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Comparative analysis of data using machine learning algorithms: A hydroponics system use case

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ABSTRACT

This paper makes a comparison of machine learning algorithms for the analysis of four hydroponic datasets. Data have been gathered daily from hydroponic systems to predict the output of the hydroponic systems. This research compares the performance of the federated split Learning, Deep neural network, extreme Gradient Boosting (XGBoost), and Linear regression algorithms on four different hydroponic systems. These algorithms have been used to analyze the datasets of Nutrient Film Technic (NFT), Floating (FL), Aggregate (AG) and Aeroponic (AER) hydroponic systems. The results have indicated the performance of each model for each hydroponic system and how each algorithm have used the various multiple input features to make predictions of the onion bulb diameter and the errors encountered by each model. From the results obtained, it has been observed that the R square score is varied for each hydroponic system. This variation in the result has been also reflected in the Mean absolute errors obtained. This research determines which of the algorithms predict the optimal Onion bulb diameter (mm) using days after transplant (days), Temperature (°C), water consumption (Litres), Number of Leaves (NL), Nitrogen (mg/g), Phosphorus (mg/g), Potassium (mg/g), Calcium (mg/g), Magnesium (mg/g), Sulphur (mg/g), Sodium (mg/g) as independent variables. The results will be a guide in the choice of hydroponic system to adopt for food production based on the climatic parameters of the location, which is one of the numerous contributions of this research.

1. Introduction

Smart agriculture is the advent of a new agricultural era, where the Internet of Things, big data analysis, artificial intelligence, cloud computing and remote sensing improve agricultural practices [1,2]. The agricultural production systems are improving accordingly in terms of nutrient, water and energy efficiency. Machine learning and Big Data Technologies, have enabled farmers to use sensors and other monitoring devices in decision making on the choice of fertilizer, pest management, yield improvement, soil & water management, livestock management, and prediction of crop yield [3]. The need for safe food, available space, soil problems, water, adverse weather conditions has led to the rise of the soilless culture systems (hydroponics) in greenhouse [4] or lately in plant factories with artificial lighting (PFALs), and smart PFALs which from the early 2020s are expected to be autonomous in decision making and energy reliant [5]. All such systems need special environmental monitoring, which nowadays is achieved by IoT systems [6]. Soilless culture is an alternative solution in restricted and environmentally degraded areas, including local varieties, such as Nerokremmydo of Zakynthos, a Greek big bulb sweet onion [7]. Evolution of Agriculture has led to the application of robots in tilling of the soils, raspberry pis have been used for the gathering of climatic data from the farm, automation of farm machinery, automation of animal processing, forecasting of the farm harvest, and monitoring of farm conditions. The authors in [8] have discussed that the use of the Nutrient Film Technic of hydroponic can grow lettuce vegetables successfully. However, the water loss experience has not been measured during the growing of the crops either via evaporation or leakage or absorption, and the amount of light used by the plants has not been measured.

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According to [9], they have proposed a technique to improve the master's node capability to effectively determine the range in which an error occurs frequently using the Markov chain model. However, their model has not been able to monitor the communication of the hydroponic system with an agricultural automotive robot on the motion. It is discussed in [10] that using a machine learning algorithm, the crop growth rate can be predicted for tomatoes cultivation based on the nutrient solution provided. It has been reported in their paper that Sodium (Na) and Potassium (K) nutrients uptake by the tomato crop has a higher uptake value compared with other nutrients in the solution used for growing the plant. Despite the remarkable achievement of their research, their approach did not consider other hydroponic parameters such as dry weight matter of the crops, and relative crop growth rate. Their approach has not been tested on crops grown using rain or recycled water to ascertain its performance. The authors in [11] have discussed that hydroponics farming has improved the growth of plants in a controlled system, their work has discussed the total leaf length to stem Diameter ratio where multiple input variables are considered for a hybrid set of machine learning and neural networks algorithm. However, a comparative performance of technology impact on hydroponic and soil cultivated crops has not been conducted. It has been discussed in [12], that the hydroponic systems enable the farmers to produce an improved yield in quantity and quality of crops. Crops use less quantity of water compared with the crops planted on soils, their survey investigation has not extensively reviewed enough existing literature on the hydroponic research.

We will explore a comparative analysis of the following hydroponic systems, namely Aggregate, Aeroponics, floating and Nutrient Film Technic hydroponic systems, in this study a big bulb Onion crop has been grown on four systems and from the data captured, the Linear regression, Deep neural network, XGBoost and Federated split learning models will be used to analyze each hydroponic systems dataset. The Objective of this study is to propose which of these hydroponic systems will be using Temperature (°C), water consumption (Litres), Number of Leaves (NL), Nitrogen (mg/g), Phosphorus (mg/g), Potassium (mg/g), Calcium (mg/g), Magnesium (mg/g), Sulphur (mg/g), Sodium (mg/g) as independent variables while the Onion bulb diameter (mm) is the label to predict an optimal Onion bulb diameters before the crop matures for harvest. The Lasso regression and K-Nearest neighbour algorithm has been used to develop a model which used Electrical conductivity, the potential of hydrogen (pH) of water, and temperature as the input variables, and the model predicts the nutrients in the plants as the output. The percentage error, and accuracy from the model evaluation has not been provided [13]. In this work, a centralized XGBoost model and a decentralized Federated split learning model is used to predict the Onion Bulb diameter and losses respectively for the four hydroponic systems. The mean square errors, Root mean square errors from the four hydroponic systems using the DNN models, and XGBoost has been obtained.

Fig. 1 shows the architecture of the Floating hydroponic system, in this architecture, the edge devices (Raspberry pi) captures the climatic parameters and sends this to the servers in the cloud via wireless connectivity.

Our contributions. In this work we propose the following contributions (1) The Floating hydroponic system use an Adam optimizer with a Learning rate of 0.01 for a Federated split Learning model, can obtain convergence within 25 iterations and it performs better than the Aggregate, Aeroponic, Nutrient Film Technic hydroponic systems for an Onion crop. (2) The Aggregate hydroponic system using a centralized XGBoost model gives a higher R squared values compared with the Aeroponic, floating, Nutrient Film Technic hydroponic systems. (3) Using the DNN model, the Floating hydroponic system converges faster with loss values of 1.898% which was quite lower than the loss values for the Nutrient Film Technic, Aggregate, Aeroponics hydroponic systems. Section 2, presents Technologies for smart farming, section 3 gives the methodology used for this work, while section 4 illustrates the results and section 5 discuss the results. Section 6 is the conclusion and section 7 is area for future works.

