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Article

Model Building and Efficiency Improvement of Generative AI in Agricultural Planning

Mengqiu Shao [1,*] Hongkun Liu [1], Guoqing Cai [2] and Wei Xu [1]

[1] Applied Computer Science Fairleigh, Dickinson University, Vancouver, BC, Canada
[2] Information Studies, Trine University, Phoenix, AZ, USA
* Correspondence: Mengqiu Shao, Applied Computer Science Fairleigh, Dickinson University, Vancouver, BC, Canada

Abstract: In recent years, artificial intelligence has been widely used in the field of agriculture, and information content such as data collection has also gradually emerged. This paper outlines the basic concepts of large models and explores the application of AI in agriculture. The adaptability in industry planning is analyzed and the application status is evaluated according to three categories of language model, visual model and multimodal large model. The subsequent development direction is discussed, emphasizing the need for AI-generated intelligent models to enhance agricultural decision-making to improve the management effect and realize the sustainability of agricultural production.

Keywords: generated AI; agricultural planning; model building; efficiency improvement

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1. Introduction

AI generation has a direct application effect on agricultural planning, and it is gradually appearing in production efficiency control, environmental resource utilization and sustainable design [1]. With the help of big data machine learning algorithm, intelligent decision-making for agricultural production is also applied in the field of planting management and intelligent optimization [2-4]. This model is to analyze the effect of AI generation and improve agricultural decision-making, it aims to control the output based on real-time data, reduce costs, improve management efficiency, and enhance resource utilization and innovation. Also, for the follow-up agricultural field. Intelligent management provides a theoretical basis.

2. Overview of the Generative AI Technology

2.1. Transformer Model

The core of the core innovation of the transformer model is its self-attention mechanism is the innovation of the self-attention mechanism, which mainly calculates the different elements and similarity scores of sequence classes, and makes the dynamic adjustment of the whole element. This model can conduct complementary analysis of sequence information, rather than make global processing like traditional data, and has a direct and important role in complex text structure and language translation [5]. Different from the traditional RNN, the calculation of this model processes the real-time data. When training the big data, the related sequences can be regulated to improve the management effect.

The transformer architecture is also able to effectively handle longer sequences without losing information details by increasing the sequence length, allowing it to perform well in many practical tasks. Transformer Innovation has revolutionized the field of natural language processing (NLP). Pre-trained models based on pre-trained models based on the transformer architecture, such as BERT and GPT, have achieved remarkable results in multiple NLP tasks [6].

GPT is trained using the decoder in transformer to predict the next word in the text sequence by autoregressive generation. The decoder can capture the contextual information through the self-attention mechanism, realize the text generation task, and effectively understand the context relationship of the input, so as to generate the coherent language content. These technological breakthroughs have far outperformed transformer in NLP tasks, and have been widely used in text classification, sentiment analysis, machine translation and other fields. Transformer self-attention mechanism and parallel computing capabilities give it incomparable advantages in the field of natural language processing and other tasks that require long sequence data, becoming an important infrastructure of modern artificial intelligence.

The acking of transformer architecture enables large-scale models to efficiently handle complex tasks, especially in the field of natural language processing, as model size and training data increase, the transformer architecture becomes more effective. We quantitatively study the extension of large-scale language model, and put forward two classical rules: KM law and Chinchilla law [7,8]. While keeping the data and computing resources unchanged, increasing the size of the model can significantly improve the performance, additionally the model can also be further optimized by increasing the amount of training data and computation.

$$\mathrm{L(N)} = \left(\frac{\mathrm{Nc}}{N}\right)\alpha\mathrm{N}, \alpha\mathrm{N}\sim 0.076, \mathrm{NC}\sim 8.8\times 10^{13} \tag{1}$$

$$\mathrm{L(D)} = \left(\frac{\mathrm{Dc}}{D}\right)\alpha\mathrm{D}, \alpha\mathrm{D}\sim 0.095, \mathrm{DC}\sim 5.4\times 10^{13} \tag{2}$$

