Regular paper
Journal of the KIECS. pp. 99-106, vol. 18, no. 1, Feb. 28. 2023, t. 117, pISSN 1975-8170 | eISSN 2288-2189
http://dx.doi.org/10.13067/JKIECS.2023.18.1.99

# 작물 생산량 예측을 위한 심층강화학습 성능 분석

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# Performance Analysis of Deep Reinforcement Learning for Crop Yield Prediction

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요 약

최근 딥러닝 기술을 활용하여 작물 생산량 예측 연구가 많이 진행되고 있다. 딥러닝 알고리즘은 입력 데이터 세트와 작물 예측 결과에 대한 선형 맵을 구성하는데 어려움이 있다. 또한, 알고리즘 구현은 획득한 속성의 비율에 긍정적으로 의존한다. 심층강화학습을 작물 생산량 예측 응용에 적용한다면 이러한 한계점을 보완할 수 있다. 본 논문은 작물 생산량 예측을 개선하기 위해 DQN, Double DQN 및 Dueling DQN 의 성능을 분석한다. DQN 알고리즘은 과대 평가 문제가 제기되지만, Double DQN은 과대 평가를 줄이고 더 나은 결과를 얻을 수 있다. 본 논문에서 제안된 모델은 거짓 판정을 줄이고 예측 정확도를 높이는 것으로 나타났다.

ABSTRACT

Recently, many studies on crop yield prediction using deep learning technology have been conducted. These algorithms have difficulty constructing a linear map between input data sets and crop prediction results. Furthermore, implementation of these algorithms positively depends on the rate of acquired attributes. Deep reinforcement learning can overcome these limitations. This paper analyzes the performance of DQN, Double DQN and Dueling DQN to improve crop yield prediction. The DQN algorithm retains the overestimation problem. Whereas, Double DQN declines the over-estimations and leads to getting better results. The proposed models achieves these by reducing the falsehood and increasing the prediction exactness.

키워드

Crop Yield Prediction, Deep Reinforcement Learning, Deep Q Networks(DQN), Double DQN, Dueling DQN
작물 수확량 예측, 심층강화학습, 심층Q-네트워크, 이중 DQN

## Ⅰ. Introduction

Crop yield prediction is one of the most important tasks to ensure efficient crop planning and food safety in the country. Everyday the production fluctuate in the markets basis supply and demand of the crop. Agriculture is a significant zone to society because an enormous amount of foodstuffs is needed for human beings. Nowadays, many countrysides still need experience because of

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• 접 수 일 : 2022. 12. 27
• 수정완료일 : 2023. 01. 19
• 게재확정일 : 2023. 02. 17
• Received : Dec. 27, 2022, Revised : Jan. 19, 2023, Accepted : Feb. 17, 2023
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the lack of foodstuffs knowledge for planting people. Increasing food production is an effective process to prevent food shortages. Food protection rising and starvation decreasing are valuable and vital goals. Consequently, crop preservation, land inspection, and crop yield forecasting are of notable importance for multinational food shows[1]. The policymaker relies on exact forecasts, to create the proper import and export reviews to support nationwide nutrition safety. The edit person corresponding to this manuscript review and assenting it for the contribution of publication is Dongxiao Yu and agriculturists additionally benefited from yield forecasts to make financial and designing determinations. Agriculture management, particularly crop yield observation, is essential to decide nutrition safety in a province[2]. In addition, crop yield prediction is especially hard because it varied complicated components. Crop yield mostly relies on climate circumstances, landscapes, soil quality, pest infestations of yield activity, etc. The crop harvest procedures and techniques are varied with period and non-linear profound and complicated to the combination of a vast spread of connected aspects that are described and affected by non-arbitrate runs and exterior views. Normally, significant parts of the farming work are not described in a basic stepwise estimation, particularly with complicated, insufficient, illegible, and inconsistent datasets. At present, many experiments indicate that ML models have comparatively better-progressed possibilities than traditional analysis[3]. The rest of this paper is organized as follows. Section 2 introduces the publication's study of the previous results. The proposed methods for crop yield forecasting are illustrated in Section 3. Section 4 clarifies the results completely. Finally, Section 5 concludes our research shortly and represents future works.

## Ⅱ. Related Works

Machine learning(ML) is part of artificial intelligence (AI) in which computers are conducted without a mistakable program. These procedures fixed non-linear or linear-based farming networks with ideal prediction capacity[4]. In ML agricultural work, the strategies are achieved from the knowledge procedure. These procedures require over train to perform exact work. After the dataset is trained, the algorithm creates ideas to try the facts. Additionally, ML reaches an umbrella that has different effective approaches and methods by using the most superior farming algorithms of AI and deep neural networks(: DNN)[5].

