Application note: Autonomous operation mode identification of agricultural machinery with large language models

Weixin Zhai[1,2], Zhou Guo[1,2], Ruijing Han[1,2], Zhi Xu[1,2], Xiaoyu Cheng[1,2], Shuhua Song[3], Sun-OK Chung[4], Bingbing Hu[5], Mahmadyorzoda Usmon Mamur[6], Nozim Aliev[6], Jiawen Pan[1,2*], Caicong Wu[1,2]

(1. *College of Information and Electrical Engineering, China Agricultural University, Beijing 100083, China*;
2. *Key Laboratory of Agricultural Machinery Monitoring and Big Data Applications, Ministry of Agriculture and Rural Affairs, Beijing 100083, China*;
3. *GEOVIS Wisdom Technology Co., Ltd., Qingdao 266100, China*;
4. *Department of Smart Agricultural System, Graduate School, Chungnam National University, Daejeon 34134, Republic of Korea*;
5. *SINOMACH Digital Technology Corporation Co., Ltd. Nanjing 210000, China*;
6. *Tajik agrarian University named Shirinsho Shotemur, Dushanbe, 734003, Republic of Tajikistan*)

Abstract: Leveraging extensive trajectory data to analyze the operation modes of agricultural machinery for gathering precise spatial information is an important fundamental task for subsequent agricultural machinery trajectory research. However, complex algorithm models hinder nonspecialized researchers from further processing agricultural machinery trajectory data. In the present application note, ChatGPT is taken as an example and a complete prompt guide for large language models (LLMs) is provided for autonomously identifying the operation mode of agricultural machinery. This guide provides low-cost workflows for processing agricultural machinery trajectory data when computer science or data science expertise is lacking. It even possesses the capability to utilize newly learned algorithms such as the random forest model, which has not been previously explored in the literature for operation mode identification, to accomplish the task. To the best of our knowledge, this is the first attempt to apply LLMs to identifying agricultural machinery operation mode based on trajectory data. The complete prompt guide is publicly available at https://github.com/kakushuu/prompt-guide/.

Keywords: operation mode identification, large language models, ChatGPT, prompt guide, agricultural machinery trajectory
DOI: 10.25165/j.ijabe.20251805.9082

Citation: Zhai W X, Guo Z, Han R J, Xu Z, Cheng X Y, Song S H, et al. Application note: Autonomous operation mode identification of agricultural machinery with large language models. Int J Agric & Biol Eng, 2025; 18(5): 215–222.

1 Introduction

Agricultural machinery equipped with GNSS (Global Navigation Satellite System) sensors, distributed across various regions, generates massive amounts of trajectory data[1]. These data contain rich and precise spatiotemporal information related to agricultural cultivation and harvesting activities. As a basic step in agricultural machinery trajectory analysis, understanding the driving scenarios and activity types related to each point in an agricultural machinery trajectory through data-driven modeling is crucial for subsequent research based on agricultural machinery trajectories[2-4]. The spatiotemporal evolution patterns underlying agricultural machinery trajectories can be explored from a big data perspective, thereby providing technical support for further research and applications such as the allocation of service resources and large-scale monitoring of various operations[5-10].

Generally, researchers classify agricultural machinery trajectory data to identify the corresponding movement pattern for each trajectory point as an initial and fundamental step[11,12]. To accomplish the above process, researchers should first conduct a comprehensive literature review of relevant publications and patents. Subsequently, a computational model is developed based on the learned knowledge. Nevertheless, the aforementioned process involves substantial manual effort and requires a domain-specific skill set encompassing coding proficiency, expertise in computer science, and a comprehensive understanding of data science principles. Furthermore, the computational accuracy of the model cannot be guaranteed. Looking back to the initial objective, it is observed that many researchers were simply interested in deriving precise spatio-temporal information like operation area and operation duration[13-15]. Nevertheless, their enthusiasm for further

