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Contactless Weight Monitoring of Grow-out Nile Tilapia in a Recirculated Aquaculture System Using Multiple Linear Regression Supervised Machine Learning Approach

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Abstract— Fish weight is the most important characteristic in aquaculture, conservation, fisheries, and management because it is related to the growth of each fish in a specific area.
Through the studies presented, this study aims to develop a contactless weight monitoring of grow-out Nile-tilapia in a recirculated aquaculture system using the parameters being supervised such as Ammonia, Temperature, and Total Dissolved Solids (TDS). This can help the fish farmer to analyze and determine the fish growth and fish weight without actual contact with the fish. With the integration of the Internet of Things (IoT) in this research, it will be a more secure and reliable system that is in demand nowadays. A real-time and efficient monitoring system is really wanted for some critical parameters which can improve the value and determine future projection by using the previously saved data.
Starting from the water quality parameter detection index by the following sensors: pH, TDS, Temperature, and dissolved oxygen. Ammonia is supervised in a mathematical method by means of the temperature and pH level. This will be interpreted by the main program stored in Arduino UNO. The reading will be sent online and processed using the derived AI model then water quality parameter reading, and prediction results will be displayed in the designed interface on a laptop or PC which will provide information for fish farmers as their guide to take necessary action.
Results showed that the use of IoT in monitoring water quality parameters in a recirculating aquaculture system was a real-time and efficient technique. As evidence of the efficiency of the developed system, there is a 98% precision of the prediction model for the fish weight. Therefore, the developed a system that can be a viable method to provide contactless fish weight monitoring which will be helpful in the fishery industry research.

Index Terms—Fish weight, IoT, Linear regression, RAS, TDS.

I. INTRODUCTION

Recirculating Aquaculture System (RAS) delivers high-density fish farming and is known to be the future technology for the world's sustainable aquaculture community to fulfill the needs of aquatic species over the coming decades without affecting the environment. RAS provides a regulated environment that allows for fish growth rate management and a predictable harvesting schedule. The two parameter groups that must be checked in RAS are direct and indirect. As natural elements, pH, temperature, dissolved oxygen, and other water quality parameters exist. The indirect parameter is derived from a computation based on stock capacity, which affects the composition of various natural characteristics. The success of RAS will be determined by extensive data collecting and analysis. [1]
Aquatic products are becoming gradually known because of their high nutritional value. Size information is a vital parameter that can be used to measure the growth, weight, gender, grading, and even species identification of fish. [2]
The importance of fish size information in the economy of any aquaculture firm is growing. In the fisheries sector, size information can be used to monitor fish growth, calculate feeding quantities, and sort or harvest fish. [3]
With the growth of production volumes, the likelihood of extensive development is being exhausted. It is essential to intensify efficiency based on research and development of improved feed productivity and a supportive environment. Such research is tested in laboratories with carefully designed experimentations aimed at the isolation of individual factors and evaluating their effect on the fish under study. During the experimentations, It was observed that one of the most important controlled parameters is the fish weight, the effect of external factors on growth, and the fish weight gain rate. [4]

Because weight relates to the growth of individual fish in a specific habitat, fish weight is a significant performance factor in aquaculture, conservation, fisheries science, and management. To explain the relationship between fish weight and length, a power regression model is typically utilized. Nevertheless, this necessitates costly measurements of fish length. The current experiments use machine learning approaches to predict fish weight from images of fish, skipping the length measuring stage. [5]

The most typical fish measurement technology comprises catching, weighing, euthanizing, and returning fish to the laboratory environment. This strategy leads in significant labor costs. [6], [7]; similarly, the fish will be stressed which significantly affects the adequacy and reliability of tests, because stress affects energy and resistance in fish, as well as increases mortality. For these reasons, “contactless weighing” technologies are being developed. [4]

Automatic contactless weighing is real-time harmless to fish data acquisition, image analysis, and estimation of fish length and its area in the lateral projection [8]. This method is based on the hypothesis of correlation between fish visual characteristics and its weight. [4]

Though Machine learning algorithms have been applied to fisheries science, the studies focused mainly on other fields, like fish species recognition using convolutional neural networks. There has not been much work on machine learning for fish weight prediction. [9]

Linear regression is a statistical technique that attempts to demonstrate a link between variables. It examines several data points and draws a trend line. Linear regression is used to assess the nature and degree of the relationship between a dependent variable and a set of other independent variables. [10] Linear Regression is an excellent tool for analyzing relationships between variables, but it is not recommended for most practical applications because it oversimplifies real-world problems by assuming a linear relationship between variables.

