique health benefits from their consumption. Among the various post-harvest operations, grading and sorting are the most time intensive that demand automated processing techniques, one of the crucial parameters that are essential in grading and sorting of fruits are size and weight. Non-destructive techniques for grading and sorting which are contactless are highly beneficial in food processing industries, as they enable high-speed processing and fit the demands of industries. Computer vision and machine learning techniques assist in the accurate determination of shape and mass that decides the fruit grading. Integration of image processing techniques in fruit processing ensures the reliability of vision-based grading and sorting systems. Mass estimation of fruit supports in deciding the fruit maturity, and in turn, helps in fruit grading. Robust estimation of mass is highly essential for real time fruit processing, therefore continuous investigation efforts are underway to enhance the overall precision in mass estimation.

Survey on significant contributions on mass estimation of variety of fruits using image processing, and machine learning techniques are discussed as follows: mass and volume estimation of cherry tomatoes were investigated [1]. The study is focused on analyzing relationship between tomato mass and volume is analyzed using 2D and 3D image features. Support vector regression model (SVRM) with radial basis function (RBF) kernel is used for the estimation of volume and mass. In a work by Ganjloo *et al.* [2], image processing techniques are used for mass estimation and shape through geometrical features and decision tree-based analysis. An investigation based on image processing and artificial intelligence models is proposed by Lee *et al.* [3] for mass estimation of fruits, bagged ensemble tree regressors were adopted for prediction via correlation study of fruit image. Regression-based models are developed by Okinda *et al.* [4] for the prediction of egg volume, and shape-based information extracted are employed as Regression model inputs. A detailed study on various computer vision systems is conducted by Nyalala *et al.* [5], regarding weight and volume estimation of poultry-based products. Mass estimation of symmetrically shaped fruits is, researched by Yani *et al.* [6] using computer vision techniques. Assessment of fruit quality through automatic mass prediction is suggested by Gokul *et al.* [7] using image processing techniques.

In other works, investigation on models for mass estimation and volumes of lime fruits are investigated by Jayarmi and Taghizadeh [8] using non-destructive techniques viz. physical attributes of objects. Classification of fruits based on their maturity and mass indicator is introduced by Iqbal *et al.* [9] using color based features discriminant analysis is carried out for feature selection and classification. Artificial adaptive neuro-fuzzy inference models based mass estimation of Sweet lime are devised [10]. The goodness of fit is employed to check the proficiency of the models proposed. In a different work [11], machine learning techniques and neuro-fuzzy inference systems are extended for the prediction of lime fruits. A self-built database is used for validation of the weight estimated. The fruit and vegetable mass estimation of irregularly shaped objects is investigated [12]. Volume estimation of strawberries, mushrooms and tomatoes using geometrical measurements by Concha-Meyer *et al.* [13] using correlation-based analysis and regression analysis is applied between the weight and volume measurements of datasets. Mass modeling of Sohiong fruit is investigated by Vivek *et al.* [14] physical and mechanical properties are used to predict the mass. In the literature, various models are reported by [15]–[17] focused mainly on modeling of volume and mass of a variety of fruits and objects. Some of the state of art papers that are reported in the recent years are reviewed and the highlights of the same are presented for comprehensibility in the Table 1.

Table 1. Key concepts used in literature automated mass estimation

Samples	Features	Dataset	Methods	Models	Reference
Olive fruit	Major axis, Minor axis, And area	3,600 samples	Image processing, manual measurements	Linear regression model	Ponce *et al.* [18]
Pistachio kernel	Length and area	2,000 samples	Image processing, manual measurements	Random-forest (RF) model	Vidyarthi *et al.* [19]
Mango	Thickness and Diameters	61 samples	Image processing	Artificial neural network model (ANN)	Utai *et al.* [20]
Orange	Area, eccentricity, perimeter, length, width, area, color, contrast, texture, and roughness.	300 samples	Image processing	Adaptive neuro fuzzy inference system-fuzzy sugeno model	Javadikia *et al.* [21]
Yellow melon	Area and diameters	135 samples	Image processing, manual measurements	Linear regression model	Calixto *et al.* [22]
Citrus fruit	Area	5,000 samples	Image processing	Naive bayes classifier and ANN model	Shin *et al.* [23]
Fishes	Area	2,500 samples	Image processing	Convolutional neural network model	Konovalov *et al.* [24]
Almond	Length, breadth and area	1,000 samples	Image processing, manual measurements	Stacked ensemble model (SEM) with ANN, RF, support vector regression (SVR), k-nearest neighbor and kernel ridge regression	Vidyarthi *et al.* [25]