Generative AI mainly refers to the analysis of the big data model to compare and analyze the of the generated content or artificial intelligence information similar to the original data [9]. Different from the traditional judgment AI, the center of generative AI is to predict tasks and create new information, which is widely used in images, text and audio [10]. Generation is the core framework of AI, including generative network and variational autoencoder generation network, to judge the authenticity and false of information, so that the generated content is reasonably controlled, and has a wide application in the fields of art creation [11], medicine and agriculture [12,13]. Through natural language processing, it can automatically make regression control for the relevant information in the field, and also manage and predict it combined with data processing and coding content [14]. As an important content of the current agricultural field, generative AI is based on effective information resource analysis, under the content of agricultural model processing, it can better meet the needs of modern production, but also complement data, information resources, content and development direction [15].

3. Application Scenarios of Generative AI in Agricultural Planning

3.1. Language Large Model

The development of language models in agriculture is gradually moving towards large-scale dedicated models and has made significant progress in multiple application scenarios. For example, the AgriBERT model proposed by Rezayi et al. significantly improves the ability of the model to match food and nutrient composition by combining the specialized knowledge map of the agricultural field with a large number of academic journal data. In the field of plant science [16], the PLLaMa model based on Llama2-7B and Llama2-13B has successfully achieved a high accuracy of answering multi-choice questions by continuing pre-training and fine-tuning [17]. With the development of technology, many large agricultural models have also been successively applied to intelligent agricultural systems. For example, the "big cultivation model" developed in collaboration with Anhui Provincial Department of Agriculture and Rural Affairs and iFlytek processes massive data [18]. For example, the Shennong 1.0 model developed by China Agricultural

University makes real-time calculation with large-scale data [19]. Shennong 1.0 integrates large-scale data to build an analytical platform, enabling service and management information integration. It also connects to massive data sources, constructs a knowledge graph, builds a quantitative database, and provides intelligent mapping, knowledge training, and decision-support services. These models demonstrate strong potential in agricultural intelligence, data processing and decision support, promoting the further development of smart agriculture.

3.2. Visual Large Model

As a representative of visual large model, SAM model has powerful image segmentation ability, and has made significant progress in the application of agricultural field, especially in planting, animal husbandry and agricultural remote sensing [20]. For the segmentation of leaves of potato plants, the performance of the SAM model was studied by Williams et al. After segmentation with SAM, the next four optimization steps are taken: first color check to ensure the accuracy of the mask; then the whole plant mask is removed to avoid the interference of invalid areas; then, the unconforming areas are eliminated by shape filtering; finally, the mask containing multiple blades is eliminated, to ensure that each mask corresponds to one blade, so as to improve the accuracy and precision of the segmentation results. This process is compared with the Mask R-CNN model. Although the SAM model is slightly inferior to the supervised learning-based Mask R-CNN in segmentation accuracy, its zero-sample segmentation ability effectively reduces the dependence on manually labeled data and provides important support for the development of intelligence in the agricultural field. Especially in agricultural applications, SAM can segment images based on simple prompts by simple prompts without additional manual participation, which greatly improves the work efficiency.

In Figure 2, the potential of the SAM model for accurate segmentation of crop and weed images was also evaluated by Carraro et al. They used the Crop and Weed Field Image Dataset (CWFID) to explore the performance of SAM in distinguishing vegetation foreground from background through semantic segmentation technology. In the experiment, the SAM model successfully completed the crop and weed segmentation task by prompting from a small number of points or borders. Nonetheless, the model shows over segmentation in the case of automatic labeling, indicating that further optimization and adaptation of SAM in agricultural image segmentation without additional training. Overall, SAM model shows strong ability in zero-sample learning and segmentation efficiency, but further improvements of adaptability and accuracy are needed to achieve higher application results in agricultural environment.