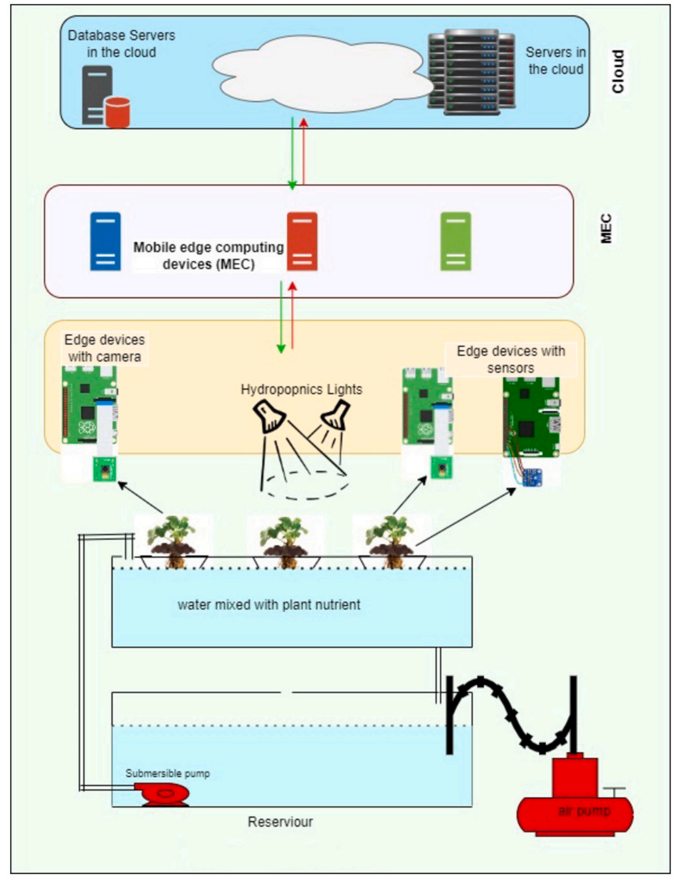

Fig. 1. Floating Hydroponic system.

2. Technologies for smart farming

Hydroponic systems are more suited for high value vegetables, avoiding soil born pests. It needs precise support of mineral nutrition by adopting the nutrient solution applied to the plants during growth. These demand continuous monitoring, which is achieved by the use of automations such as IoT [14]. Applications of such systems are already in progress; lettuce production in an NFT system controlled by IoT and monitoring pH level, water volume, nutrient solution, room temperature and humidity, on a real-time basis [8,15], crop growth rate prediction for tomatoes cultivation based on the nutrient solution provided using a hydroponic farming system [16]. Aquaponics, an integrated agri-aquaculture system that combines aquaculture (mostly fish), hydroponic systems and nitrifying bacteria can be monitored by 19 sensors, including water temperature, diluted oxygen, pH, EC, CO2, etc. for better operation and optimizing all steps involved in a more sustainable and profitable way [17]. In a DFT (Deep Flow Technique), where plants are supported in floating rafts and their roots are continually in an recirculated and aerated nutrient solution, mustard greens performed ideally by the use of Raspberry pi, ensuring the proper re-circulation times of the nutrient solution [18].

As discussed in [19], their modified system controls the hydroponic systems and captures data on the human responses to alarms from the hydroponic, such alarms as refilling the water reservoir when its depleted. The authors in [20], discuss that smart farming has improved farming methods so that information can be accessed remotely on the farm, any time and from any location. However, no information has been provided on the number of independent & dependent features and, machine learning algorithm used for the analysis of their dataset.

According to [21], their platform enables farmers to have access to information from their mobile phones on weather conditions, provide farming information exchange with their customer. The authors in [22] have used IoT sensors to monitor and collect data from the smart farm and also monitor the sensor connectivity within their platform. The users can remotely view the data collected from their mobile app. The analysis of the data collected either for prediction or forecasting has not been mentioned.

The light quantity, temperature, humidity, and carbon (IV) oxide within a smart farm can be measured using various sensors [23]. They have collected all these data and use them to predict future light intensity within their region. However, the independent features, labels and machine learning algorithm used for forecasting were not discussed. The authors in [24] discuss challenges that are experienced by farmers using IoT sensors such as security of the network where it is deployed, procurement of the sensors, and lack of broadband connectivity since the farms are in rural areas where network connectivity is very poor. No government regulations affect the use of sensors in agriculture and the adverse effect of using these sensors on crops or animals within a smart farm has been indicated. The authors in [25] discussed that sensors can be used to capture climatic data from a smart farm, such data include temperature, humidity, and moisture of the soil, their work only captured the data but did not analyze the data, they did not also capture image data from the crops. According to [26], the LoRaWAN platform can be used for IoT data capturing and storage in their database server, this platform also provides visualization of the data. However, due to lack of training of the dataset, no prediction results have been provided. The platform is not an open-source platform so it's not economically viable for use by poor farmers and researchers.

2.1. Linear regression

The dependence of one or more variables using a linear dependence function for a regression model is known as Linear regression, [17].

The relationship between variables can be established using regression analysis. Equation (1) gives a relationship between the independent variables and the dependent variables,

$$H = f(d, c) \tag{1}$$

where H is the dependent variable and d is the independent variable and c is an unknown value. Regression can be represented in single or multivariate format, this is seen in equations (2) & (3) respectively.

$$H = a + Qd + p \tag{2}$$

$$H = a + Q_1 d + Q_2 d + \ldots + Q_n d + p \tag{3}$$

where a & q are coefficients, and p is the error observed in the regression analysis. In this research work the independent variables include, days after transplant (days), Temperature (°C), water consumption (Litres), Number of Leaves (NL), Nitrogen (mg/g), Phosphorus (mg/g), Potassium (mg/g), Calcium (mg/g), Magnesium (mg/g), Sulphur (mg/g), Sodium (mg/g) while the dependent variable is the onion bulb diameter (mm).

