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Research article

Artificial neural networks and genetic algorithm approach to determine length-weight, length frequency relationships of Lessepsian crab, *Charybdis* (*Goniohellenus*) *longicollis*, Leene, 1938 in the Iskenderun Bay, Turkey

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Abstract: Mathematical models are created to have information about growth of living beings. Biometric models such as length-frequency and weight-length are also distributions that give information about growth of livings. In this study, the growth of *Charybdis (Goniohellenus) longicollis* Leene, 1938 is given by von Bertalanffy growth curve, which is a continuous growth model, using length frequency (Carapace Width) data. The TropFishR package program in the R program is used to estimate the von Bertalanffy growth curve. Electronic Length Frequency Analysis of Response Surface Analysis and Genetic Algorithm methods included in this package program are applied, and both methods are compared according to the Rn max value. As a result, the Rn max values of the estimated von Bertalanffy parameters for the Genetic Algorithm is better than Response Surface Analysis. In addition to classical linear regression method, Artificial Neural Networks method is used to estimate the weight-length relationship of the species. The Artificial Neural Networks (ANNs) method is presented by two models. In the first ANNs model, CW was used to estimate the weight. In the second model, age was added, which was estimated in the first part of this study, to the first ANNs model. Mean Squared Error, R^2 and Mean Absolute Percentage Error criteria are taken into account when comparing the three models used in weight estimation. It is seen that the Artificial Neural Networks model with the age variable added to the weight estimation has the best performance.

Keywords: Artificial Neural Networks, Genetic Algorithm, Growth, Length-weight relationship.

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Lessepsiyen Crab, *Charybdis (Goniohellenus) longicolis* Leene, (1938) is distributed worldwide in the Red Sea, Persian Gulf, Indo-west Pacific Ocean up to the East African coasts and the Mediterranean Sea (CIESM,2015). On the Mediterranean coast of Turkey, the first recording was made in Mersin in 1954 (Holthuis, 1961). This invasive species later settled along the northeastern Mediterranean coast of our country and formed large populations (Ozcan et al., 2005; Marun, 2016). It has spread from all the Levantine coasts to the Aegean on our coasts. Portunidae is the most successful family in colonization of Mediterranean coasts.

Knowledge about the growth and population of a living thing is very important in terms of managing ecosystems and exploited the long-term continuity of the species (Schwamborn and Moraes-Costa, 2019). While obtaining information about the growth of a living creature, age, length, weight parameters are used. These parameters are used especially in order to have information about fish stocks and to use existing stocks correctly (Kindong et al., 2020).

There are many approaches based on demographic information and accurate age estimates used in calculating vital functions. In many fish species, the age can be calculated accurately from regular age bands found in otoliths and other hard structures. However, age determination is very difficult since crustaceans periodically change their molts and do not have hard permanent elements. Despite this, due to the increase in the production amount of economical crustacean species all over the world, the need to calculate the population dynamics of the species and the correct vital values is increasing.

Population dynamics models are predicted by the interactions of individual growth, fecundity and survival processes. Fecundity and survival methods can be determined quite accurately for fish populations and can be determined by traditional fishery prediction approaches. However, due to the typical discontinuous growth of crustaceans, it is difficult to determine the growth pattern in crabs with conventional fishery approaches. Therefore, accurate population dynamics modeling should be related to the nature of the discontinuous growth of crustaceans. Length-frequency distribution models are also widely used to predict the continuous growth characteristics of crustaceans. Length-frequency analysis is based on the forms of length-frequency distribution that can be explained as cohorts or age classes.

Length-frequency data are used to model growth and to obtain information about the life span of species in data where age determination cannot be made and information on the creature is limited (Clottey, 2020). Length-frequency models are frequently used in literature because of their low cost and easy application (Petersen, 1891; Pitcher, 2002). Also, the use of the Electronic Length Frequency Analysis (ELEFAN) method in length-frequency data analysis, where there is limited information, is quite common (Pauly and David, 1981; Pauly and Morgan, 1987). ELEFAN method has been presented with FISAT and FISAT II programs over the years and transformed into a platform that users can easily model (Pauly and David, 1981; Pauly and Morgan, 1987;). Later, Pauly and Greenberg (2013) transferred it to the R program with "ELEFAN in R" package program. Mildenberger et al. (2017), developed TropFishR package in R and optimized ELEFAN with two methods (Genetic Algorithm and Simulated Annealing). Thanks to TropFishR (Mildenberger, 2017) package, usage of ELEFAN method has become widespread. Many researchers have used the TropFishR package in different types species of length-frequency distributions, estimation of growth parameters and creation of growth models (Schwamborn and Moraes-Costa 2019; Clottey, 2020; Kindong et al., 2020; Wang et al., 2020), and in selecting "bin size" which means the group size of the length-frequency data (Wang et al.,2020).