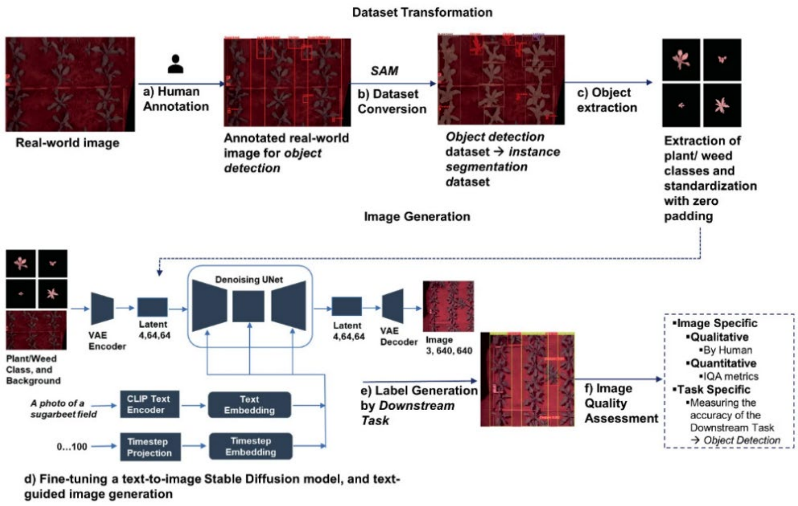

Figure 1. Visual large model.

3.3. A Multimodal Large Model

In agriculture, the dissemination of knowledge usually requires combining various forms of information, such as images and text. In order to integrate this heterogeneous information more effectively and provide comprehensive knowledge services, methods based on multimodal models have become an important research direction. This kind of model can integrate images, text and label information, providing more practical solutions for the promotion of agricultural knowledge. The multimodal model ITLMLP, proposed by Cao et al., combines three input methods: image, text and label, and incorporates structures such as CLIP and SimCLR, specifically for the identification of cucumber diseases. Through comparative learning and few-sample learning, the model can surpass CLIP, SimCLR and SLIP in multiple indicators, showing strong recognition ability. Moreover, the model also demonstrated good performance in identifying other plant diseases, highlighting its strong generalization ability. Another study by Tan et al., with experimental applications in the GPT-4 model, never identified fields in time and space. This model shows the GPT 4 in the image processing function. The performance is excellent, but it is prone to error in complex environments, such as including aerial images, ordinary images and infrared images. For the analysis of crop nutrition information can be knowledge decision, through multiple information detection, including the detection of cotton diseases and pests, weed identification and detection of cotton core, GPT-4, when processing images, for complex image layered function memory effect is good, has also been widely used in image processing, behavior informatics analysis, etc., and is able to summarize the image details, shows the potential in the field of poultry management.

4. Model Construction of Generative AI in Agricultural Planning

4.1. Data Collection and Preprocessing

Collect agriculture-related data, including information on climate, soil type, crop growth cycle, yield, etc. Then, the data is cleaned, deweighted and standardized to ensure the data quality and consistency. Furthermore, key factors are extracted by feature engineering to provide effective input for model training, with the data source $D = D1, D2, \dots, Dn$, where Di represents the i th data source. Data type: $T = T1, T2, \dots, Tm$, where Tj represents the j th data type (such as remote sensing data, meteorological data, soil data, etc.).

1) Data cleaning

Dclean = D Dnoise, where Dnoise is the noise data. Missing values were filled in by using interpolation, mean, median, etc.

2) Data integration

Dintegrated = D1 D2... Dn, incorporating data from different data sources.

3) Data conversion

And xnorm = xmaxxmin inxxmin, zoom the data to the [0,1] interval.

$$z = \frac{x-\mu}{\sigma} \tag{3}$$

Where μ is the mean and σ is the standard deviation, the data are transformed into a distribution with mean 0 and standard deviation 1.