IoT is the networking of physical devices and computers which enable them to collect and share data. IoT allows remote sensing and monitoring of these devices. This internetworking and connectivity is allowing automation in various fields.[11], [12], [13] In this study the data that will be used to monitor and evaluate water quality will be actual data collected in fish ponds using an Arduino microcontroller device connected to the online web system which is possible with the help of a technology called the Internet of Things (IoT).

The experimental findings demonstrated that the proposed system has a high accuracy and success rate in estimating fish length. The regression analysis of estimated and manually measured body length revealed a strong linear association with $R > 0.91$ and a mean relative error of 2.55%. These findings suggested that the proposed technique for non-contact and automatic assessment of fish body length might be used in a fish farm.[14]

Based on the findings of this study, fish health and well-being can be accomplished with proper management of water quality factors. This study discovered that both in the wild and in cages, there was positive allometric growth. The wild fish was in better overall health than their caged counterpart, hence water quality management must be maintained for maximum growth and productivity in the winam gulf cage culture method. Further research is needed to improve cage culture in the winam gulf of L Victoria, Kenya, particularly on certain growth-specific environmental conditions that directly or indirectly affect fish growth and nutrition levels. Knowledge on nutritional needs and economic viability will be valuable to main environmental stakeholders around the Gulf of Mexico, as well as other investors participating in semi-intensive and intensive aquaculture. The current study was limited in scope because it only looked at niloticus stakeholders in the Winam gulf. As a result, this study suggests that future research should include other fish species in other aquatic ecological systems. The study also advises a longer study period for assessing the association between length and weight, as well as condition factors to account for seasonality and other environmental variables. [15]

The primary purpose of this study was to continue developing best practices approaches to automatic estimation of harvested fish weight from images. Weight-from-area and weight-from-image models were used to achieve this goal. Estimating object mass from images is an innovative area of computer vision that could have a big impact in the industrial world. This study demonstrated how a standard "off-the-shelf" segmentation CNN, such as LinkNet-34 from, could be efficiently trained utilizing only 100-200 training image-mask pairs; (ii) a linear learning rate annealing schedule; and a decreased learning rate for the ImageNet-trained encoder (ResNet-34). Simple mathematical models automatically segmented and fitted fish masks with or without fins, attaining 4-10% MAPE values (mean absolute percentage errors consistent with earlier studies, 1,400 test photos not utilized in the fitting procedure, and from different geographical areas).[16]

The study followed the requirements of the Animal Care Committee of the Universidade Estadual de Maringá in Paraná, Brazil. A total of 3,000 masculinized juvenile Nile tilapia (starting weight = 28.64.16 g; standard length = 13.80.16 cm; age, 60 days) were randomly distributed into three hexagonal cages (11 m3 each) in the Paranapanema River (22°34'07"S; 52°33'34"W). An extruded meal yielding 332 g kg1 of crude protein and 3,230 kcal kg1 of digestible energy was created using a combination of vegetable and animal protein sources. To preserve the quantitative and necessary amino acid profile indicated for Nile tilapia, crystalline amino acids were