2.2. XGBoost

The XGBoost algorithm optimizes the objective function of the model while regularising the model. It is a gradient boosting algorithm that inserts the negative gradient of the loss function in iterations continuously so as to achieve optimization [18]

$$\sum_{i=1}^{m} L(W_i, B_i) + \frac{1}{2}\sigma\gamma^2 \tag{4}$$

where γ is the output value. The first part is the loss function and the second part is the regularisation of the tree. The XGBoost Algorithm optimizes the model by minimizing the loss function to make predictions.

2.3. Deep neural network

According to the authors in [19], Artificial neurons are components of deep neural networks (DNN). DNNs are represented by Layers, and they are indicated as nodes in graphs. DNN computes the total weights of all its input layers, then optimizes the sum of its weights and bias to produce output.

$$y_i = \phi\left(\sum_{i=0}^{n-1} H_t W_{tm} + b\right) \tag{5}$$

where y_i is the output of the neuron, W_{tm} are the neuron's weights, n is the number of weights, H_t are the neuron's inputs, b is the bias of the neuron, and ϕ is the activation function [18].

3. Methodology

In the Department of Agriculture, University of Peloponnese, Kalamata, Greece, an onion crop trial has been carried out using the 4 most known hydroponic systems; Aeroponics, Floating, Aggregate and Nutrient Film Technic. The trial has produced a series of raw data, for a period of 92 days after transplant (DAT) from the nursery to the systems. The dataset included Temperature (°C), water consumption (Litres), Number of Leaves (NL) and mineral concentrations of onion plants, i.e. Nitrogen, Phosphorus, Potassium, Calcium, Magnesium, Sulphur and Sodium (mg/g dry weight) and the diameter of the onion bulb. The dataset parameters were recorded as described in [8].

This research aims to use computer algorithms to evaluate their dataset. The model's results from the analysis of the dataset will be compared with their baseline results. The dataset independent features are days after transplant (days), Temperature (°C), water consumption (Litres), Number of Leaves (NL), Nitrogen (mg/g), Phosphorus (mg/g), Potassium (mg/g), Calcium (mg/g), Magnesium (mg/g), Sulphur (mg/g), Sodium (mg/g) while the Onion bulb diameter (mm) is the label. The days after transplant are the measured consecutive days after the crop was transplanted from the nursery, water consumption is the measurement of the water absorbed by the plant which was calculated based on the dry weight of the crops and obtained weight after placing the crop in the oven. The daily temperature has been measured in degrees Celsius, and the number of leaves were counted each day after the transplant of the crop from the nursery. Linear regression models, deep neural network models, extreme gradient boosting (XGBoost) models, and Federated split learning models were developed and the dataset has been trained by each model separately, the results obtained are discussed in section 4. Metrics such as Root Mean Squared Errors (RMSE), Mean Squared Errors (MSE), R squared values (R^2), and loss during epoch training were obtained and the various outputs for each algorithm were analyzed.

4. Results

4.1. Deep neural network

The results obtained from the DNN model are shown in Table 1 the TensorFlow library has been used, when fitted to the Aeroponics, Aggregate, Floating and Nutrient Film Technic hydroponic systems dataset. The model converges appreciably with a Loss value of 2.69%, 10.46%, 1.90% and 3.15% respectively. The floating system converged faster than the other system since it loss values dropped to single digits after 18 epochs of training. This is reflected in the validation loss and validation mean squared error with values of 2.28% for the floating hydroponic system and this is the lowest values from the four hydroponic systems. The AER hydroponic system evaluated its dataset with the fastest computational time of 2.80 seconds, unlike the AG, FL, NFT hydroponic systems which has a computational time of 3.14 seconds, 3.22 seconds, 3.05 seconds respectively.

Table 1
Deep Neural Network models results for each hydroponics system for the Onion crop.

	AER	AG	Floating	NFT
Loss (%)	2.6909	10.4604	1.8988	3.1474
Mean Squared Error (MSE) (%)	2.7661	11.3189	1.8647	3.2460
Validation Loss (%)	166.8054	13.4045	2.2832	206.1946
Validation Mean Squared Error (MSE) (%)	166.8054	13.4045	2.2832	206.1946
computational time (seconds)	2.80	3.14	3.22	3.05

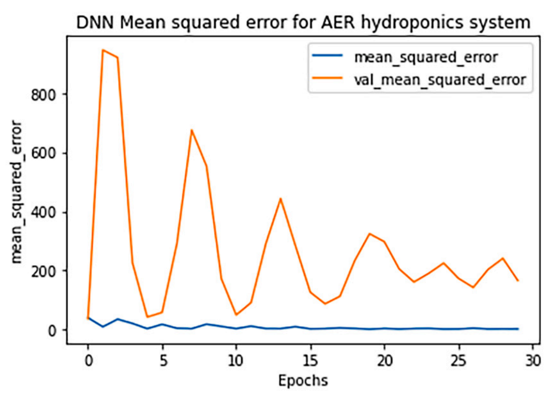

Fig. 2. AER DNN model MSE for the Onion crop.

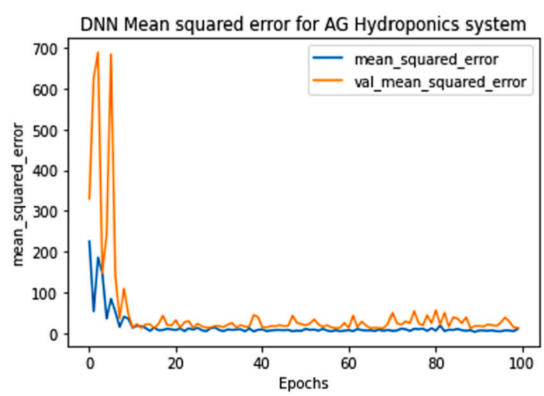

Fig. 3. AG DNN model MSE for the Onion crop.

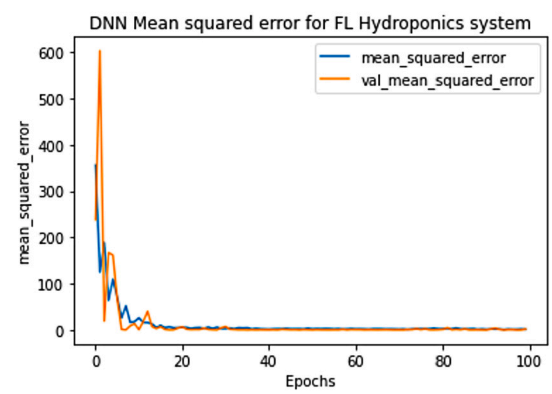

Fig. 4. FL DNN model MSE for the Onion crop.