From various literatures we observe that, they extensively employed predefined geometrical features for measuring the features of fruits and objects and observed that a set of predefined features used identified through assumption-based procedures and adopted for prediction of mass using machine learning models. It is also inferred from a couple of works that the issue of generalization is noticed with regard to a generic algorithmic procedure designed for mass estimation of multiple fruit types. However, as food processing is more specific to a particular fruit type and hence having a generic approach may simply increase computational complexity and loss of accuracy. The literatures were aimed at the development of heuristic or handcrafted feature models which may enhance the scope of achieving high recognition accuracy with optimal number of training samples.

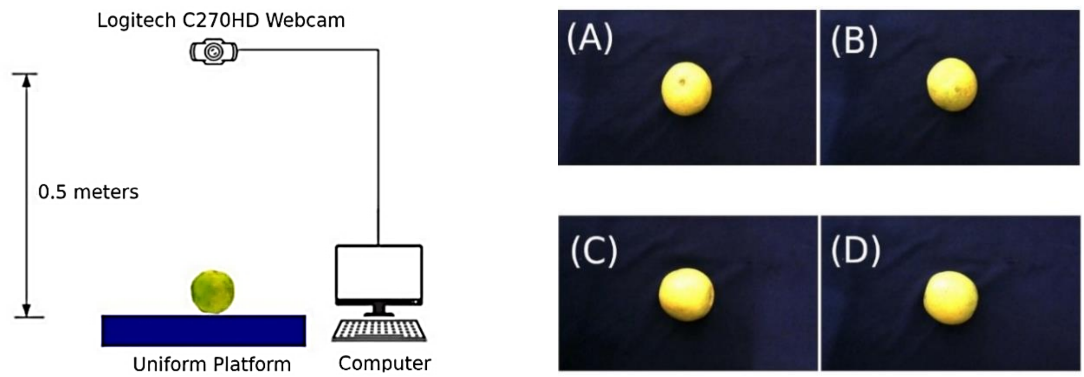
2. METHOD

2.1. Experimental setup and dataset collection

Experiments were conducted between October 2020 and May 2021 at Amrita Vishwa Vidyapeetham, Mysuru Campus, India. Citrus limetta were collected from various local markets of the Mysuru district. Fruits selected for dataset creation are mostly non-defective, ranging from various sizes and ripeness. Each Citrus limetta is labeled, weighed by a calibrated electronic scale with an accuracy of ± 0.01 g and ground truth data is tabulated.

2.2. Image acquisition setup

Images were acquired by equipping an imaging system with a Logitech HD270 webcam mounted on a tripod camera stand 0.5 meters perpendicularly above a plain uniform background. The camera is connected to a Windows 10 laptop via a USB port. Inbuilt camera software provided by Microsoft was used to acquire the images at the resolution of 1280×720 pixels. Each Citrus limetta was imaged in four different orientations, capturing the variation in the geometrical measurements with orientation and position. In Figure 1 of image acquisition setup, Figure 1(a) shows the experimental setup used for image acquisition and Figure 1(b) shows the sample images acquired covering various orientations.



