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온도 변화에 따른 파프리카 성장 예측 모델을 위한 기계 학습 알고리즘 비교 연구

사라바나 쿠마르 벤카테산•, 임 종 현*, 신 창 선*, 조 용 윤°

A Comparative Study on Machine Learning Models for Paprika Growth Prediction Model with Temperature Changes

SaravanaKumar Venkatesan•, Jonghyun Lim*, Chanagsun Shin*, Yongyun Cho°

요 약

일반적으로, 스마트팜 내외부 온도 변화는 작물의 생장, 생산, 병해충 발생 및 경영 효율성에 밀접하게 영향을 미치는 요인이기 때문에 온도변화에 대한 적절한 대응이 중요하다. 에너지를 효율적으로 사용하고 온도를 최적으로 제어하기 위해서는, 재생 에너지, 데이터 분석, 기계 학습과 같은 스마트 기술이 온실에서 적극적으로 적용될 필요가 있다. 데이터 분석이 가능한 머신러닝 기술은 기존 데이터를 기반으로 미래를 예측할 수 있는 강력한 신뢰할 수 있는 모델 중 하나로 최근 다양한 분야에서 활용되고 있다. 본 논문은 스마트 팜 내·외부 온도변화와 에너지 사용에 따른 기계학습 기술 기반의 작물생장 예측 모델을 제안한다. 이를 위해 제안된 연구는 태양광 에너지 생산 데이터와 온실에서의 온도 변화 데이터 분석과 함께 SVM(Support Vector Machine), RF(Random Forest), XGB(eXtreme Gradient Boosting), 그리고 GBM(Gradient Boosting Machine)과 같은 기계 학습 모델을 사용한 작물 생장 예측 효율성 실험을 통해 최적의 모델을 제안한다. 실험 결과, SVM 및 GBM 기반 모델은 RF 기반 모델에 비해 좋은 예측 성능을 보였다. 특히, GBM 기반 모델은 스마트팜에서의 에너지 사용량에 따른 온도 변화 예측에서 다른 모델에 비해 유용한 것으로 판단되었다. 따라서, 제안되는 GBM 기반 모델은 스마트팜에서의 작물 생장을 위한 효율적인 온도 및 에너지 제어 서비스 응용 개발에 활용될 수 있다.

키워드 : 기계 학습, 데이터 분석, 온도 변화, 스마트 팜, 신재생에너지, 작물성장 예측
Key Words : Machine learning, Data analysis, Temperature change, Smart farm, Renewable energy, Energy usage prediction

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• First Author : Department of Information and Communication Engineering, Sunchon National University, skumarvsk1288@gmail.com, Ph.D. Reserch Student, 학생회원
° Corresponding Author : Department of Information and Communication Engineering, Sunchon National University, yycho@scnu.ac.kr, 정회원
* Department of Information and Communication Engineering, Sunchon National University

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ABSTRACT

Since temperature changes of smart farms are factors which are closely related with crop growth, production, insect infestation, and management efficiency, the appropriate response against the changes is important. To use energy efficiently and control the temperature optimally, smart technologies like renewable energy, data analysis and machine learning need to be actively applied in greenhouses. Machine learning with data analysis is a powerful model that can predict the future with existing data, and has recently been used in various fields. This paper proposes an optimal energy utilization prediction model using machine learning for crop growth with temperature changes in smart farms. The proposed study proposes an optimal model through prediction efficiency experiments using machine learning models such as support vector machine, random forest, eXtreme Gradient Boosting, and gradient boosting machine. As a result, SVM and GBM-based models showed prediction performance better than RF-based models. SVM and GBM-based models showed better predictive performance compared to RF-based models. In particular, the GBM-based model is more useful than other models in predicting temperature changes according to energy consumption. The proposed model can be used to develop various service applications for temperature and energy control for crop growth in smart farms.