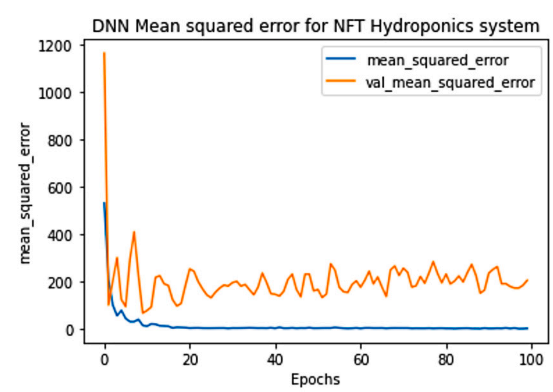

Fig. 5. NFT DNN model MSE for the Onion crop.

From Table 1, the validation loss for the AER and NFT hydroponics system are 166.81% and 206.19% respectively while the validation Mean squared error for the AER and NFT hydroponic systems are 166.81% and 206.19% respectively. It can be inferred that the AER and NFT models are under fitting and these models will require more training for evaluation, the volume of the dataset must be increased which is readily not available for this research, additional dataset will invariably increase the computational time of the model and make the AER and NFT systems unacceptable for prediction of the onion bulb diameter. The floating hydroponic system model fits very well as can be seen in Fig. 4, there is no under fitting or over fitting experienced by the model for its evaluation, therefore the floating hydroponic systems are the optimal system which should be considered for Onion bulb diameter using the DNN model.

Figs. 2 & 3 shows the AER DNN model Mean Squared Error and validation Mean Squared Error and AG DNN model Mean Squared Error and validation Mean Squared Error for the Onion Bulb crop. The MSE values for both AER DNN model and AG DNN model are lower than the validation MSE, this depicts our model is not over or under fitting and it converges.

Fig. 2 shows the AER DNN model MSE for the onion crop. It can be inferred from the graph that the AER DNN model validation MSE is fluctuating, dropping and increasing consistently which indicate the model is over fitting, the model cannot generalise the validation dataset, confirms that the AER hydroponic system is not suitable to be considered for the prediction of the optimal Onion bulb diameter. A different scenario is obtained from the AG hydroponic system, where the model generalises very well on the dataset and a good fit is seen in Fig. 3. It can be inferred that the AG hydroponic systems which produces a loss value of 10.46% can be considered as a suitable hydroponic system for prediction of the Onion bulb diameter using the DNN model. Figs. 4 & 5 show the FL DNN model MSE and validation MSE, and the NFT DNN model MSE and validation MSE for the Onion bulb crop. The MSE and validation MSE values for the floating hydroponic system are lower than the values obtained for the NFT hydroponic system. The computational time for the NFT is lower than the computational time for the floating hydroponic system.

An over fitting is experienced by the DNN model in the NFT system which can be seen in Fig. 5 indicating the DNN model does not generalise very well with the NFT dataset. The Floating hydroponic systems can be inferred to be the optimal system which generalises with the dataset and does not over fit or under fit with the dataset, this is seen in Fig. 4 and it also produces the lowest loss, MSE, validation loss and validation Mean square error values of 1.90%, 1.86%, 2.28%,2.28% respectively.

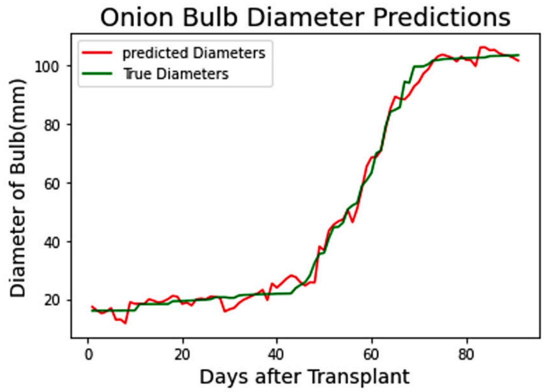

Fig. 6. AER Linear regression diameter predictions against the Baseline for the Onion crop.

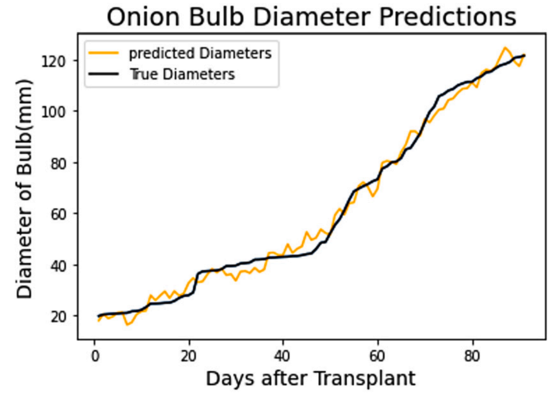

Fig. 7. AG Linear regression diameter predictions against the Baseline for the Onion crop.

4.2. Linear regression

Figs. 6, 7, 8, 9, shows the predicted Onion diameter values obtained from the evaluated Linear Regression models for each hydroponic system using independent features namely days after transplant (days), Temperature (°C), water consumption (Litres), Number of Leaves (NL), Nitrogen (mg/g), Phosphorus (mg/g), Potassium (mg/g), Calcium (mg/g), Magnesium (mg/g), Sulphur (mg/g), Sodium (mg/g) while the Onion bulb diameter (mm) is the label. The developed model which is an automated system will enable them to forecast their Onion Bulb diameter before they mature with all other conditions satisfied by the farmers. Figs. 6, 7, 8, 9 show the predicted Onion Bulb diameter for the AER, AG, FL, and NFT hydroponic systems respectively. From this analysis the farmer can forecast the Onion Bulb diameter for days they did not capture any readings such as on the 45^{th} day of the transplant, the forecast Onion bulb diameter will be 40 mm as can be seen from Fig. 6 for the AER hydroponic system. From Fig. 7, the predicted Onion bulb diameter will be 100 mm on the 70^{th} day of the transplant which is determined by the automated system. This will help the farmer in evaluating the Onion bulb production.