Due to its successful results in every field, the usage of Artificial Neural Networks (ANNs) also become widespread in the ecological field (Sun, 2009). While Yu et al., (2006) used the ANNs method to indicate the growth model of shrimp, they show how powerful ANNs in this space. They applied eight regression functions together with ANNs to the data set and compared them with Root Mean Squared Error (RMSE) and R^2criteria. Tirelli et al. (2011), evaluates the reliability of various current classification techniques in modeling *Austropotamobius pallipes* presence/absence and ranks their performances; Türeli et al. (2011) estimated the weight of blue crabs using ANNs and General Linear Model (GLM) methods. They used the MSE and Correlation Coefficient (R) criteria for comparison. Sor et al., (2017) in calculating the effects of species prevalence on the performance of prediction models; Hernández et al., (2017) in determining the water quality in *Litopenaeus vannsamei* aquaculture ponds, and Özcan (2019) in creating the weight-length model of *Alburnus mossulensis* used the new computational model ANNs. Modeling the spatial distribution of three species belonging to the Portunidae family (Luan etal., 2018); in the estimation of the potential distribution of the invasion crab *Eriocheir sinensis* (Zhang et al.,2019) ANNS method was used.

In the first part of this study, TropFishR (Mildenberger et al., 2017) package was used to create the length-frequency model of the *C. (G.) longicollis* Leene 1938. By using the Response Surface Analysis (RSA) and ELEFAN Genetic Algorithm (GA) methods included in this package, von Bertalanffy growth parameters were estimated, and age estimation was made using the growth equation constructed with these predicted parameters.

In the second part of the study, Linear Regression and ANNs method were used to obtain weight-length model of *C. (G.) longicollis*. When using the ANNs method, two models were created. While the length-weight relationship was examined in the first model, the age parameter obtained in the first part was included in the second model. Multi-Layer Perceptron (MLP) algorithm is used in ANNS approach. This algorithm was implemented in the R program with the "neuralnet" package program developed by Günther and Fritsch (2010). Mean Squared

Error (MSE) and MAPE criteria were taken into consideration in comparing the three constructed models.

As a result, it is aimed to reach the growth dynamics of the population in the most accurate way. Because it is very important to establish an accurate growth model in any stock assessment. Growth means participation in the recruitment of fisheries population. Fisheries management studies based on stock forecast results often include estimation for growth.

Material and Method

Field sampling and measurements

The Yumurtalık Bay (36o 42' N; 35o E - 35o 49' E), where the study is conducted, is located on the northwest side of the Iskenderun Bay, with an average length of 14 km, a width of 8.4 km, an area of 118 km^2 and the deepest point at the entrance of the bay at 46 m. Crab samples were collected monthly between July 2014 and June 2015 with stratified random trawlers, on a Mediterranean type shrimp trawler with a boat named "MAVI SU 3". Samples were obtained from a total of 3 shots, with 45-minute shots each, between 0-50 m. The samples were anesthetized on ice and brought to the laboratory. In the laboratory, sex, weight, carapace width and carapace length measurements of each individual were taken and numbered.

Length-Frequency Model

Frequency distribution histograms were created by dividing the monthly carapace width data into 4 mm class intervals. The length-frequency distribution was made using the ELEFAN function. This function was applied to the data with the TropFishR package (Mildenberger et. al., 2017) in the R program.