Ⅰ. Introduction

Paprika is the most widely grown fruit globally, and it is one of the healthiest fruit crops and vitamins for human nutrition. Since they adapt paprika plants to long growing seasons in hot climates, they take a long time to germinate from seed. Transplants are the most convenient way to produce them. They even like the heat, as do all vegetables. So select a bright spot in your garden or a sunny jar for your paprika pepper transplant to soak up some heat. To transplant paprika peppers, wait until the temperature has officially warmed up outside. They are highly vulnerable to cold, and temperatures of 27.63℃ degrees or less can be lethal up to two weeks after transplanting your paprika and other vegetables. Harden off your paprika pepper plant for those two weeks to make the transition easier. Pinch off any flowers or small fruit that are forming on your young transplants before transplanting to direct the plant's energy toward rising roots and gaining power[1].

Paprika peppers need a high-quality, well-draining soil that retains moisture but not excessive moisture. Since these peppers are picky with their drink, have a healthy, moist mix on hand at all times. Mulch to help maintain the balance, especially if you're having a really hot spell. The paprika peppers could grow without fertilizer during the season if you began with fertile soil. The optimal greenhouse temperature and sun radiation requirements for paprika production vary, with acceptable temperature limits often being between 25°C and 28°C and solar radiation of 10% -12%[2,3]. Temperature and solar radiation were both monitored at the plant's head for the most accurate findings, and these were the most important elements in determining the greenhouse's sensitive microclimate. It was critical to maintaining the proper temperature and humidity conditions during the growth of the crops in order to achieve optimal growth efficiency. Temperature and sun radiation were also utilized as major markers for predicting growth.

Solar energy is widely used in domestic hot water heating and various fields, including building, drying cooling, etc., to generate electricity. Because of its rate of use of solar energy its decay, instability, and low radiation intensity are relatively low. Also, in order to resolve the conflict between people growth and food scarcity, many researchers are concerned about storing temperature methods for agricultural production. Solar radiation is one of the most common temperature methods for agricultural production[4]. Studying the functions of the agricultural product and drying system drying properties are the directions of four (SVM, GBM,

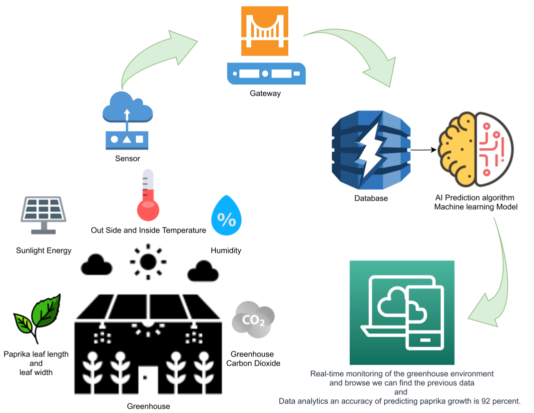

그림 1. 온실 온도 및 태양 복사 데이터 수집 방법.
Fig. 1. Greenhouse temperature and solar radiation data collection method.

RF, XGB) machine learning models important research work projects in solar radiation[5]. Paprika production temperature data collection method, shows in Figure 1.