From the linear regression Onion bulb diameter predictions shown in Figs. 6, 7, 8, 9 for the AER, AG, floating and NFT hydroponic systems respectively, it can be inferred that all the Linear regression model fits very well with the dataset and this indicates the model generalises with the dataset for each hydroponic system, despite all their good performance as seen in the graphs the NFT hydroponic system generalises optimally than the others since there is a near perfect match of the predicted Onion bulb diameter values with the original onion bulb values as shown in Fig. 9, therefore using the regression model the NFT hydroponic systems is the optimal choice for the Onion bulb diameter prediction.

4.3. XGBoost model

Another machine learning algorithm that has been used for the analysis of the Onion bulb diameter is extreme gradient boosting algorithm (XGBoost), the model from the XGBoost algorithm has been used to determine the R square values for each of the hydroponic system.

Table 2 shows that the Aggregate hydroponic system produces the highest R square (R^2) value of 0.996% while the Floating, Aeroponic, and Nutrient Film Technic hydroponic R^2 values are 0.981%, 0.995%, and 0.988% respectively. It can be inferred from these R^2 values obtained from the XGBoost model that the predictions are very close to the observed values, also establishes the fact that there is a correlation between the independent variables and the Onion Bulb diameter, these results indicate the high-performance of our developed model. Figs. 10, 11, 12, 13, demonstrates the XGBoost model's high performance in the

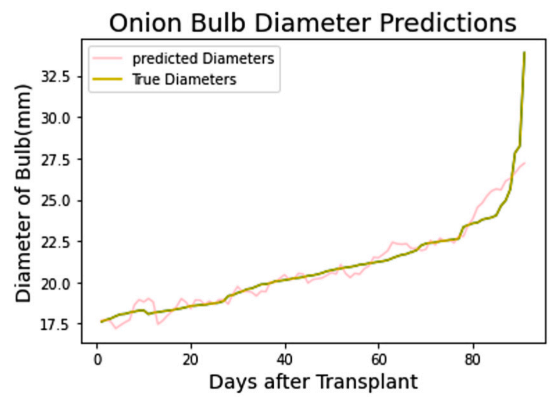

Fig. 8. Floating system Linear regression diameter predictions against the Baseline for the Onion crop.

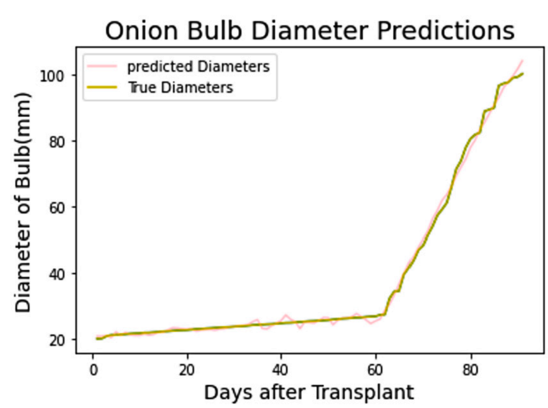

Fig. 9. NFT Linear regression diameter predictions against the Baseline for the Onion crop.

Table 2
XGBoost models results for each hydroponic systems for the Onion crop.

	AER	AG	Floating	NFT
MSE (%)	5.98	3.49	0.09	4.3
RMSE (%)	2.45	1.87	0.31	2.07
k-fold CV average score (%)	0.99	1	0.95	0.98
Mean cross-validation score (%)	0.99	0.99	0.94	0.99
R square value (%)	0.995	0.996	0.981	0.988
computational time	481 ms	1.35 s	1.34 s	496 ms

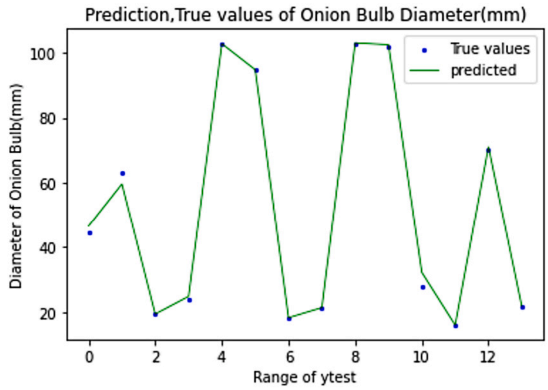

Fig. 10. AER XGBoost predictions for Onion Bulb Diameter.

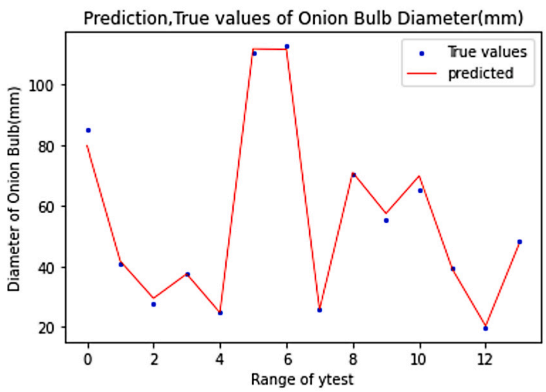

Fig. 11. AG XGBoost predictions for Onion Bulb Diameter.

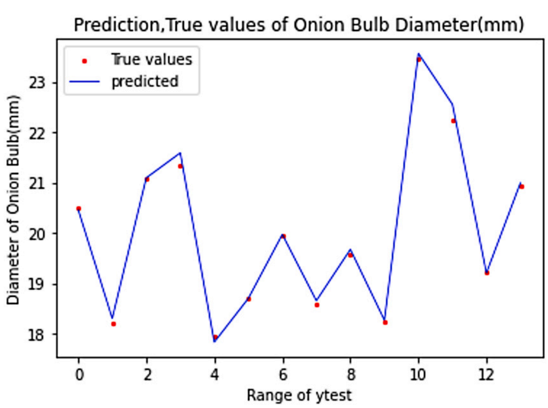

Fig. 12. Floating XGBoost predictions for Onion Bulb diameter.

predicted values and the high R squared values obtained from the xgboost model indicate the predictions are optimal.

It can be inferred from Table 2 that the Aeroponic hydroponic system has the lowest computation time of 481 milliseconds, indicating the model converged faster using the Aeroponic system for prediction despite the fact it has the highest mean square error values, and a high R^2 value of 0.995%, the model performed optimally for the Aeroponic system.