The von Bertalanffy (1938) growth model in crabs, in which age determination and parameters are made according to the length-frequency distribution, is as follows:

$$L_t = L_\infty(1 - \exp(-K(t - t_0)))$$

Where L_t is the length in age t (CW); L_∞ is asymptotic length (CW); K is the von Bertalanffy growth constant; t_0 is the theoretical age at which the length is equal to zero. t_0 cannot be calculated from the equation given here. The calculation of this value is possible with the following equation developed by Pauly (1980):

$$\text{Log}(-t_0) = -0.3922 - 0.2752\ \text{Log}(L_\infty) - 1.038\ \text{Log}(K)$$

Therefore, age group (modal group) estimation of the crab was made according to this equation. The methods used in length-frequency distributions decided the model by choosing the best L_∞ and K values calculated by goodness of fit tests (Pauly and David, 1981; Pauly and Morgan, 1987). The ELEFAN method is one of them. When creating the model, how well the predicted parameters fit the model is calculated with Rn (Mildenberger et.al., 2017). Rn can be get by calculating the "available sum of peaks (ASP)" and "explained sum of peaks (ESP)" values using $Rn = (10^{ESP/ASP})/10$ formula (Pitcher, 2002). The model is created by selecting the parameters that maximize the Rn value. The best fitting model is the one where Rn approaches 1 (Mildenberger et.al., 2017).

In this section, the TropFishR package program which developed by Mildenberger et al. (2017) in the R program was used in order to model the length-frequency distribution. RSA and ELEFAN GA methods that are in the TropFishR package are used. Also, carapace width (CW) of this species was used as a length attribution.

Length-weight Model

It is possible to obtain information about the organism from weight-length models as well as models obtained from length-frequency distributions. Weight-length modeling is created by Ricker (1973) with the equation expressed as W $=aL^b$ where, a is a constant term and b is the slope term. Linear Regression (LR) method is often used to estimate the parameters of this equation. In order to apply LR, it is necessary to make logarithmic transformations to weight and length variables. The length variable in this equation is CW of this species.

Unlike traditional models such as LR, no linearity is required in ANNs models (Günther and Fritsch, 2010). This is very valuable as it makes it easier to make predictions from non-linear complex models (Ataseven, 2013). In this study, MLP, which is an ANNs algorithm, is used (Priddy and Keller, 2005).

MLP algorithm is a feed forward algorithm (Faris et al., 2014). Since the flow of information is forward, it is called a feed forward algorithm (Peter and Precious, 2018). Information from the input layer is transferred to the output layer through hidden layers. Here, the input layer actually means the independent variable/s; the output layer means the response variable (Ataseven, 2013).

In this section, weights estimated using the ANNs approach as an alternative to the linear regression model commonly used in length-weight models will be compared. Two models will be used in the ANNs approach. The first is the model in which only length is used in weight estimation (Model I: W = CW), which is also used in linear regression, and the second is the model formed by adding the estimated age in the first part to this model (Model II: W = CW. + Age)

In order to apply the MLP algorithm, missing value, if any, was first extracted and the data was normalized. Later, 60% of the data randomly selected was transferred to the train and 40% to the test set. After these processes, Model I and Model II were applied to the data. R^2 and MSE criteria were used to compare LR and ANNs models. In addition, MAPE criterion was used to determine how well the obtained weights were predicted.

Statistical Criteria

MSE is obtained by dividing the difference between the actual value and the predicted value by the number of observations and taking the square root. The MSE value is expected to be lower for a better model.

MSE=$\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{n}$

The determination coefficient is a measure of how well a model fits the data. Being close to 1 indicates that the model fits the data well.

$R^2=1-\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y}_i)^2}$

Like MSE and R^2, MAPE determines how close the predicted values are to the real values.

A better model is expected to have a low MAPE value.

MAPE=$\frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right|$

In all metrics, $\hat{y}_i$ is the estimate, y_i is the actual value, n is the number of observations, and $\bar{y}_i$ is the mean.

Results

In the data, there are a total of 843 individuals. While the CW mean and standard deviation (mean±s.s.) for the whole data set is 38.62mm ±6.71, the weight average is 12.67mm±7.22. The minimum and maximum CW for whole data set is 14.73mm, 57.08mm respectively. The minimum and maximum W for whole data set is 1.34g, 43.42g respectively.

Length-frequency model

RSA and ELEFAN GA methods were applied by selecting bin size 4. The estimated parameters are as follows (Figure 1).