Ⅱ.Related Works

Recently, smart farm big-data statistical analysis skill, many researchers have examined the temperature and solar radiation and IoT and machine learning models based environmental prediction problem. Nonrenewable sources of energy are declining rapidly as it takes millions of years to replenish, over-demand and utilize in agriculture and the industry is severely affected by the environment and its consumption rate is high for its reproduction. The continuing operation of production encouraged utilization of renewable energy sources to meet growing energy demand and encouraged the use of renewable sources of energy, but despite its massive availability of renewable sources of energy must be used to its full potential[6]. Crop growth variables including average wind speed, air temperature, and relative humidity (Rh) are required for commercial greenhouse operations. In overshoots in the middle east, such characteristics are frequently relevant. Mold fans and evaporator cooling pads are used to manage temperature in such green conventional heating, ventilation, and air conditioning (HVAC) systems. Such systems are unable to adapt to day-to-day fluctuations in heat load[7]. Using multiple machine learning (ML) methods, specific location hourly meteorological data forecast solar power as recorded between 2002 and 2006. Data Mining Processes were used to select the most appropriate input variables based on the information obtained by these scales. The company comes with three different ML algorithms that have been reviewed according to data groups created using DMP (ANN), (SVR) (KNN)[8]. Chemical fertilizers, insecticides, and an artificial approach to boost the output of transplanted seeds are examples of these. These may be successful in the short term, but they disrupt the internal body system in the long run. Customers have been increasingly cautious about their food intake in recent years, preferring food free of chemicals and hazardous pesticides. Organic farming has brought with it a money-based hybrid of crop harvesting, in which organic fertilizers and pesticides are employed to preserve quality and nutritional qualities. The correct crop for organic farming should be chosen based on soil type and climate. This decreases the risk of pre-harvest crop losses due to factors such as soil pH, irrigation, climatic conditions, and life-threatening environmental stress[2]. Solar radiation prediction models learning multiple machine developed and rated in nine locations representing different global climates. As a novelty, air temperature measurements from in-day temperature dataset were used. This is because of the ease with which different new input variables can be provided. According to the results, most of all the models are based on the Hargreaves-Samani and Bristow-Campbell self-aligned empirical methods, which implement RMSE enhancement in dry climates from 7.56% to 45.65% in humidity[9]. The indoor temperature is controlled only by ventilation (natural and dynamic) while the external conditions must be favorable to conserve external heat and cooling energy. Ventilation parameters are determined by the rule-based control scheme, which is not optimal[10]. However, the hardest task for solar resources is to make its integration with the electrical system, which can happen from time to time. Here, we look at their behavior in current and solar forecasting, compare two machine learning techniques for depth-learning (DL), and support vector regression (SVR). The absolute percentage error of the predictions using our test DL and SVR from Spain is 7.9% and 8.52% respectively[4]. A complete analysis is provided that focuses on major methods of energy-saving technologies based on modeling of heat and mass transport, as well as artificial intelligence for climate management. Following a brief and concise assessment of existing greenhouse systems in terms of their role in total energy consumption; effective shape and structure, energy-efficient, and new technologies are analyzed in detail for potential use in greenhouses for significant reductions in energy consumption and also to contribute to property[11].This paper is to better understand the relationship between smart farm temperature and solar radiation output and various production. We also analyses the efficacy of various machine learning models (SVM, GBM, RF, XGB) in predict temperature change and solar radiation energy.

Ⅲ. Material & Method

In this study, we have used the greenhouse paprika data in the year January 2019 to May 2021

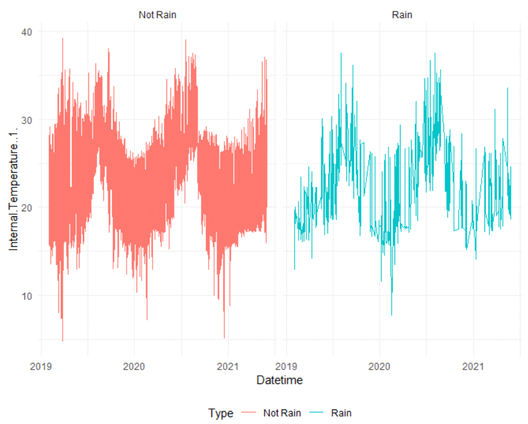

그림 2. 스마트 농업 데이터의 파프리카 온도 수 (2019~2021)
Fig. 2. The number of paprika temperature in the smart farming data (2019 to 2021)

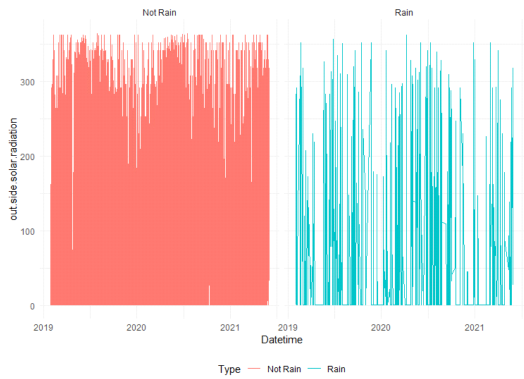

그림 3. 스마트 농업 데이터의 파프리카 태양 복사 수 (2019~2021)
Fig. 3. The number of paprika solar radiation in the smart farming data (2019 to 2021)