We compare the baseline R square (R^2) values for each of the hydroponic systems. These baseline values have been calculated manually from the Department of Agriculture, University of Peloponnese, Kalamata, Greece. Fig. 14 shows the comparison of the R square values of the baseline and the XGBoost model results, it can be inferred that the difference between the true Onion bulb diameter and the predicted R^2

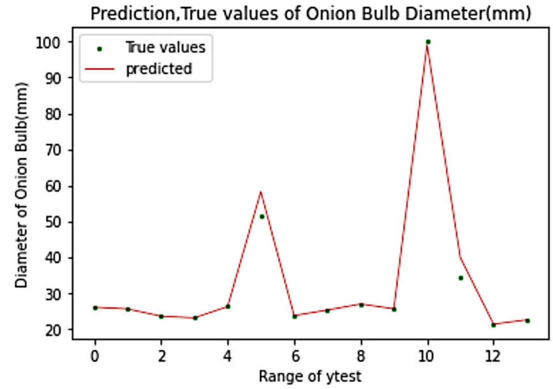

Fig. 13. NFT XGBoost predictions for Onion Bulb Diameter.

values for the AER hydroponic system is 0.003%, the AG hydroponic system has an R^2 difference of 0.001%, while the floating hydroponic system baseline R^2 value has 0.016% higher than the predicted R^2 value, the NFT baseline R^2 value is 0.009% higher than the XGBoost predicted R^2 value. These values indicate that the model predicts very well with extremely minima errors.

The XGBoost model has been used to make predictions of the Onion bulb diameter for the AER, AG, Floating & NFT hydroponic systems. Figs. 10, 11, 12, 13 show the predicted Onion bulb diameter versus the original Onion bulb diameter for the AER, AG, Floating & NFT hydroponic systems respectively, it can be inferred that the four hydroponic systems performed very well with regards to the predictions of the Onion bulb diameters, the AER, AG, floating hydroponic system had more dataset points which are not a match to the original onion bulb diameter in their system but the NFT hydroponic system produced an optimal prediction performance as can be seen in Fig. 13 where only two dataset points of the predicted Onion bulb diameter are not a match to the original Onion bulb diameter, therefore the NFT hydroponic systems are the preferred system for the Onion bulb diameter predictions using the XGBoost model.

4.4. Split learning

Split learning is a decentralized technique of machine learning where the Federated Aggregate model is split into two or more parts for training purposes. The updated weights of the last layer or cut layer are sent to the server for the update. None of the clients nodes see the raw data of each other. These provide data privacy among all the edge nodes within the network. The split learning model has been used to evaluate the Onion bulb diameter datasets for the different hydroponic systems. It can be inferred from Figs. 15, 16, 17 for the Aeroponic system where the model parameters have been hyper tuned using both the Stochastic gradient descent (SGD) and Adam optimizers for different learning rates values of 0.01, 0.1, and 0.0000001. The Adam optimizer with a learning rate of 0.1 is the optimal parameter where the model converges optimally with minimal loss values for the Aeroponic hydroponic system. This is due to the optimization efficiency of the Adam optimizer which combines the AdaGrad and RMSProP algorithm in handling spare gradients for noisy datasets. In the Aggregate hydroponics system, as shown in Figs. 18 and 19, where the SGD and Adam optimizers are used to hyper tune the split learning model. The Adam optimizer using a learning rate of 0.1 is more efficient in achieving convergence of the model for the Aggregate hydroponic system. In the Floating hydroponic system, optimal convergence has been achieved with the SGD optimizer with a learning rate of 0.000001 at less than 5 epochs as shown in Fig. 20. The Adam optimizer achieved convergence with a learning rate of 0.01 at higher epochs as shown in Fig. 21. Figs. 22 & 23 show the loss values obtained from the training of the split learning model for the Nutrient Film Technic hydroponic system. The convergence has been achieved

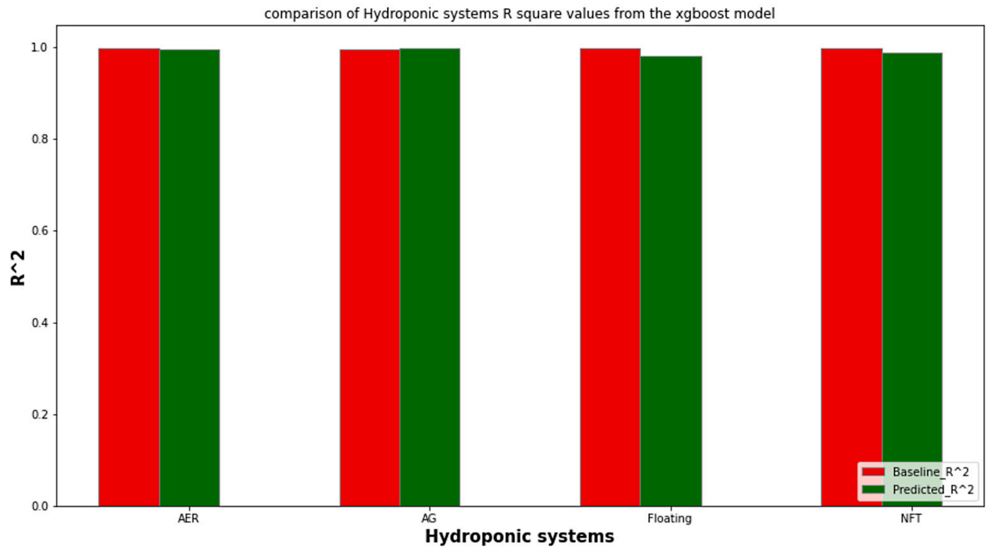

Fig. 14. Comparison of the True R square and predicted R square values for the Onion crop.

with learning rate values of 0.000001 and 0.01 for the SGD and Adam optimizers respectively but the Adam optimizer achieved a lower loss value than the SGD optimizer. It can be inferred from the Split learning results that each hydroponic system achieves convergence at different time of training using different learning rates and optimizer. It is observed that for multiple edge nodes in a decentralised network for a hydroponic system, particular attention should be given to choice of optimizer and learning rate value during training of the model for optimal convergence within a smart farming network. This work shows that SGD optimizer converges for a split learning model in a hydroponic system at extremely low values as seen in Fig. 21 while the Adam optimizer converges at optimal performance in the floating hydroponic system, but using a much higher learning rate value of 0.1 as seen in Fig. 20. Each hydroponic system model uses different learning rate and optimizer for its model performance and this work has shown that each hydroponic system uses different federated split learning parameters to obtain model performance and researchers can consider these results when considering design of their models for different hydroponic systems.