supplied. For 100 days, fish were hand-fed until they were satiated. Throughout the feeding trial, water quality measurements were examined on a daily basis. The average water temperature was 28.51.3 °C, the pH was 7.340.21, and the dissolved oxygen ranged from 6.2 to 6.6 mg L1. At the start of the experiment, and every 20 days thereafter, 12 fish were randomly selected from each cage, starved for 24 hours, and collected to determine individual weight, standard length, and whole-body composition. For proximate analysis, whole-body samples of fish were pooled, ground, and kept at 20 °C.
At the conclusion of the experiment, a significant daily weight gain (7.5 g) was found (Table 3). Although controlled chemical and physical water quality parameters are available in indoor experiments, the advantage of conducting experiments in rivers is the high rate of water turnover, which results in high and constant levels of dissolved oxygen and water temperature, allowing for a high daily weight gain in fish. In the current study, fish gained weight on a daily basis. Nile tilapia body composition varies with body weight and can be determined using the length-weight relationship. Body composition prediction equations built from linear regression analysis can be used to satisfy the needs of certain consumer markets.[17]
The literature on these challenges is examined in this work, and a fresh strategy is presented. It is demonstrated that in a controlled situation, utilizing a single camera for image collection is appropriate since it allows for better regulation of sample size and image acquisition circumstances. For fish picture improvement, a mixture of homomorphic filtering, contrast limited adaptive histogram equalization (CLAHE), and guided filtering was applied. The fish were subsequently segmented using morphological and 2D saliency detection operators. Lastly, the fish length was calculated by doing a third-degree polynomial regression on the fish midpoints. Many regression algorithms were used to compute the length in order to estimate the weight. This method was proved to be the best for predicting fish weight based on length. [18]
The study made use of three sets of hake box photographs. The images were captured using the same webcam (pixel resolution of 1280x760). The first collection (562 photos) of hake boxes was gathered at the Palma auction center's conveyor belt. The camera was positioned top-down, slightly above the fish boxes, and the photographs were captured during the bidding process, when the conveyor belt briefly stopped. The second batch (56 photos) was captured in the lab using the identical camera settings. 163 randomly selected images from the first set and 14 randomly selected images from the second set were utilized for network implementation. The Mask R-CNN was successfully implemented and fine-tuned with a data set of 2602 manually segmented heads.
In terms of the detection performance of the constructed system, an observer recognized 200 visible hake heads in the 42 pictures used as input. Concerning the system's measurement performance (accuracy and precision achieved when estimating the fish length itself), the relationship between HLcm and TL revealed that the four linear models considered in the previous section (whether using logtransformed values or not) had excellent explanatory power, with r (Pearson correlation coefficient) greater than 0.9 (remember that the terms bias and (in)accuracy and variability and (im)precision are used throughout the article). [19]
Two monoculture experiments were carried out on mono-sex all male Nile tilapia (Oreochromis niloticus) and thin-lipped mullet (Mugil capito/Liza ramada, Bouri tobara, Tobara) in eighteen (nine / fish species, three initial weights x three feeding levels)Hapas stocked in an earthen pond for five months. Commercial diet fed fish (30% crude protein). The results showed that both variables (initial body weight and feeding rate) influenced all parameters examined, including feed and nutrient consumption, growth performance, chemical composition, and the cost of food necessary to produce one kilogram of body gain.[20]
Using a Raspberry Pi microcontroller and two low-cost USB cameras, this research provides a low-cost monitoring and Hough gradient method-based weight prediction system for Nile Tilapia (Oreochromis niloticus). This study intends to increase fish growth rates by using image processing to monitor fish growth instead of the standard method of getting fish measurements. The results of the paired t-test indicate that the weight algorithm used to measure the weight of the fishes is accurate and suitable for use. Ten Nile Tilapia were grown in two intense aquaculture setups, one for automated fish weighing via image processing and predictive analysis and the other for human weighing. The fishes' growth rose by 47.88% in response to the weight prediction program.[21]
The suggested 2D computer vision method is intended at non-intrusively calculating the weight of Tilapia fish in turbid water settings. Furthermore, the proposed solution avoids the issue of employing high-cost stereo cameras by instead using a low-cost video camera to view underwater life through a single channel recording. An in-house curated Tilapia-image dataset and Tilapia-file dataset comprising Tilapia of varying ages are used. The suggested method comprises of a Tilapia detection step and a Tilapia weight estimation step. Then, a Mask Recurrent-Convolutional Neural Network model is trained to recognize and extract the picture dimensions (i.e., in terms of image pixels) of the fishThe proposed method then translates the Tilapia's extracted image dimensions from pixels to centimeters. A trained model based on regression learning is then used to estimate the Tilapia's weight. To find the optimal models for weight estimation, linear regression, random forest regression, and support vector regression have been created. In a turbid water environment, the proposed method gives a Mean Absolute