(29 months) shows in figure 2 and figure 3. These paprika data are based on date time, inside temperature, inside humidity, outside temperature, outside solar radiation, calorie kw, paprika crop output production, etc. The real data were collected from paprika smart farms of the Jeonnam Agricultural Research and Extension Service in South Korea. The statistical collection for the greenhouse paprika growth was most popular among the past researchers, including machine learning. Correlation is the first step in data analysis before moving on to more intensive analysis and selecting interrelated variables, the next step is to model the variable relationship using machine learning.

3.1 Machine Learning Environment

This study on the application of various functions to train the Paprika growth forecast model with temperature changes. An effective way to think about model training from the beginning is to use transfer learning and more recently the use of the machine learning model to differentiate between simplicity, safety and fit strength. It is significant to create the model in a machine learning environment as simple as possible, considering the relationship between parameters such as time required to train the model, accuracy, reuse of the model, security and size of the database. Machine-learning to train a model from scratch requires a lot of CPUs time, memory, or both and requires more data than a network architecture model, while transfer learning provides better results and computational capabilities. Requires programming knowledge and data production techniques, while model training using machine learning is cost-effective, with close knowledge of programming, without extensive model training. While machine learning models have many advantages, GBM models require improvements such as data import, data processing, and feature engineering from third parties.

3.2 Support Vector Machine

A binary classification model, the support vector machine (SVM) method used. Two-dimensional class data in a straight line is the most acceptable segmentation line at the center of two classes, and it should build an optimal resolution plane as classification criteria in a high-dimensional data set.

When solving a classification problem, the distance from the adjacent sample point to the end surface should be very large, i.e., the minimum distance multiplied by two points separating the edges[12].

3.3 Gradient boost machine

The gradient boost machine algorithm uses an ensemble to simplify the removal of bias, noise, and variance, all of which diminish the forecasting model efficiency. The GBM algorithm runs intuitively and follows the experimental feedback of the remaining models in order to maintain the new model in which the method value mathematical function is improved[13].

3.4 Random forest

Random forest is a supervised machine learning method that is useful for solving regression and classification issues as well as determining nonlinear connections between the goal and input (Breiman, 2001). Belgiu and Drăguţ (2016) created the forest using a series of independent decision trees, each tree having a subset of random characteristics[13]. Each tree gets a vote in regression problems, and the prediction value is the average estimate of all decision trees. This technique can identify the relative significance of each input characteristic, which is useful in determining how each feature contributes to RF output prediction[14].

3.5 eXtreme Gradient Boosting

XGB is a fast and efficient implementation that enhances the elevation slope created by an accurate learner by combining multiple lag trees. The purpose of the training in the XGB model is to minimize and eliminate training losses by avoiding one another. The second row of this process is based on the admissions training implemented through the gradient algorithm[13]. The XGB model is implemented by the XGB tree set in R. Higher parameters include tree maximum depth and learning rate. The more complex the wood, the more complex shapes it will learn, but it is more likely to fit. The learning rate models the error generalization.

The most important factor in evaluating the performance success of prediction techniques is accuracy. As a result, the widely used error metric prediction is utilized both in estimating sample outcomes and comparing them to one another[15]. Some metrics such as R2 (R-Squared), MAE (mean absolute error) and RMSE (root mean square error) were currently used to determine the performance success of the prediction models used in the paper[16].

Ⅳ. Data Analysis Temperature and Solar Radiation

Figure 4 shows the trends of monthly average results measured and analyzed with temperature and solar radiation data collected daily from paprika smart farms of the Naju Agricultural Research and Extension Service in South of Korea during the year 2019 to 2021. The reason for this is that the monthly average daily is higher than the weekly average data temperature and solar radiation measured in the year 2019 to 2021 for Agricultural Research has an upward trend from June to October. The monthly average value daily change in greenhouse temperature and solar radiation creates a curvature of a parabolic, with an irregularity in June