Received date: 2024-05-19 **Accepted date:** 2025-06-17

Biographies: Weixin Zhai, PhD, Associate Professor, research interest: big data of spatio temporal, big data mining of agricultural machinery, cartography and geographic information system, Email: zhaiweixin@cau.edu.cn; **Zhou Guo**, PhD, research interest: big data mining of agricultural machinery, Email: guozhoucau@163.com; **Ruijing Han**, MS, research interest: big data mining of agricultural machinery, Email: hanrj2@cau.edu.cn; **Zhi Xu**, MS, research interest: big data mining of agricultural machinery, Email: xuzhihh@163.com; **Xiaoyu Cheng**, Master, research interest: data science and big data technology, Email: chengxiaoyu@cau.edu.cn; **Shuhua Song**, PhD, Research Scientist, research interest: spatial big data mining, cartography and geographic information system, Email: song-shuhua@163.com; **Sun-Ok Chung**, PhD, Professor, research interest: precision agriculture, Email: sochung@cnu.ac.kr; **Bingbing Hu**, MSr, research interest: precision agriculture, Email: 1353232901@qq.com; **Mahmadyorzoda Usmon Mamur**, PhD, Professor, research interest: precision agriculture, Email: rectortau31@mail.ru; **Nozim Aliev**, PhD, Professor, research interest: precision agriculture, Email: nnozim@gmail.com; **Caicong Wu**, PhD, Professor, research interest: unmanned driving and autonomous operation of agricultural machinery, big data mining of agricultural machinery, Email: wucc@cau.edu.cn.

***Corresponding author: Jiawen Pan**, PhD candidate, research interest: computational intelligence, computer vision. College of Information and Electrical Engineering, China Agricultural University, Beijing 100083, China. Tel: +86-15588880367, Email: cau_panjiawen@cau.edu.cn.

research has been dampened by the significantly time-consuming process of processing trajectory data from agricultural machines.

With the arrival of artificial general intelligence (AGI), there is extensive and promising potential for synergies between AI and precision agriculture. This has motivated us to develop an AI-powered assistant that provides a low-cost and simple workflow, enabling nonexpert researchers to efficiently access the required information. The emergence of large language models (LLMs), including GPT-3.5 and GPT-4 and its further releases, has made it possible to achieve this process, and these models have been demonstrated to be feasible in various fields[16-21]. This implies that LLMs can be used to integrate interdisciplinary knowledge, effectively handle labor-intensive and time-consuming tasks such as literature review, computational model learning, and data analysis, and ultimately complete agricultural machinery trajectory processing. Therefore, under this motivation, ChatGPT was chosen as an example and a prompt guide was developed. With its advanced language comprehension capabilities, ChatGPT can effectively assist in reviewing and summarizing research articles, offering comprehensive introductions, insightful suggestions, and algorithmic functionalities across various research domains[16,17,19]. This guide trains ChatGPT to cooperate with human researchers via artificial intelligence assistance. Its purpose is to enhance text understanding, facilitate agricultural machinery trajectory data processing, and ultimately accelerate the research process with minimal prerequisite coding expertise. In the present application note, ChatGPT-4 is utilized as the foundation for autonomously identifying the operation mode of agricultural machinery. The identification workflow involves assigning an expert to ChatGPT-4 to provide algorithmic knowledge, clarify terminology, conduct mode identification experiments using different algorithms, evaluate results, and iteratively fine-tune parameters until an optimal outcome is achieved. The proposed workflow, based on the GPT-4 architecture, provides enhanced language understanding and generates contextually relevant responses. This prompt engineering approach enables researchers, regardless of their familiarity with machine learning, to accomplish operation mode identification of agricultural machinery, thereby bridging the gap between the fields of agricultural science and computational science more effectively. Moreover, it is investigated whether the random forest (RF) model, which has not been previously utilized for operation mode identification in existing literature, can be applied effectively with ChatGPT. Experimental results revealed its capacity to leverage the newly acquired algorithm to perform operation mode identification.

2 Materials and methods

2.1 Dataset

To validate the effectiveness of our approach, a public experimental dataset consisting of agricultural machinery trajectories obtained from different provinces in China in June 2021 was utilized. These trajectories obtained from combining harvesters with GNSS positing sensors can record real-time data such as longitude, latitude, speed, direction, and altitude. This dataset was provided by the Key Laboratory of Agricultural Machinery Monitoring and Big Data Application, Ministry of Agriculture and Rural Affairs. The time intervals of the points in each trajectory are 5 s. Trajectory data are recorded in table file format, involving attributes such as coordinates (longitude and latitude, WGS84), speed (m/s), direction (°), and time stamps ($YYYY:MM:DD$–$hh:mm:ss$). The data can be directly dragged to be uploaded to the dialogue with ChatGPT. Three representative samples with high-quality trajectory data were selected for each grain type (wheat and paddy) to ensure effective demonstration. These samples exhibit stable sampling intervals, high sampling frequency, and absence of positional drift. Moreover, the three samples per grain type cover common operating modes, with evenly distributed proportions of data categories. Therefore, more trajectory samples are used for comparison experiments. For example, within the wheat datasets, the three trajectory samples comprise 4 920 597 and 4861 points respectively, distributed across different counties and spanning distinct dates. Each represents a single combine harvester's one-day operational trajectory. Their derived field sizes are 85 966 m^2, 4026 m^2, and 60 913 m^2 respectively. The relevant public datasets can also be found at: https://github.com/Agribigdata/Field_road_dataset.