Error of 42.54 g, an R2 of 0.70, and an average weight error of 30.30 (23.09) grams, demonstrating the feasibility of the proposed framework. [22]
The morphometry of Tilapia zilli and Oreochromis niloticus from the lower Benue River near Makurdi was investigated in this work. Each collected fish was given seven morphometry measurements (body weight, standard length, total length, dorsal fin length, caudal fin length, head length, and body width). The mean morphological parameters of Tilapia zilli were 12.83 g, 8.00 cm, 9.95 cm, 4.50 cm, 3.19 cm, 2.27 cm, and 4.44 cm, respectively. Similarly, the mean morphometry of Oreochromis niloticus was as follows: body weight: 15.51 g, standard length: 9.00 cm, total length: 10.76 cm, dorsal fin length: 5.85 cm, caudal fin length: 3.68 cm, head length: 2.67 cm, and body width: 4.41 cm. The only significant link between Tilapia zilli morphometry was between head length and overall length. Correlation analysis of Oreochromis niloticus morphometry found a significant positive correlation between standard length and bodyweight, total length and body weight, standard length and total length, dorsal fin length and body width, and head length and dorsal fin length only. Using regression analysis, there was a high link between log of body weight and standard length in Oreochromis niloticus with an R2 value of 0.8689, whereas a weak relationship was established in Tilapia zilli with an R2 value of 0.0889 during the study. The study concludes that the two Tilapia species are distinct, with distinct morphological traits utilized to identify them.[23]
Thus, this research aims to develop a contactless weight monitoring of grow-out Nile-tilapia in a recirculated aquaculture system using the parameters being monitored such as Temperature, Ammonia, and Total Dissolved Solids (TDS). This project also used the Internet of Things (IoT) for a more secure and reliable system which is extremely needed nowadays.

II. Methodology

In this study, the software, hardware, algorithm, and needed data to build the recirculated aquaculture system were identified and with the assistance of the Bureau of Fisheries and Aquatic Resources, Local unit, through this agency, the researcher has further learned and developed his knowledge in the field of aquaculture, especially Tilapia which is the selected aquaculture for this study.
Required water parameters were made available by The Bureau of Fisheries and Aquatic Resources as well as the aquaculture tolerance range, which includes the best water parameters for tilapia and the feeding rate and schedule to serve as a guide for the researcher during the experimentation period. The ideal dense capacity per area in an intensive culture system. was then determined by the researcher.
The parameters that were collected through personal interviews which significantly affect the health, growth, and survivability of Tilapia are Ammonia (NH_3), Dissolve Oxygen, Total Dissolved Solid, Temperature and water pH level, these parameters were monitored using an Arduino microcontroller. BFAR also provided the method in determining the Average Body Weight (ABW), Daily Feed Ration (DFR) and Feed Conversion Ratio (FCR) for the appropriate feeding rate schedule. These parameters and methods were also tested and corroborated through other research to prove that they significantly affect aquaculture survivability, this collected data was used in formulating the water quality assessment, feeding rate, and schedule together with the design and build of recommended Recirculated Aquaculture System RAS.

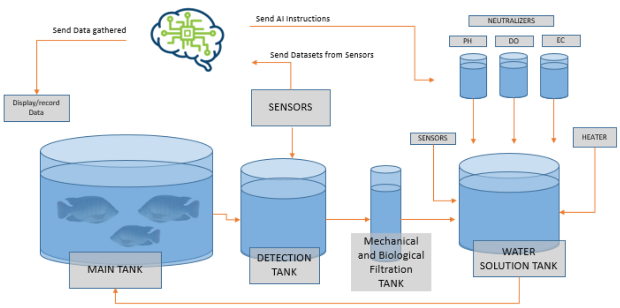

Figure 1 RAS Architectural Diagram

Figure 1 shows the Recirculating Aquaculture System architectural diagram. The RAS is composed of different water tanks and sensors. The Main tank is considered the fish stocking tank. The different sensors will be placed in the Detection tank. The filtration tank will be composed of mechanical and biological filtering methods. The Treated water will go to the Water solution tank which will be filled in a fish tank.