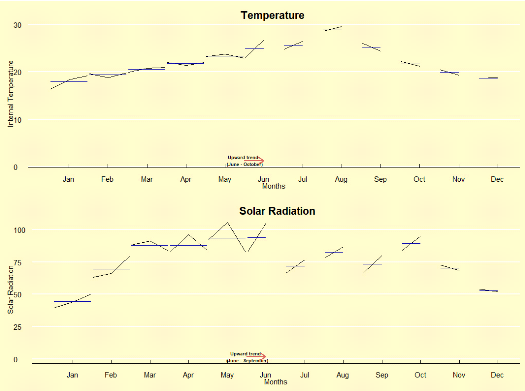

그림 4. 스마트 형태의 온도 및 태양 복사에 대한 계절적 상승 추세(2019~2021)
Fig. 4. Seasonal upward trend for temperature and solar radiation in smart fams (2019 to 2021)

to October and June to September from 2019 to 2021. Because of this variation, the machine learning model RF results Compared to other models gave a poor result to the greenhouse[3].

The most high-value predicting method for greenhouse temperature and solar radiation is GBM shown in table 1. When examining the cause of this situation, the GBM model is related to 2019, 2020 and 2021 data, with the long-time monthly average daily value being the temperature data used for greenhouse solar radiation and training data. This situation is considered to have given a positive result in the study model developed for GBM so that it was able to actualize the 2022 forecasts well. When looking at the MAE values for greenhouse paprika, this value is computed as a negative for all models[17]. This means that the predictive results of all the samples used in the study are averaged and the measured data are calculated to be higher than the mean. In fact, the variation in monthly average greenhouse temperature and solar radiation is expected to exhibit a parabolic curve, but there were fluctuations in greenhouse temperature and solar radiation from April 2019 to September 2020 in Figure 5 and Figure 6.

These data were used to train GBM and ensured a positive approach in training GBM. Therefore, GBM exhibits better results. Greenhouse temperature and solar radiation MAE values are studied, which means that this value is generally found to be

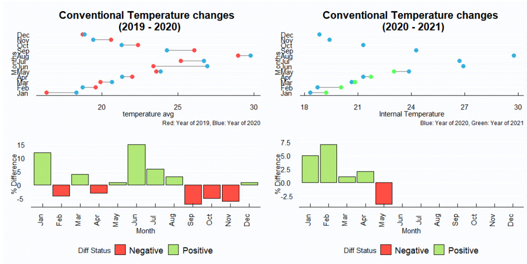

그림 5. 월별 온도 변화 평균 결과 (2019~2021)
Fig. 5. Monthly temperature change average result (2019 to 2021).

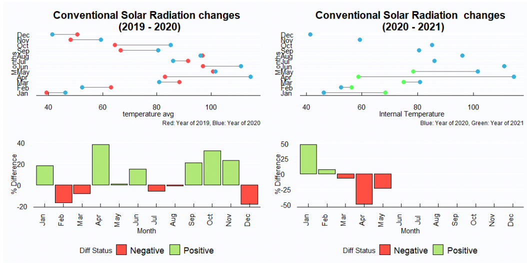

그림 6. 월간 태양 복사 변화 평균 결과 (2019~2021)
Fig. 6. Monthly solar radiation change average result (2019 to 2021)

negative for all samples. This means that the predictive results of all the samples used in the study are averaged and the measured data are calculated to be lower than the mean. Unexpected variation, especially in April and September, played a significant role in the scenario of this negative trend.

V. Result and Discussion

The results of the statistical dataset analysis accuracy of the ML models used in this study are in Table 1. Since R-Squared is measured and defines the relationship between the predicted values, it is desirable that this value be close to 1. Considering all the ML models in terms of R-Squared, we can see that the table 1 R-Squared value of all the models is greater than 0. 9454. The average R-square accuracy for the GBM, SVM, RF and XGB models is 0.9260, 0.9454, 0.0.9830, and 0.98054, respectively[18]. These show methods that accurately reflect the monthly average daily greenhouse solar radiation and temperature curves.