2.2 Identification workflow with ChatGPT-4.0

In this paper, ChatGPT, a widely used LLM framework, is selected as the groundwork for identifying autonomous operation mode of agricultural machinery. ChatGPT-4.0 is an advanced conversational AI model developed by OpenAI. It utilizes the GPT-4.0 architecture to provide improved language understanding and generate more contextually relevant and coherent responses in chat-based interactions. The proposed identification workflow can be separated into several steps, as indicated in Figure 1. We begin by designating the role of an expert in identifying agricultural machinery operation mode to ChatGPT-4.0, ensuring that the primary task is understood. Leveraging its vast linguistic sources, ChatGPT-4.0 possesses a foundational understanding of basic algorithms. To strengthen its ability to perform operation mode identification, ChatGPT-4.0 is provided with several algorithm research documents, including knowledge about decision trees (DT), density-based spatial clustering of applications with noise (DBSCAN), and RF. Additionally, it is clarified that terms such as "operation mode identification", "field-road classification", and "field-road segmentation" convey the same meaning, allowing ChatGPT-4.0 to grasp their equivalence. Furthermore, specialized trajectory research documents related to operation mode identification were uploaded, allowing ChatGPT-4.0 to acquire expert knowledge and delve into identifying agricultural machinery operation modes using DT, DBSCAN, and RF. Specifically, for DT and RF algorithms, ChatGPT-4.0 will initially calculate the differences in speed, direction, and the haversine distance between adjacent trajectory points. Next, following task initiation confirmation for ChatGPT-4.0, three trajectory data samples were supplied to the ChatGPT-4.0. Drawing upon acquired algorithmic knowledge, ChatGPT-4.0 proceeds to perform operation mode identification, generating results in Excel format. These results contain information that can be visualized to assess the algorithm's performance. Evaluation metrics, including precision, recall, and F1 score, are presented alongside manually labeled data, serving as the ground truth. Users can evaluate the results based on their basic understanding of agriculture to determine whether parameter fine-tuning is necessary for improved outcomes. Subsequently, the procedure can be repeated according to the user's objective until an optimal outcome is attained.

2.3 Prompt learning strategy

We utilized an interactive prompt with ChatGPT to complete the entire experiment, enabling us to identify autonomous agricultural machinery operation mode. By engaging in interactive conversations with the ChatGPT, its language capabilities are leveraged to effectively communicate and provide input, allowing us to explore and accomplish diverse operation mode identification