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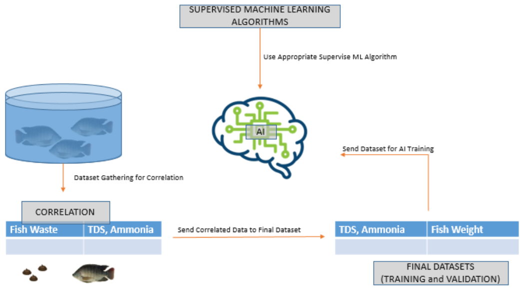

Figure 2 Dataset Gathering and AI Training Validation block diagram

Figure 2 shows the block diagram for the extraction of biophysical variables of the Recirculating Aquaculture System to be used in the development of the AI model as well as the training and validation of the developed AI model.
After the RAS and the sensors were installed, water quality index reading such as Ammonia, pH, Dissolved Oxygen, and TDS were collected. Readings were compared to the available water quality indexes suitable for tilapia survivability and growth.

To gather information for the development of an artificial intelligence model to estimate the precise quantity of feeds. Initially, the average weight of the tilapia was identified which will eventually be placed inside the tank. The researcher follows the BFAR-suggested Feeding Rate and Schedule below for the intensive culture system for the duration of the testing period.

Table 1 BFAR Feeding Rate and Schedule for the Intensive Aquaculture System

Days	**Type of Feeds**	**Feeding Rate**	**Feeding Frequency**	**Ideal Weight of Stocks**
1 to 15	Fry mash	10% of BW	4 x a day	1.75 g @ day 15
16 to 31	Fry mash	6% of BW	4 x a day	25 g
32 to 46	Starter	6% of BW	4 x a day	50 g
47 to 61	Grower	5% of BW	3 x a day	72 g
62 to 76	Grower	4% of BW	3 x a day	100 g
92 to 105	Finisher	3% of BW	2 x a day	121 g
106 to 120	Finisher	2% of BW	2 x a day	150 g

To get data inputs for the machine learning in predicting the Tilapia's correct amount of feed consumption, the water Total Dissolved Solid (TDS), temperature, and pH level were monitored to get the average values on a daily basis. Fish and food waste caught in the filtration tank were collected and measured daily. To guarantee that most of the waste was collected, the collection was done manually using a net.

This study utilized multiple linear regression machine-learning algorithms for the development of the AI model. The researcher used this procedure to forecast the ABW, the researcher used Total Dissolved Solids (TDS), Total Stocking Capacity (TSC), and Ammonia as variables.

II. RESULTS AND DISCUSSION

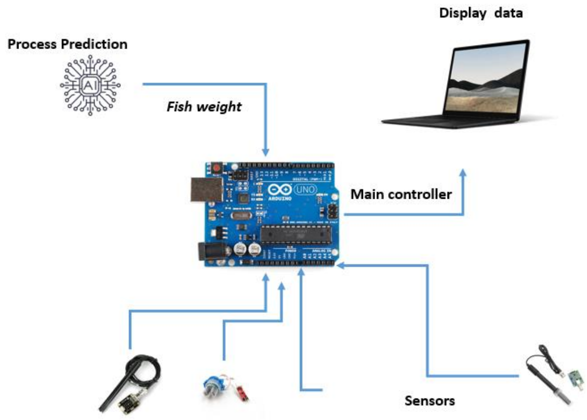

Figure 3 Block Diagram of the Intelligent RAS

Figure 3 shows the block diagram of how the RAS operates. The system starts with the detection of the water quality parameter index by the following sensors: pH, Temperature, TDS, and dissolved oxygen. Ammonia was supervised in a mathematical method by means of the temperature and pH level. The Interpretation from the sensors will be sent to the Arduino UNO where the main program is saved. The reading will be sent online and then processed using the derived AI model and afterward, water quality parameter reading and prediction results will be displayed in the interface on a laptop or PC to provide information to the fish farmer as their guide to take necessary action.

A total of 150 grow-out tilapia with 72 grams average weight were used for carrying out tests. The feed consumption given daily was based on the BFAR feeding schedule and feeding rate calculation.
The variables for the development of the AI model were identified after extracting the biophysical variables. By utilizing Jupyter notebook and Python 3, a multiple linear regression was developed to forecast the accurate amount of feeds. The researcher developed multiple linear regressions to predict the average body weight of tilapia (ABW) using the TSC, TDS, and Ammonia levels.