MAE values are important for the long-term monthly average performance of the model. Positive MAE values show they made ratings above the measured values, while negative MAE values show that the results of the predictions are higher than the measured values. Considering the results based on MAE, it can be seen that the models have low errors. Monthly average daily greenhouse temperature and solar radiation values MAE values also show negative or positive trends according to estimates that are higher or lower than the monthly average daily greenhouse temperature and solar radiation values[19] As a result, the average MAE value is 0.9739, 0.6844, 0.3698, and 0.4858, mm-year (2019 to 2021) for the GBM, SVM, RF and XGB models, respectively. RMSE models provide information that is always positive that reveals short-term performance. It is desirable that the RMSE value be close to zero[15].

Considering the RMSE values, the lowest RMSE values are found in the RF model for greenhouse paprika growth. In addition, the GBM model has the highest RMSE values.

The RMSE value of the GBM, SVM, XGB and RF models is accurate to be 1.333, 1.1534, 0.6848, and0.6456 mm-year (2019 to 2021), respectively. Based on the RMSE estimate, it was found that less than 5% of all models. In the study, if the RMSE value is less than 5% of the forecast results, the results will be classified in the high accuracy category. Fig 7, Fig 8, Fig 9 and Fig 10 show that in those analysis, all models used in this study have high accuracy in RMSE because it is averagely found to be in this prediction, all the models used in this study were found to be average RMSE has high accuracy to be 1.333 for the empirical, GBM models respectively.

표 1. 기계 학습 모델의 교육 및 테스트 데이터 비교 결과
Table 1. Training and testing data comparison results of machine learning models

Model name	Training data			Testing data		
	RMSE (°C)	R2	MAE (°C)	RMSE (°C)	R2	MAE (°C)
GBM	1.333	0.92	0.97	1.24	0.90	0.99
SVM	1.153	0.94	0.68	1.05	0.89	0.72
RF	0.64	0.983	0.36	0.68	0.95	0.40
XGB	0.68	0.980	0.48	0.70	0.96	0.52

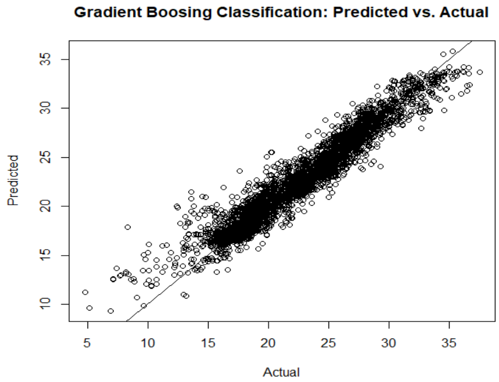

그림 7. 예측 GBM 결과 및 실험 테스트 값.
Fig. 7. Prediction GBM results and experiment test value.

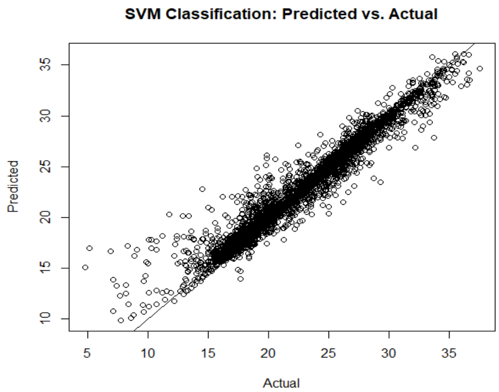

그림 8. 예측 SVM 결과 및 실험 테스트 값.
Fig. 8. Prediction SVM results and experiment test value.

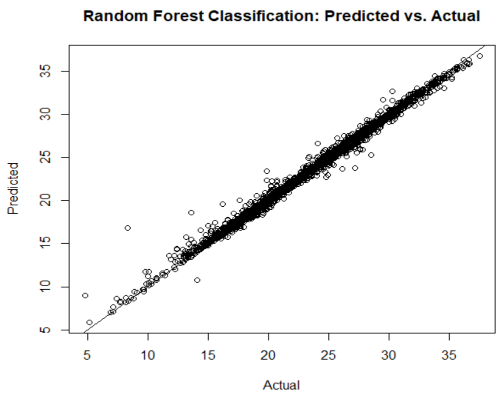

그림 9. 예측 RF 결과 및 실험 테스트 값.
Fig. 9. Prediction RF results and experiment test value.