(a) (b)

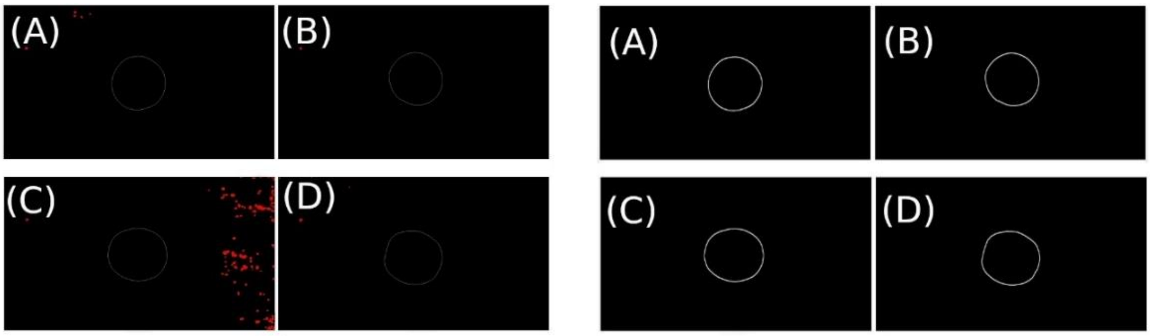
Figure 1. Image acquisition setup (a) image acquisition setup and (b) sample images acquired in different orientations

2.3. Pre-processing

Pre-processing in the proposed method is only a basic clean-up procedure carried out for smoothening out the image so that object extraction can be accurate. The raw image was initially subject to grayscale image conversion. In order to erode the irrelevant border components, the grayscale image is subject to Gaussian smoothing. The aim of smoothening is to suppress irrelevant distortions, so that features of objects will be enhanced for subsequent processing. In order to extract the region of interest Canny edge detection operator is consulted as there was significant discrimination between the foreground and the background. Finally, small object removal along with the morphological operation, dilation was performed to remove noisy pixels and maximizes the edge strength of boundary of the object and filling of small openings on the boundary. Figure 2 shows the outcomes of the image pre-processing with edge detection in Figure 2(a) and after small object removal in Figure 2(b).

2.4. Feature extraction

In the proposed method, two novel distance-based handcrafted features devised and various parameters that are consulted from the region of interest are indicated in Figure 3. A total of six different 2D features of the citrus limetta were identified, two of which were handcrafted features. The features are projected area (A_p), boundary length (B), major-axis length (L_1), Minor-axis length (L_2), the two handcrafted features top parallel chord length (λ_1) and bottom parallel chord length (λ_2).



(a) (b)

Figure 2. Pre-processing (a) highlighted noisy pixels after canny edge detection and (b) outcome of small object removal along with morphological dilation

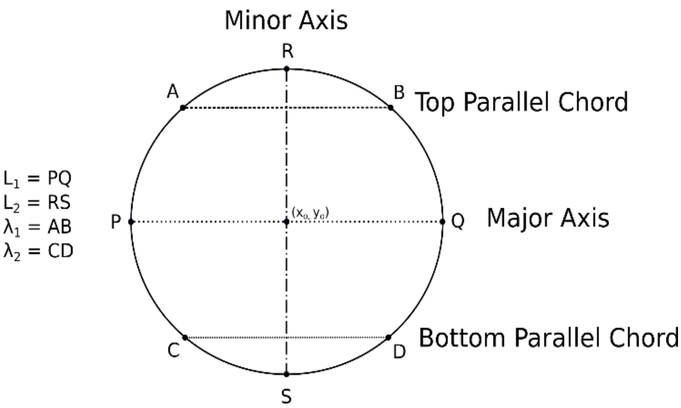


Figure 3. Geometrical feature extraction models

A_p is the projected area of Citrus limetta which the object takes up when projected onto the image plane or the total number of pixels inside the boundary of the object. B is the boundary length of the object computed by counting the number of pixels in a closed contour points set. The distance parameter L_1 as the distance between the major-axis endpoints P and Q designated by (P_1, P_2) and (Q_1, Q_2) respectively, expressed using Euclidean distance function given by the (1).

$$L_1 = \sqrt{(Q_1 - P_1)^2 + (Q_2 - P_2)^2} \quad (1)$$

Similarly, distance parameter L_2 is the distance between the minor-axis endpoints R and S designated by (R_1, R_2) and (S_1, S_2) respectively, expressed using Euclidean distance metric given by the (2).