The coefficient of each multiple regression and then the test was derived using the predict function and manually using the coefficient.

```
In [5]: reg = linear_model.LinearRegression()
        reg.fit(df[['Tilapia','TDS','NH']],df.ABW)
Out[5]: LinearRegression()

In [6]: reg.coef_
Out[6]: array([ -4.50171682,   0.59371423, 480.79824817])

In [7]: reg.intercept_
Out[7]: 460.8446037923983

In [8]: reg.predict([[122,457,0.026922]])

        C:\Users\ACER\AppData\Local\Programs\Python\Python310\lib\site-packages\sklearn
        \base.py:450: UserWarning: X does not have valid feature names, but LinearRegre
        ssion was fitted with feature names
          warnings.warn(
Out[8]: array([195.9066056])

In [9]: -4.50171682*122+0.59371423*457+480.79824817*0.026922+460.8446037923983
Out[9]: 195.90660529963094
```

Figure 4 Development of the AI model for weight prediction

Figure 4 shows the derived linear coefficient of the test data and compared the predicted result using the predict function () versus the computed result using the derived coefficient. The result shows the same predicted result.

By the use of Jupyter notebook python 3 for the development and training of the AI model with the recorded data that was collected in almost 3 months. Then the developed AI model underwent cross validation using the feature sklearn in python 3 through the use of 10000 test data shown in the figure.

```
In [10]: def Snippet_132():
             print()
             print(format('check Fish Weight Prediction Model accuracy using cross valida
             import warnings
             warnings.filterwarnings("ignore")

             from sklearn.model_selection import cross_val_score
             from sklearn.tree import DecisionTreeClassifier
             from sklearn.datasets import make_classification
             x,y = make_classification (n_samples = 10000,
                                        n_features = 3,
                                        n_redundant = 0,
                                        n_classes = 2,
                                        random_state =54)
             dtree=DecisionTreeClassifier()
             print(); print(cross_val_score(dtree,x,y, scoring="accuracy", cv=7))
             mean_score = cross_val_score(dtree,x,y, scoring="accuracy",cv=7).mean()
             std_score= cross_val_score(dtree,x,y, scoring="accuracy",cv=7).std()
             print();print(mean_score)
             print();print(std_score)
         Snippet_132()

***check Fish Weight Prediction Model accuracy using cross validation in python
***

[0.98460462 0.97760672 0.97410777 0.98180546 0.98459384 0.98109244
 0.98039216]

0.9804001376617827

0.002614560244468089
```

Figure 5 AI Model

Figure 5 shows that the developed AI model achieved 98.04% linearity, and this proved the accuracy of the predicted weight.

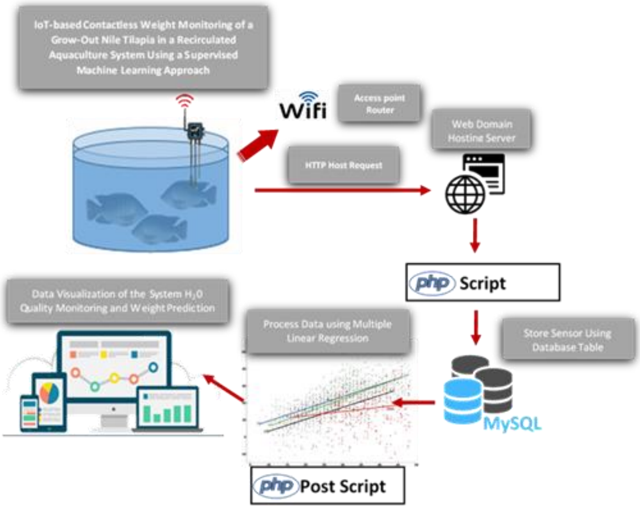

Figure 6 Project Implementation Plan

Figure 6 shows the project implementation plan of the project where it will be running as an IoT device.

With the testing results, the use of internet of things was real time and an efficient method of monitoring water quality parameters in a recirculating aquaculture system. The efficiency of the developed system is evidence based on the 98% accuracy of the prediction model for the fish weight. Thus, the developed system can be a viable method to provide a contactless fish weight monitoring which will be helpful for the fisher folks.

III. Conclusion

The developed contactless weight monitoring of grow-out Nile-tilapia in a recirculated aquaculture system using the parameters being monitored such as Temperature, Ammonia, and Total Dissolved Solids (TDS) was achievable and is reliable and real-time with the use of the Internet of Things (IoT).

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