DL is a part of ML that specifies the outcomes of different performances of input data. DL algorithms set a possibility model for crops under different climatic situations[6]. Data scientists use diverse ML models to derive actionable senses from general facts. Another fascinating area of AI is DL. It is a vital algorithm that is used for facilitating the logic of various programming. Reinforcement learning(RL) is a qualified machine learning model to make determination successions. The agent comprehends to act an aim in uncertain, potentially confusing situations. Established on the agent's activity, the events award it. The technique shows the appliance as the agent and its environment as the state. In current periods progressed and created DRL of artificial intelligence, is deep for smart determination creating in different fields such as power management, robotics, fitness care[7], intelligent grid, match approach, finance, image processing, Natural Language Processing, Sentiment analysis with a vast combination of RL strategies with DL techniques[8]. This technique is effectual to fix a broad range of difficult determination schemes which are the earlier further machines. To sum up, it is an effective model for designing intellectual farming networks. The typical

DRL models contain deep networks, numerous agent DRL, and deep Q-network[9-10]. We suggest a supervised wise farming work using the DRL algorithm in this research. A DQN-launched DRL algorithm is used to support the yield's prediction performance with the most satisfactory reward iterations. Many deep learning algorithms are not specified by the preferences in title composition emanating the senses instantly from the facts such as Autoencoders and deep belief networks[11-12]. These algorithms can occasionally fall to reserve for the delay while solving unclear intakes. Almost techniques obey desirous processes which are sub-optimal, understanding one layer of attributes at a moment not fixing its lower attributes of slowly and inadequately computations. This suggestion overcomes the above strategies and facilitates smart agriculture and so leads to improving the production of food.

## Ⅲ. Methodology

There are a lot of great implementations of reinforcement learning algorithms. They are Deep Q Learning(: DQN), Actor-Ctritic(: A2C), Proximal Policy Optimization(: PPO), and among others. All of these algorithms use a similar process to produce an agent:

- Initially, the weights are set to random values.
- As the agent plays the process, the algorithm continually tries out new values for the weights, to see how the cumulative reward is affected, on average. Over time, after playing many processes, we get a good idea of how the weights affect the cumulative reward, and the algorithm settles towards weights that performed better.
- Of course, we have smoothed over the details here, and there's a lot of complexity involved in this process.
- So it gets the final reward of +1, avoids the -1 and -10, and tries to make the match last as long as possible.

In this section, the proposed three algorithms of Deep Q Networks(: DQN), Double DQN and Dueling DQN are consulted. The implementation of these DQN, double DQN, and dueling DQN on the crop dataset are expressed in the following section.

### 3.1 Deep Q-Networks(: DQN)

In Deep Q-Learning(: DQN), the neural network input is the state or the observation and the neurons output is the numeral acts that an agent accepts. For the neural network training, the target is the Q-values of each actions and the input is state that the agent is in. DQN algorithm problem is the overestimation of the true rewards. The Double DQN algorithm is suggested to correct it. Double DQN uses the decoupling of the selected action from the action evaluation. This declines the overestimations, which leads to getting better results. The loss and reward of DQN performance are demonstrated in Fig. 1.

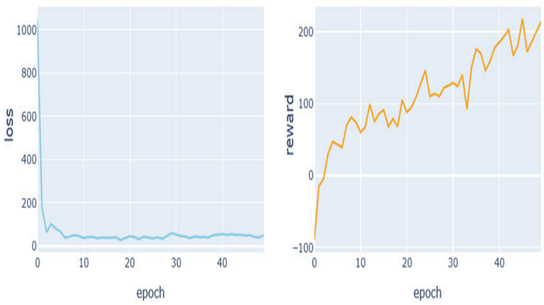


Fig. 1 Plots showing the loss and reward of DQNs

### 3.2 Double Deep Q Networks

Double DQN operates two duplicate neural network samples. One comprehends during the experience repeat, such as DQN, and the different one is a duplicate of the previous attack of the foremost model. The Q-value is computed with the second model. The loss and reward of double DQN performance are demonstrated in Fig. 2.