$$L_1 = \sqrt{(Q_1 - P_1)^2 + (Q_2 - P_2)^2} \quad (2)$$

2.4.1. Handcrafted features

Along with conventional geometrical measurements that are employed for feature extraction of Citrus limetta, two novel distance-based parameters such as top parallel chord length (λ_1) and bottom parallel chord length (λ_2) are also extracted and are defined as the Euclidean distance-based measurements of the chords that are parallel to the major-axis and present at a distance of three-fourth of semi minor-axis length $(3 \div 4 \times L_2 \div 2)$ away from the center of the ellipse (x_o, y_o), assuming the major-axis is in the horizontal orientation. λ_1 is the Euclidean distance length between the endpoints of the top parallel chord viz. A and B designated by (A_1, A_2) and (B_1, B_2) respectively, is given by the (3) as specified in Figure 3.

$$\lambda_1 = \sqrt{(B_1 - A_1)^2 + (B_2 - A_2)^2} \tag{3}$$

Where λ_2 is the Euclidean distance length between the endpoints of the bottom parallel chord viz. C and D designated by (C_1, C_2) and (D_1, D_2) respectively, is given by the (4) as specified in Figure 3.

$$\lambda_2 = \sqrt{(D_1 - C_1)^2 + (D_2 - C_2)^2} \tag{4}$$

2.5. Statistical correlation test and feature analysis

Pearson's statistical correlation test was performed using RStudio (Version 1.4.1106) to determine the linear dependence between the dependent feature (M) with respect to the independent features extracted $(A_p, B, L_1, L_2, \lambda_1, \lambda_2)$. According to the results of Pearson's statistical correlation test, the correlation coefficients are close to unity, indicating that there is a strong correlation between the independent features $(A_p, B, L_1, L_2, \lambda_1, \lambda_2)$ and the dependent feature (M). The two handcrafted had correlation co-efficient equal to 0.95 and other conventional features which had correlation co-efficient equal to 0.98 or 0.99. Based on the values of regression analysis performed using lm (linear-model) function in R-Studio, it was observed that the p-values for individual independent features to predict the dependent feature were less than 0.01. Therefore, the six extracted features were considered for the proposed model configuration as they were found statistically significant and viable for estimating the weight. To observe the impact of the handcrafted features on the performance of the model, the conventional features configuration considers projected area (A_p), boundary length (B), major-axis length (L_1), minor-axis length (L_2) as independent features for the predication of weight.

2.6. Prediction modeling

In order to estimate the mass of the citrus limetta based on the extracted features, two regression models were explored namely, multiple linear regression and support vector regression with linear, polynomial, and RBF kernels. The models were implemented using Python programming language (Python 3.7.5) using the scikit-learn (version 1.0.1) library. A k-fold cross-validation (k=10) method was used to validate the models. The k-fold cross-validation method divides the randomized dataset to specified k-folds, one fold is used for testing the model and the remaining folds are used for training the model, the evaluation score for each possible unique test-train groups generated are averaged as the result. k-fold cross-validation is mainly used in machine learning to gauge the capabilities of a model on unseen data. The hyper parameters for the SVRM models were found using the grid search method which iteratively searches for the optimal parameters from the combinations of set of given parameters using the 10-fold cross-validation and the results are shown in Table 2. The dataset consists of 250 samples, which is divided into the training dataset, consisting of 150 data samples 60% and a testing dataset, consisting of 100 data samples 40%. The dataset was synthetically increased from 200 samples to 250 samples using the reweighting technique.