Using the decentralised network models, this is the federated split learning model where the raw dataset is partly trained by the edge node and partly by the server during evaluation, the parameters for each hydroponic systems have been hyper tuned to obtain optimal performance of convergence for each hydroponic system. Different optimizers have been considered for the hyper tuning of the hydroponic systems such as Adam and SGD optimizers using different learning rates values ranging from zero (0) to one (1) to obtain the optimal convergence as shown in Figs. 15, 16, 17, 18, 19, 20, 21, 22, 23 which represent the results of the AER Loss using Adam optimizer (Learning rate = 0.0000001), AER Loss using Adam optimizer (Learning rate = 0.1), AER Loss using SGD optimiser (learning = 0.0000001), AG loss using Adam optimizer (Learning rate = 0.01), AG loss using SGD optimizer (Learning rate = 0.0000001), Float loss using Adam optimizer (Learning rate = 0.01), Float loss using SGD optimiser (Learning rate = 0.000001), NFT loss using Adam optimizer (Learning rate = 0.01), NFT loss using SGD optimizer (Learning rate = 0.000001) respectively, it can be inferred that the floating hydroponic systems, produced the optimal convergence using the Adam optimizer at a learning rate of 0.01, this indicates that the floating hydroponic systems is the preferred hydroponic systems for the Onion bulb diameter predictions using a decentralised split learning network.

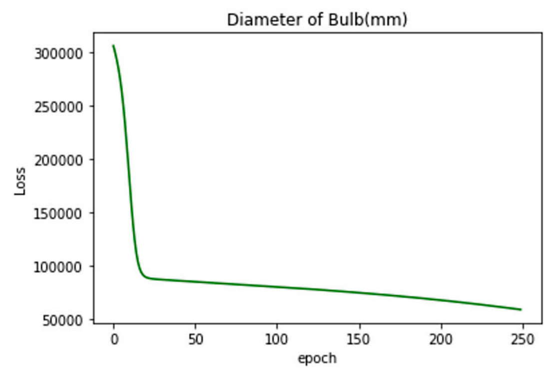

Fig. 15. AER Loss using Adam optimiser, Learning rate = 0.0000001.

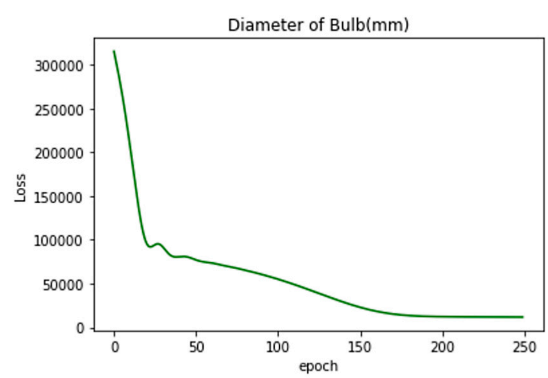

Fig. 16. AER Loss using Adam Optimiser, Learning rate = 0.1.

5. Discussion

It can be observed that using the DNN model, the Floating hydroponic system converges optimally with Mean Squared Errors of 1.86%, while the Aeroponic, Aggregate, Nutrient Film Technic converged with Mean Squared Errors of 2.766%, 11.318%, and 3.246% respectively, indicating the floating system converged optimally when fitted to the DNN model. The XGBoost model produced a very interesting result, despite the Floating hydroponic system converging optimally with the DNN model, with the lowest Mean Squared Error from the analysis, when analyzed using the XGBoost model, the Aggregate hydroponic

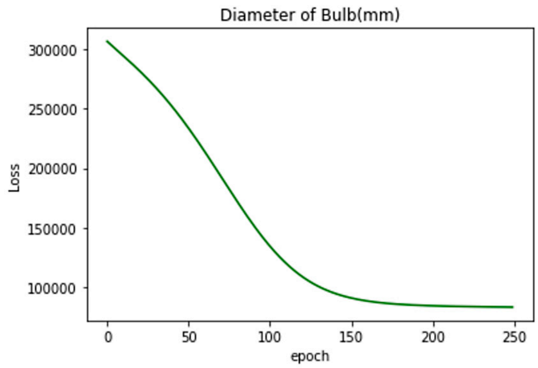

Fig. 17. AER Loss using SGD optimiser, learning = 0.0000001.

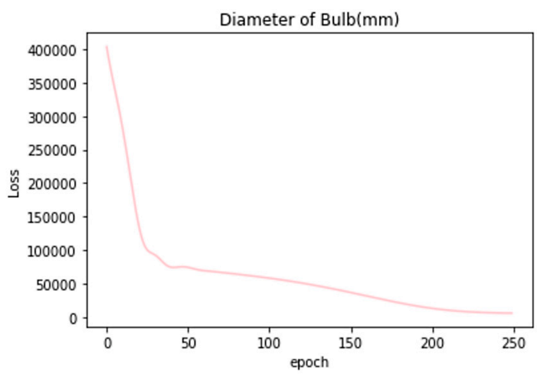

Fig. 18. AG loss using Adam optimiser, Learning rate = 0.01.

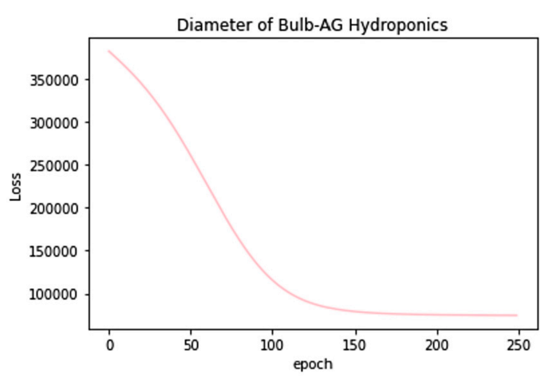

Fig. 19. AG loss using SGD optimiser, Learning rate = 0.0000001.

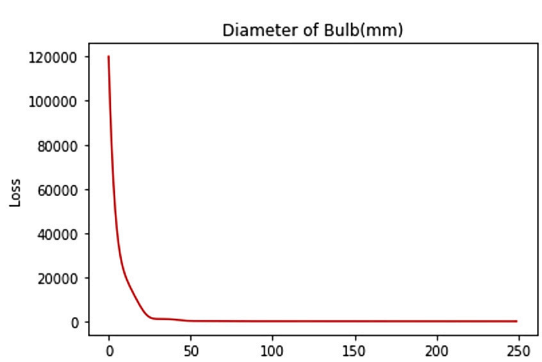

Fig. 20. Float loss using Adam optimiser, Learning rate = 0.01.