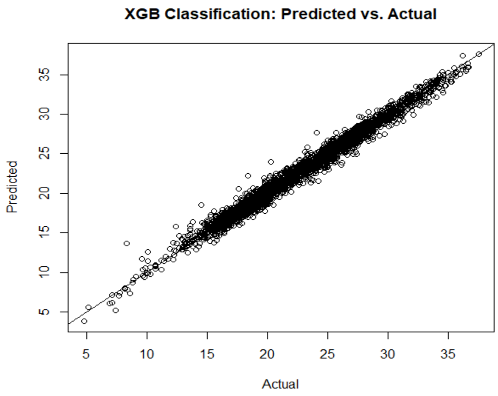

그림 10. 예측 XGB 결과 및 실험 테스트 값.
Fig. 10. Prediction XGB results and experiment test value.

그림 11. ML 모델 성능 교육 결과
Fig. 11. ML model performance training result

Since greenhouse solar radiation and temperature intensity are between test values, this problem can be solved by collecting solar radiation and temperature intensity test values at brief intervals in the future. Figure. 11 shows that the prediction results with ML models are comparatively experimented. The projected result values are extremely close, and the correlation coefficient and root-mean-square error are nearly equal. The training time of GBM is the same as SVM, RF and XGB.

Ⅵ. Conclusion

In this paper, we used machine learning models, which are GBM, SVM, XGB, and RF, to find the optimal prediction model for paprika growth by considering temperature change data and solar energy data. Through the comparative experiments, GBM-based model was found to have the optimal prediction efficiency. The suggested model identify significant input factors of paprika growth and have a powerful approach to illustrate the relationship between environmental energy usage and temperature changes for paprika growth prediction. The suggested model has RMSE 1.333, R-Squared 0.9262, and MAE 0.9739, respectively and also eliminates the problems of over-fitting and under-fitting during the training data. Therefore, the suggested GBM-based model can work well not only in paprika growth prediction, but also in real-time prediction for energy usages and production amounts according to various crop in smart farms. Future studies can be aimed at collecting more data and testing the suggested model with data gained from more than one real test-bed. And, those can also be attempted as an extended study using neural networks to improve efficiency for energy-related prediction needs in smart farms.

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사라바나 쿠마르 벤카테산 (SaravanaKumar Venkatesan)

Currently pursuing PhD in the Department of Information and Communication Engineering, Sunchon National University. He received his Bachelor degree in Mathematics from Madras university and Master of science Information and Communication Engineering at sunchon National University in South Korea. His current research interests include Big Data Analytics, Data Mining, Mathematics

<관심분야> 정보통신공학과

[ORCID:0000-0002-8977-8411]

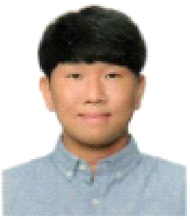
신 창 선 (Chanagsun Shin)

Received the PhD degree in Computer Engineering at Wonk Wang University. Currently, he is a professor of the Dept. of Information &Communication Engineering in Sunchon National University. His researching interests include Distributed Computing, IoT, Machine Learning, and Agriculture/ICT Convergence.

<관심분야> 정보통신공학과

[ORCID:0000-0002-5494-4395]

임 종 현 (Jonghyun Lim)



Completed Master degree in Information and Communication Engineering from Korea. He currently studying for PhD degree in Information and Communication Engineering at Sunchon University. His area of interest includes System Software, Ubiquitous.

<관심분야> 정보통신공학과

[ORCID:0000-0001-6832-4077]

조 용 윤 (Yongyun Cho)

Received the PhD degree in computer engineering at Soongsil University. Currently, he is an assistant professor of the Department of Information & communication engineering in Sunchon National University. His main research interests include System Software, Embedded Software and Ubiquitous Computing.

<관심분야> 정보통신공학과

[ORCID:0000-0002-4855-4163]