Table 2. Support vector regression (SVR) hyperparameters for various kernels

Models	C	Ɛ	Degree
Linear-SVR	0.001	10	-
Polynomial-SVR	150	8	1
RBF-SVR	750	1	-

3. RESULTS AND DISCUSSION

The models were evaluated on the testing dataset and the performances of the models with various evaluation metrics such as R^2, mean-absolute error (MAE), mean squared error (MSE) and root mean squared error (RMSE) with two different configurations, the results of which are presented in Table 3. The models were validated using the k-fold cross-validation technique (k=10) on the entire dataset, and the results of the validation tests as displayed in Table 4. Figure 4 depicts the scatter plots for the relationship between the estimated weight and the measured mass in Figure 4(a) using multiple linear regression (MLR) model, Figure 4(b) using linear support vector regression (SVR) model, Figure 4(c) using SVR polynomial and Figure 4(d) support vector regression (SVR) radial bias function (RBF) models. The results indicate that the models were accurate in estimating the weights of the Citrus limetta with minor differences between estimated weights and the measured weights. The models performed with close proximity to each other, and out of all the models investigated the RBF-SVR model shows the best performance on both configurations with an R^2 value of 0.98151, with an average accuracy of 96.614% and with an average relative error of 3.386% on the test dataset with proposed configuration. The linear-SVR, polynomial-SVR and multiple linear regression models showed an average relative error of 3.936%, 3.731%, 3.846% and average accuracy of 96.064%, 96.269%, and 96.154% respectively in the proposed conventional with handcrafted features model configuration.

Table 3. Performance of the models to estimate the mass on test dataset with two configurations

Configuration	Regression model	R^2	MAE (in g)	MSE (in g)	RMSE (in g)
Conventional features	MLR	0.97914	8.05956	135.05266	11.62122
	Linear-SVR	0.97830	8.21393	140.52383	11.85427
	Polynomial-SVR	0.97922	8.05081	134.56667	11.60029
	RBF-SVR	0.97976	7.86438	125.08693	11.18423
Conventional with handcrafted features	MLR	0.97923	8.20018	134.51022	11.59785
	Linear-SVR	0.97831	8.43624	140.46166	11.85165
	Polynomial-SVR	0.97930	8.02617	134.03429	11.57732
	RBF-SVR	0.98151	7.16062	119.73611	10.9424

Table 4. 10-fold cross-validation results for the models to estimate the mass with two configurations

Configuration	Regression model	R^2	MAE (in g)	MSE (in g)	RMSE (in g)
Conventional features	MLR	0.97912	7.67018	122.17714	11.05338
	Linear-SVR	0.97892	7.76509	123.55969	11.11574
	Polynomial-SVR	0.97913	7.64224	121.64801	11.02942
	RBF-SVR	0.97963	6.98280	119.57198	10.93490
Conventional with handcrafted features	MLR	0.97938	7.83741	120.31454	10.96880
	Linear-SVR	0.97941	7.85050	120.17145	10.96227
	Polynomial-SVR	0.97921	7.63920	121.22217	11.01009
	RBF-SVR	0.98006	6.95012	114.59439	10.70488