In equation (1), Q-value gains are computed in Double DQN. The index of the most heightened Q-value from this model and utilize this index to get the action from the second model to determine the maximum action. By making this, we receive the predicted Q value for equation (1).

$$R_t + r\ Q^c\ (S_{t+1}\ .\ \mathrm{argmax}Q\ (S_{t+1}\ .a')) \qquad \cdots (1)$$

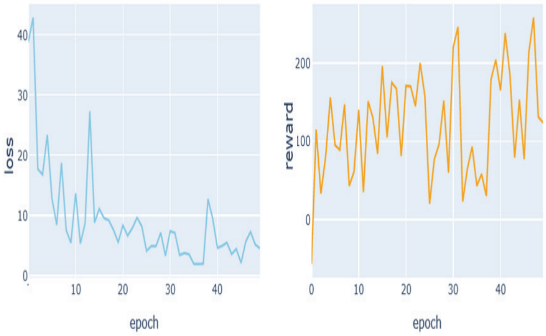


Fig. 2 Loss and reward of Double DQNs

### 3.3 Dueling Deep Q Networks

Dueling DQN computes the state value function and assess the benefit procedure for individual action. Lastly, it unites both these components into a single outcome, that evaluates Q-values. The modification is useful because it is not need to understand the accurate meaning of each stage, therefore, understanding the state-value procedure is sufficient in some circumstances. The schematic Dueling DQN is pictured in Fig. 3.

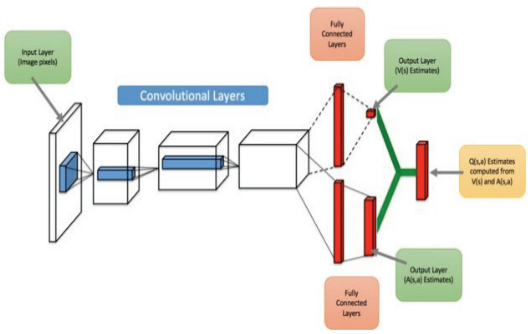


Fig. 3 Schematic Dueling DQN

The dueling DQN algorithm divides the Q-values into two portions. In equation (2), V(s) is the value function and A(s, a) is the advantage function. V(s) declares how broadly rewards gather from state s. A(s, a) declares better action which is compared to the further actions. Combine both value V and advantage A per movement and obtains the Q-values:

$$Q(s,a) = V(s) + A(s,a) \qquad \cdots (2)$$

The dueling DQN algorithm offers the exact neural network that divides its final layer into two pieces, one evaluates the state value function for state s (V(s)) and the other evaluates the benefit procedure for per movement an (A(s, a)), and lastly, it merges both pieces into a single outcome, which assesses Q-values. The Schematic Dueling DQN is shown in Fig. 3. This modification is useful because occasionally it does not understand the actual value per action, therefore, retaining the state-value procedure is adequate in some circumstances. The loss and reward of double DQN performance is demonstrated in Fig. 4.

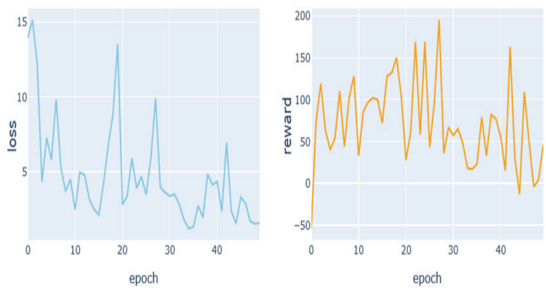


Fig. 4 Loss and reward of Dueling DQNs

## Ⅳ. Experiment and results

### 4.1 Datasets

We utilize the crop dataset from "Kaggle". The period from 2004 to 2021 data is used for the experimentation. The data consists of the rice, onion, sesamum, banana, coconut, sunflower, sugarcane, etc. This dataset includes more than 4,000 data samples.

### 4.2 Experimental Results

We operate the DQN, Double DQN, and Dueling Double DQN algorithms to forecast crops and maximize profits. The input dataset is split into train and test data in the same ratios. The attributes of input datasets are State_Name, District_Name, Season, Crops, Area, Production, etc.

The train and test dataset is provided to the proposed models. From 2014 to 2021 data are utilized for testing, and from 2004 to 2012 data are utilized for training. The loss and rewards of the train and test are evaluated. The forecasting results are shown in Fig. 5.