4.2. Generative AI model Selection and Construction

In agricultural planning, the selection and construction of generative AI models is the core link to ensure the efficient operation of agricultural decision support systems. Choosing the appropriate generative AI model is the key. Common generative AI models include generative adversarial networks (GANs), variational autoencoders (VAEs), and other deep learning-based generative models. Based on the specific requirements of agricultural planning, such as crop growth prediction, soil management, and irrigation optimization, the most suitable model for data Generation and simulation tasks can be selected.

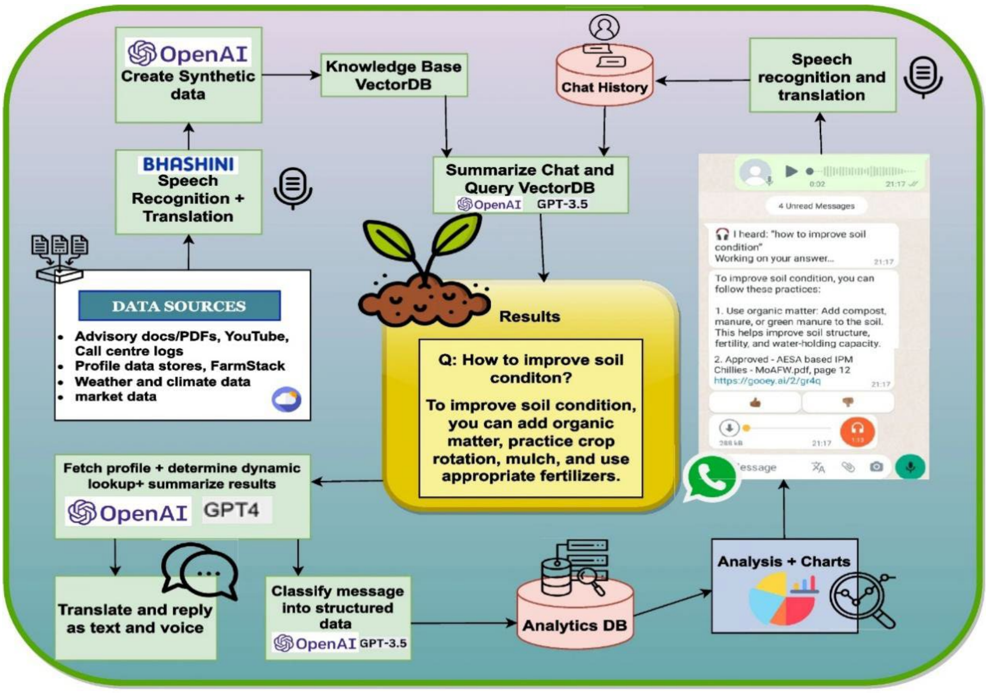

Figure 2. Construction process and application of the agricultural large model.

In Figure 2, generative adversarial networks (GANs) perform well in generating new agricultural scenarios and data simulations. It continuously optimizes the quality of the data generated by the model through two networks (generators and discriminators), which is suitable for predicting the impact of future climate change on crops, or to simulate the changes in crop yield caused by different agricultural management strategies. Variational autoencoders (VAEs) can be used to generate agricultural data with potential variables, provide diverse simulation results for different scenarios of agricultural production, and help planners make flexible decisions in uncertain environments. When building a generative AI model, it is necessary to collect a large amount of historical data and real-time data to provide enough training materials for the model. Conduct the model design and training to ensure that it can accurately capture the complex relationships in the agricultural environment. Using techniques such as enhanced learning or transfer learning can further improve the generalization ability of the model to adapt it to agricultural changes in different regions and time periods.