When RSA and ELEFAN GA methods are compared according to Rn max it can be said that ELEFAN GA fit well in parameter estimation due to the Rn max value (Table 1). For this result, the parameters obtained from the ELEFAN GA method were used to estimate t_0. It was estimated as t_0 = -0.01 according to the Pauly (1980) equation. The age group was determined with the parameters obtained from the von Bertalanffy (1938) curve and added to the dataset for the next analysis.

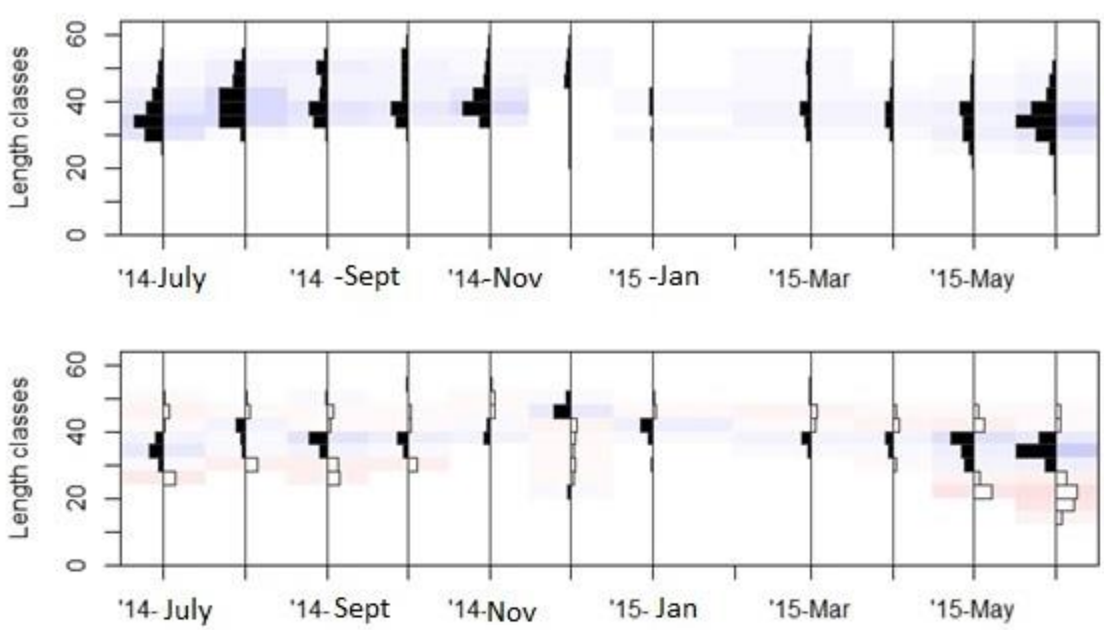

Figure 1. Graphical Representation of All Data

Table 1. RSA and ELEFAN GA Parameter Estimates

Overall	RSA	ELEFAN GA
L_∞	58	58.122
K	1.52	1.34
Growth performance index(Ø′)	3.71	3.654
Rn Max	0.38	0.59

Length-weight model

Before creating models, the weight-width relationship is presented in Figure 2. Hence, it is seen that the weight-width relationship draws a curve.

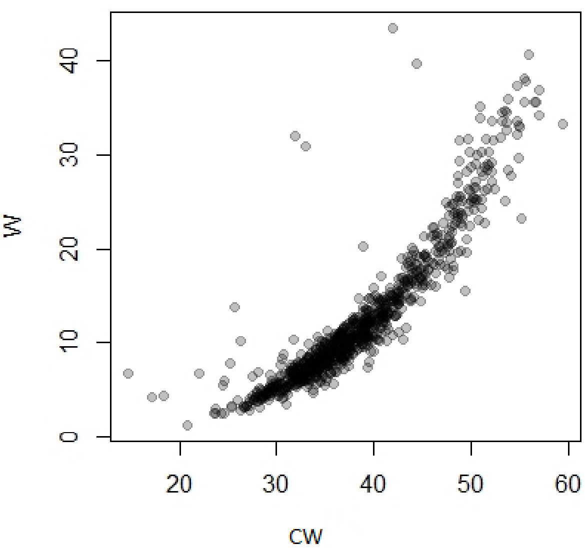

Figure 2. Weight-width Relationship

According to the regression analysis, it was found as a = -3.383 and b = 2.798. Regarding to these values, the model was found as W = 3.383*$L^{2.798}$. Performance criteria of the model are shown in Table 2. ANNs graphic of Model I is seen in Figure 3 and ANNs graphic of Model II is seen in Figure 4.