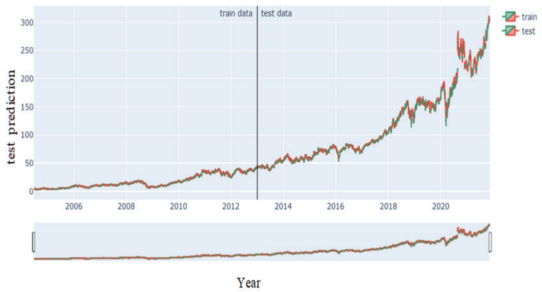

Fig. 5 Training and testing of crop dataset

We investigate the deep reinforcement learning algorithms′ performance for the downloaded crop dataset. The proposed performances of three models for DQN, double DQN, and dueling DQN are illustrated Fig. 6, Fig. 7, and Fig. 8 separately. These models developed positive profit strategies. The profit of each model is illustrated in the figures respectively. The Double Deep Q-network is the best profit compared to the Deep Q-Network and the Dueling Deep Q-Network. These three models′ results are compared. The Double Deep Q Network yields are higher compared to the other two models. We demonstrate the distribution of profits developed by the individual model and noticed that the Double Deep Q Network model is much better stability than the other two models.

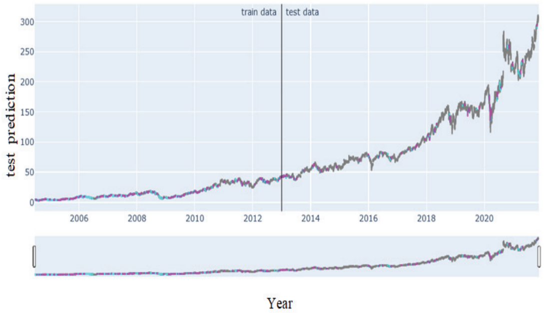

Fig. 6 DQN's performance on crop dataset.

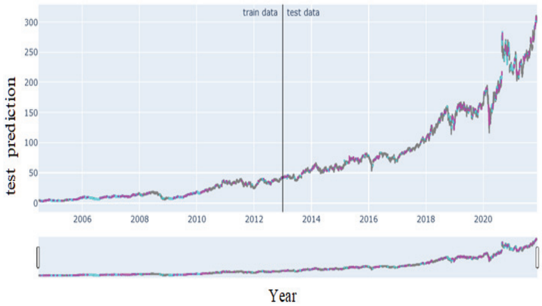

Fig. 7 Dueling DON's performance on crop dataset.

Although the DQN is powerful and outperforms human-level implementation in multiple contests successfully, it contains weaknesses. Numerous enhancements are done to crush these weaknesses. Both Double DQN and Dueling DQN, utilize two distinct Q Networks instead of DQN and aim to overcome the weaknesses of DQN. Based on this experiment, the Double DQN gets the idea of the benefit of carrying the activity on the fundamental state's of total significance. The idea of benefit is examined in current research and the experiential outcomes are displayed in table 1.

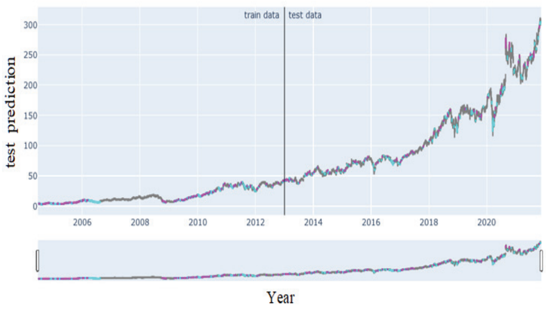


Fig. 8 Double DQN's performance on crop dataset.

Table 1: Rewards and profit of DQN, Double DQN, and Dueling DQN

| Proposed Algorithms | Train Rewards | Train Profit | Test Rewards | Test Profit |
|---|---|---|---|---|
| DQN | 147 | 150 | 46 | 174 |
| Dueling DQN | 131 | 190 | 56 | 274 |
| Double DQN | 120 | 169 | 79 | 871 |

## Ⅴ. Conclusions

Deep reinforcement learning performs the crop performance and generates profit. Also, we indicate that the Double DQN conducts the best in crop production among three DRL networks for this current investigation. The experiments demonstrate that the above DRL algorithm completes sufficiently forecasting problem solving. The proposed algorithms reacts and acts more satisfactorily than the conventional methods. We suppose that the Double DQN accomplishes more profit and usefulness than the DQN and Dueling DQN algorithms. In the near future, we need to experiment with the different datasets for the performance comparison of the proposed Deep reinforcement learning models.

감사의 글

“본 연구는 과학기술정보통신부 및 정보통신기획평가원의 지역지능화혁신인재양성(Grand ICT연구센터) 사업의 연구결과로 수행되었음” (IITP-2023-2020-0-01489)

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