4.3. Model Parameter Optimization and Training

First with a set of training parameter sets $(a_1,\ b_1)$, …, $(a_i,\ b_i)$, Where the image samples are represented as a, Image samples were identified as a sample b and $b \in (0,1)$. The specific cycle process has three steps, following as follows:

1) Initialization of the parameter weight value, according to the following equation (1), for the first m training of classifiers, and detraining of image sample weights with serial number n, To calculate the initial weight value $w_{m,n}$:

$$Q_{m,n} = \frac{w_{m,n}}{\sum_{k-i}^{t} w_{m,n}} \tag{4-1}$$

2) Represents the feature, and θ represents the threshold value:

$$\sigma_l = \sum_n Q_n |h(a_i, \sigma, e, \theta) - b_i| \tag{4-2}$$

$$D(a) = \begin{cases} 1 & \sum_{m=1}^{M} \beta_m h_m(a) \geq \frac{1}{2} \sum_{m=1}^{M} \beta \\ 0 & other \end{cases} \tag{4-3}$$

In formula (4), $\beta_m = -log\gamma_m$ (5)

5. Efficiency Improvement of Generative AI in Agricultural Planning

5.1. Decision Effectiveness Approach

As shown in Table 1, generative AI can conduct accurate analysis of agricultural data, changing from climate, soil and quantity of crop products. AI can also make complementary control of the optimal generation scheme, making adjustments based on weather changes, market environment and real-time analysis effects, as well as comprehensive optimization of crop allocation and management effects. These planning contents are no longer limited to the traditional historical limitations, but make real-time predictions based on the data, which helps to improve the overall efficiency.

Table 1. Improvement of decision-making efficiency.

The field of decision-making	Application effect	Decision improvement
Crop Selection	The optimal crop species is recommended according to soil type, climatic conditions and market demand	Increase production volume and market adaptability
Irrigation optimization	Dynamic analysis of climate change, intelligent adjustment of irrigation plan	Save water, reduce costs, and avoid excessive or insufficient crop moisture
Resource Allocation	Optimize the use of fertilizers, pesticides and other resources according to the data analysis	Improve the efficiency of resource use and reduce waste
Prediction of diseases and insect pests	Predicate potential pests and diseases in advance and generate control recommendations	Reduce pesticide use and improve crop health
Yield Prediction	Predict crop yield combined with environmental and historical data	Accurate estimate of output and optimize the market supply chain
Market Demand forecast	Analyze market data to predict future demand trends	Better docking with market demand, improve revenue

5.2. Efficiency Improvement Effect

As shown in Table 2, where the application effect of generative AI in the field of agricultural planning is shown. As can be seen from this comparison, both crop yield and water utilization have been significantly improved, the use of pesticide is reduced by 43%, and the pest rate is also reduced to 5%. From the perspective of agricultural production structure, the economic area in the unit field has increased. AI has shown obvious advantages in reducing the cost and optimizing the environment for this agricultural production, which can also help the subsequent agricultural production structure to break through.

Table 2. Efficiency improvement effect.

Territory	Pre-implementation effect	After implementation effect	Improve the range
Crop yield	The average annual output is 5000kg/mu	The average annual output is 6000kg/mu	Increase by 20%
Water utilization rate	Water resources utilization rate is 70%	Water resources utilization rate is 90%	Increase by 20%
Fertilizer utilization efficiency	Fertilizer utilization efficiency is 65%	Fertilizer utilization efficiency is 85%	Increase by 20%
Pesticide use	The amount of pesticide used per mu is 3.5kg	The amount of pesticide used per mu is 2.0kg	Increase by 43%
Cost of production	The total production cost is 12,000yuan/mu	The total production cost is 10,000yuan/mu	Increase by 17%
The incidence rate of crop diseases and insect pests	Pest and disease incidence of 15%	The incidence of pests and diseases was 5%	Increase by 10%

6. Conclusion

At present, the application of large-scale data in the agricultural field has become very diverse, and it should be based on the agricultural scale data information. Implement the analysis to understand the information integration content of large-scale data, combined with the joint efforts of enterprises, governments, research institutions and farmers, formulate effective measures to promote the sustainable development of agricultural models. Further analysis of the efficiency improvement structure of the generative AI in agricultural planning was made, and the construction characteristics of the generative AI model were understood, and the key data information was extracted to improve the management effect.

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