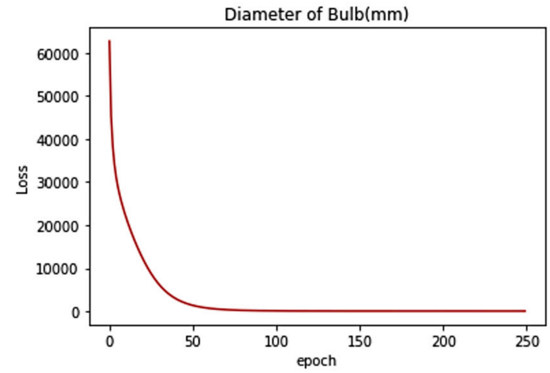

Fig. 21. Float loss using SGD optimiser, Learning rate = 0.000001.

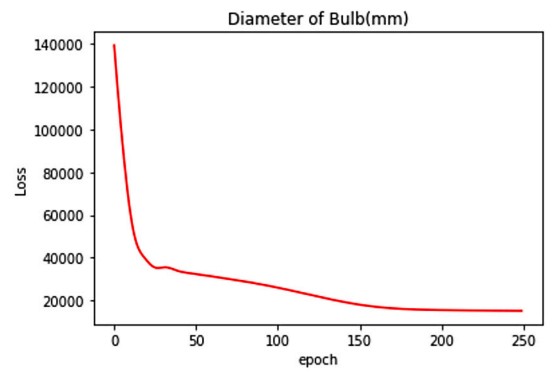

Fig. 22. NFT loss using Adam optimiser, Learning rate = 0.01.

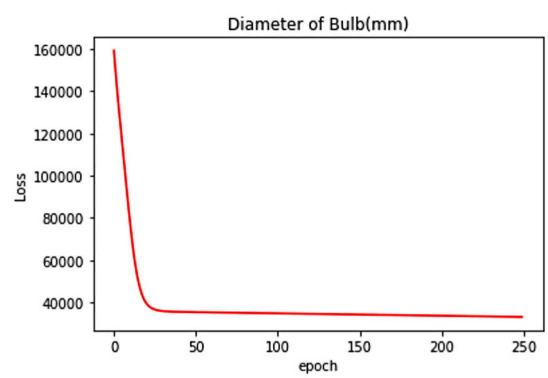

Fig. 23. NFT loss using SGD optimiser, Learning rate = 0.000001.

system produced a far better R squared value of 0.996% compared with the other hydroponic systems, it can be inferred that the predicted values are extremely close to the Baseline values, its value is higher than the Floating, NFT and Aeroponics hydroponics system with R^2 values of 0.981%, 0.988%, 0.995% respectively. In the Federated split learning network, the Floating hydroponic system converged extremely better and faster than the Aeroponic, Nutrient Film Technic, and Aggregate hydroponic systems. It converges optimally after 50 iterations using the stochastic gradient descent optimizer but its performance was further improved when the Adam optimizer was used to hyper tune it with a learning rate value of 0.01, and the model is able to converge after 25 iterations which was faster than the SGD optimizer. This indicates optimal and fast convergence was achieved for both systems using the split learning model which can be seen in Figs. 20 & 21. The Adam optimizer is more efficient in achieving an optimal convergence than the SGD optimizer. We can conclude that each model performs at a different rate using the various metrics within its parameters when they are hyper tuned to obtain optimal convergence. Researchers can use these contributions to explore further research in hydroponic systems. These findings will be a starting point in determining optimal convergence for hydroponic systems using Federated split learning model.

6. Conclusion

The Onion crop was planted in four different hydroponic systems and grown for 92 days after transplant from its nursery, a comparison of the performance of the Linear regression model, Deep neural network model, XGBoost model and the federated split learning model was conducted. The Floating hydroponic system out performed the AER, AG, NFT hydroponic systems using the XGBoost model for evaluation, the Mean Squared Errors values of 5.98%, 3.49%, 0.09%, and 4.3% for the AER, AG, FL and NFT hydroponic systems respectively. The floating hydroponic system produced the lowest MSE of 0.09% to obtain convergence. Evaluating the datasets from the four hydroponic systems using the Deep neural network model, the Floating hydroponic system showed its high performance with the lowest loss values of 1.898%, and the AER, AG & NFT values are 2.690%, 10.460%, 3.147% respectively. The NFT hydroponic system shows the closest predicted values to the true values for the Onion bulb diameter as shown in Fig. 9 using the Linear regression model. The AG hydroponic system indicated the highest R^2 values of 0.996% as shown in Fig. 14 but the AER has the lowest computational time of 481 ms using the xgboost model. Using the Federated split learning model, the Floating hydroponic system was hyper-tuned with different learning rates and optimizers, a learning rate value of 0.01, and Adam optimizer has the fastest convergence compared with the AG, AER & NFT hydroponic systems, as shown in Fig. 20.

It can be inferred that the floating hydroponic system is the optimal hydroponic system for prediction of the Onion bulb diameter using the DNN model. During evaluation of the hydroponic systems using the Linear and XGBoost models the NFT hydroponic systems outperformed the AER, AG and floating systems for prediction of the Onion Bulb diameter. The decentralised network model has been used for training of the AER, AG, floating and NFT hydroponic systems and the floating hydroponic systems produced an optimal convergence when compared with the AER, AG and NFT for different hyper tuned parameters of optimizers and learning rates.

7. Further work

It will be interesting to investigate the effect of parallel learning algorithm models on the Aeroponic, Aggregate, Nutrient Film Technic, and floating hydroponic systems. Academic researchers can use this work as an insight into findings on hydroponic systems but other features can be considered to see the impact of features such as Artificial light, the micro-nutrients (μg/g dry weight), and some climatic parameters on the Onion crop Bulb diameter within the chosen hydroponic systems.

Further investigation can be explored to determine the prediction of onion bulb diameter for the Aeroponic, Aggregate, floating, and Nutrient Film Technic hydroponic systems using the Huber and Transformed Target regressor algorithm.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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