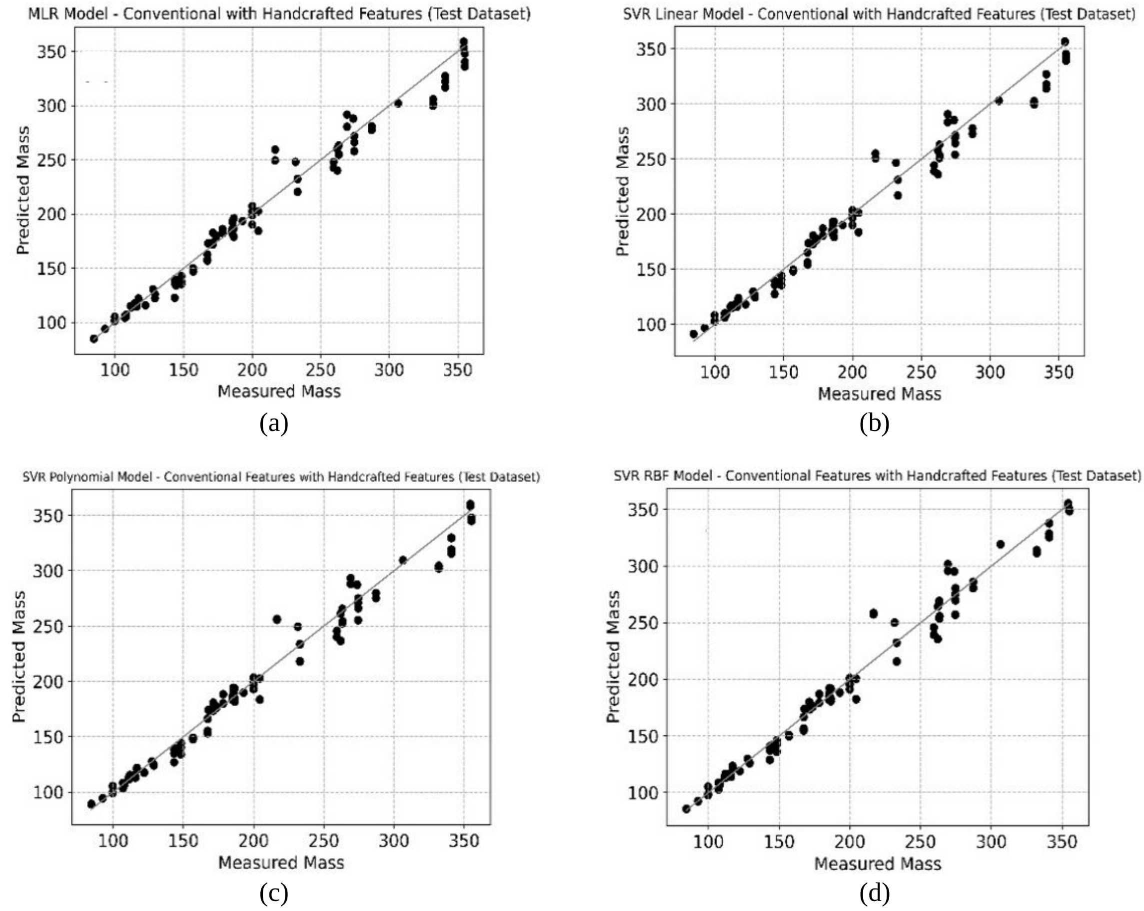


Figure 4. Scatter plots of relationship between the estimated and measured mass for regression models in proposed configuration (a) MLR model (b) SVR Linear model (c) SVR polynomial model, and (d) SVR RBF model

SVRM with RBF model similarly performed better than its counterparts in the conventional features model configuration. This shows that the RBF-SVR model is a better model for prediction of the mass of Citrus limetta using proposed geometrical features out of the models explored this is further validated from Table 4, as RBF-SVR model consistently performed best in 10-fold cross validation test. The handcrafted features model in comparison with the conventional features model, was able to increase the performance of the model in both test dataset and 10-fold cross validation results. The RBF-SVR model with proposed conventional with handcrafted features model configuration was able to reduce the root mean square error by 2.21% in the test dataset compared with conventional features model configuration.

4. CONCLUSION

In this work, regression models such as multiple linear regression and support vector regression with linear, polynomial and RBF kernels were explored and developed in order to estimate the weight of the Citrus limetta using the acquired and pre-processed images of the citrus limetta as input. Basic pre-processing techniques were applied for extracting the fruit region and the geometrical features of the fruit were calculated based on the fruit region extracted from the pre-processed images. Through statistical correlation test it was affirmed that the geometrical features extracted were viable and statistically significant for estimating the weight of the citrus limetta. Out of the models explored the support vector regression with the RBF kernel performed the best with an R^2 of 0.98151, an RMSE of 10.9424 grams, an average accuracy of 96.614% and an average relative error of 3.386% towards the proposed model configuration. The models explored were validated using the k-fold cross validation and support vector regression with the RBF kernel also performed the best among the explored models in k-fold cross validation test with all model configurations. It was observed that developing hand-crafted features that capture more data concerning the geometry of the fruit and including them as independent features along with conventional features for the model were able to consistently increase the performance of the models.

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