R^2 and MSE values, which are the comparison criteria of the models, are shown in Table 2. Comparison of the weight estimates of all models with the real values and the MAPE values obtained according to this comparison are shown in Table 3.

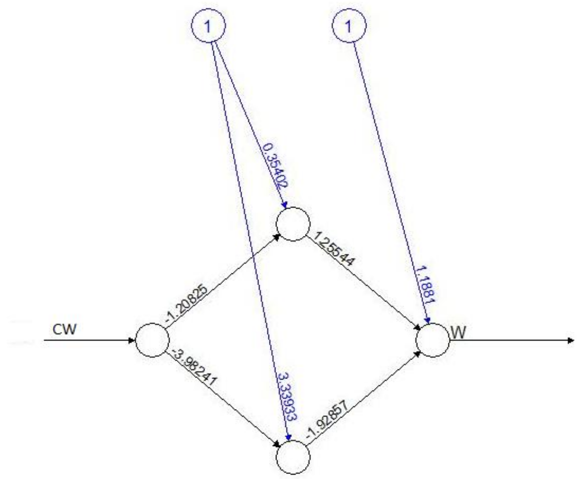

Figure 3. Model I ANNs Graph

While the input variable is only CW in Figure 3, Age group variable has also been added to the CW input variable in Figure 4. Here, age groups are obtained by drawing from the von Bertalanffy equation in the first part. While there are 2 hidden layers in Model I, the number of hidden layers is 3 in Model II. In addition, the weights of these layers are also shown in the graphics.

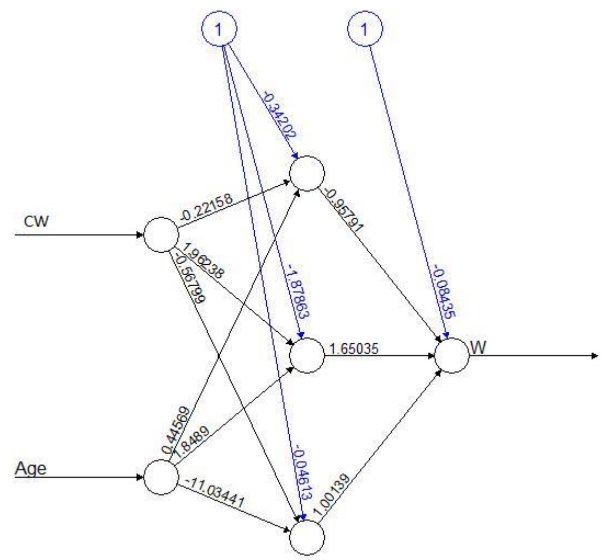

Figure 4. Model II ANNs Graph

Table 2. Metrics of Models

	R^2	MSE
LR	0.887	6.721
Model I	0.914	4.976
Model II	0.940	2.888

In the model that fits the data better, the R^2 value should be close to 1 and the MSE value should be small. Accordingly, when we look at Table 2, Model II has the highest value in terms of R^2 and the lowest value in terms of MSE. It can be seen that the ANNs model created by including the age group variable in the model is the best model. Another evidence supporting this view is the MAPE value. Length groups were determined according to the bin size of the length-frequency model which was also given in the first part.

Table 3. Predicted Weights and MAPE Values of Models

Length Groups	Real Weights	LM Weights	LM MAPE	Model I Weights	Model I MAPE	Model II Weights	Model II MAPE
22-26	9.805	9.691	1.163	9.919	1.166	9.771	0.350
26-30	10.558	10.439	1.127	10.581	0.221	10.518	0.380
30-34	10.463	10.279	1.761	10.618	1.480	10.168	2.819
34-38	13.316	13.032	2.135	13.415	0.747	13.501	1.393
38-42	13.081	12.807	2.093	12.747	2.549	13.418	2.581
42-46	14.258	14.024	1.641	14.446	1.321	14.237	0.148
46-50	13.657	13.242	3.041	13.599	0.428	13.646	0.080
50-54	14.843	14.675	1.129	14.875	0.220	14.804	0.257
54-58	14.213	14.029	1.298	14.012	1.414	14.036	1.249
Mean for MAPE			1.710		1.061		**1.029**

MAPE values are expected to be small in models that fit better and reach accurate predictive values. According to the Table 3 the model that makes the closest estimates to the actual weight values and has the lowest MAPE value is Model II. Model I is the model with the best performance after Model II. Note that ANNs models give better results than LR model.

In the light of these data, it is seen that when we want to create a weight-length model for *C. (G.) longicollis* species, ANNs can be used instead of LM and the estimates will be more accurate when the age group variable is added to the model.

Discussion

Growth models are frequently used to obtain information about the continuity of species and about them. An accurate growth model is essential for any stock forecast. Growth means participation in fisheries production. Fisheries regulation studies based on stock forecast results often include estimates for growth. In this study, it is aimed to reach the growth dynamics data of the population in the most accurate way. For this purpose, v. Bertalanffy growth parameters of *C. (G.) longicollis* were estimated by two different methods which are RSA and ELEFAN GA using the R program. In addition, the length-weight relationship was established by classical regression (LR) and ANNs methods. In ANNs, two models with and without age group were compared. In our research results, RSA and ELEFAN GA methods were compared according to Rn max values and it was determined that GA had better results. Thus, ELEFAN GA was preferred to calculate v. Bertalanffy growth parameters. In weight estimation, it was determined that the model including the age groups formed was more appropriate when the R^2 values were taken into account. As in this study, ANNs and GA methods have been used in many studies in the ecological field. The results appear to be similar our study. Nourouzi et al. (2018) demonstrated the growth of the *Coenobita scaevola* species and the determination of the factors affecting the growth of this species by using an Artificial Neural Networks. To estimate the age ANNs are used, also successful results were obtained according to $R^2$and Sum of Squared Error (SSE) criteria. Again, Ozcan (2019) used ANNs and LR methods while creating the length-weight model and compared it using $R^2$and MAPE criteria. As a result, it was stated that the ANNs method gave better results. Yu et al. (2005) used $R^2$and RMSE when comparing regression and ANNs methods for shrimp growth. They found that the ANNs method gave more effective results in shrimp growth. Munyandorero and Addis (2020) used the TropFishR package to create the length-frequency model, and they made parameter estimates of various species with ELEFAN GA as in this study. Kindong et al. (2018) compared ELEFAN simulating annealing and ELEFAN GA methods for the length-frequency growth model of *Taractichthys steindachneri*.

Conclusion

To estimate von Bertalanffy parameters, RSA and ELEFAN GA methods included in the TropFishR package program integrated into the R program were used. These methods were compared according to Rn max values and it was determined that ELEFAN GA was given better results. For this reason, ELEFAN GA was chosen for age determination, and it was found as t_0= -0.01 according to the Pauly equation. Then, age classes of the species according to the estimated parameters were carried out according to the von Bertalanffy equation. After determining the length-frequency distribution in the first part, the weight-length model was created in the second part.

Due to the widespread use of ANNs in recent years and its successful results, ANNs started to be used alternative to the traditional method LR. Three models were used for weight estimation. The first model is LR, second (Model I: W = CW) and third models (Model II: W = CW +age) are where the ANNs method is used

The three models were compared according to the R^2, MSE and MAPE criteria, and it was determined that the ANNs models gave better results than the LR model. The best model was Model II, which included the age variable. Thus, according to the findings the ANNs approach gives better results against LR. So, it can be seen that the ANNs method can also be applied to construct a weight-length model of *C.(G.) longicollis*.

As a result, these studies show that methods such as ELEFAN GA and ANNs can be used in addition to traditional methods in estimating the growth of species in the ecological field. In addition, the successful results of these methods in the literature show that their usage will become widespread.

Ethical Approval

The authors declare that no need to ethical approval.

Conflicts of Interest

The authors declare that they have no conflict of interest.

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