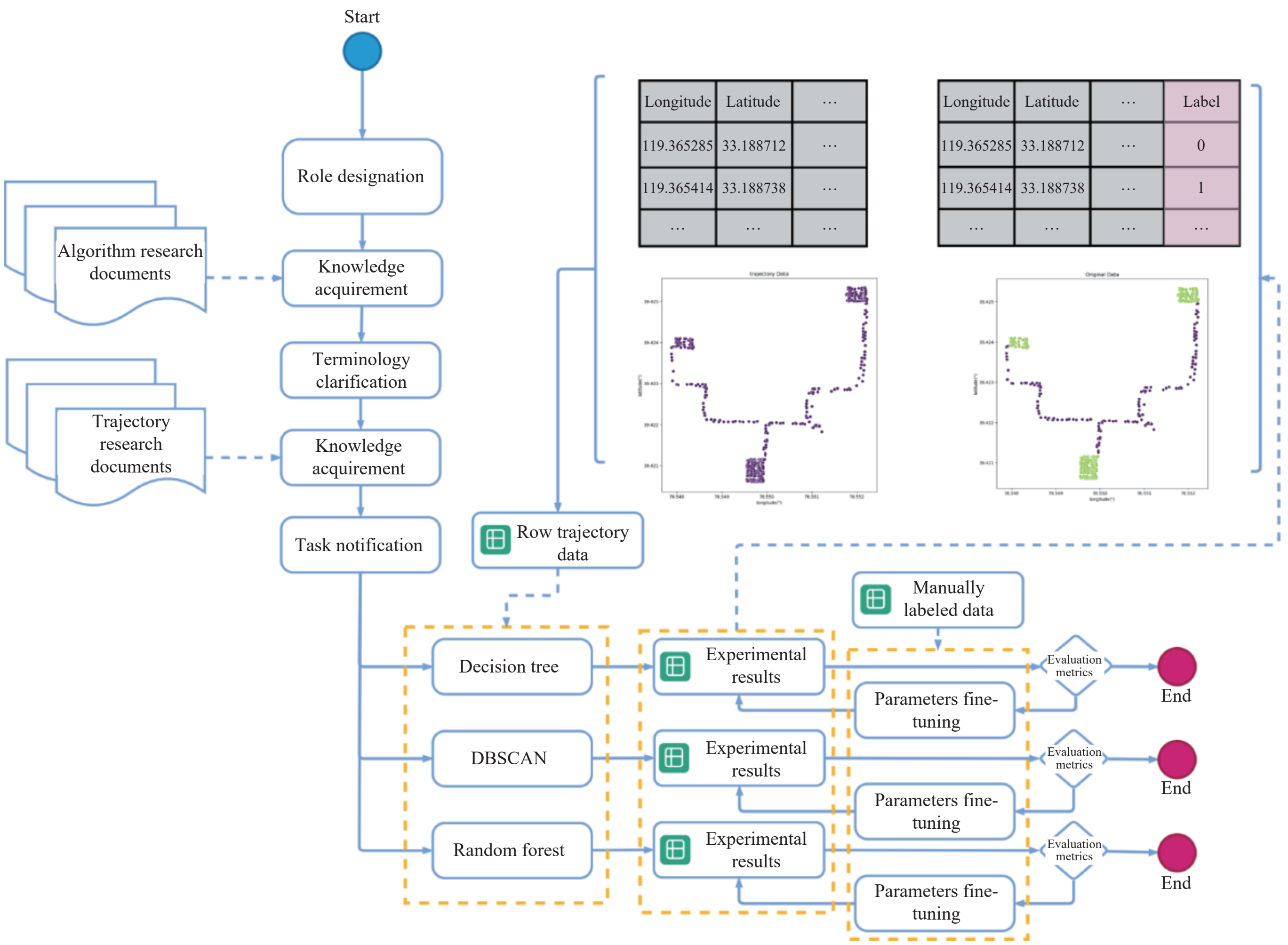


Figure 1　Agricultural machinery operation mode identification workflow with ChatGPT-4

tasks. This interactive approach facilitates a dynamic and adaptable experimentation process, ensuring flexibility and versatility in identifying various operation modes. The complete prompt guide is publicly available at https://github.com/kakushuu/prompt-guide/. The dynamic interaction between a human user without computer science knowledge and ChatGPT-4.0 is demonstrated (Figure 2). In the illustration, a person is shown engaging with ChatGPT-4.0 through a user interface, such as a chat window on a computer or mobile device. The user inputs prompts and data files, while ChatGPT-4.0 responds with generated text-based replies. The interaction is depicted as a back-and-forth conversation, highlighting the exchange of information and ideas between the human user and the AI model.

2.4　Performance metrics

To assess the effectiveness of the trajectory processing models, three performance metrics are employed: precision, recall, and F1-score. Precision measures the model's ability to correctly identify trajectory points belonging to the "positive" category within the positive dataset. Recall indicates the model's capability to accurately predict "positive" class trajectory points within the ground truth data. The F1-score represents the harmonic mean of precision and recall. The considered trajectory segment $S = s_1, s_2, \ldots, s_i$, $\forall i \in [1, N]$ contains N trajectory points and $N-1$ intervals $L_j = \overrightarrow{S_j S_{j+1}}$, $\forall j \in [1, N-1]$. Each L_j inherits its operation from the segment in which it is located. Each operation $oper_k$ ("Filed" or "Road") can be represented by precision, recall, and F1-score, respectively. The mathematical formulas are as follows:

$$Precision(oper_k) = \frac{Time(correct\_intervals(oper_k))}{Time(predicted\_intervals(oper_k))} \tag{1}$$

$$Recall(oper_k) = \frac{Time(correct\_intervals(oper_k))}{Time(ground\_truth\_intervals(oper_k))} \tag{2}$$

$$\text{F1-score}(oper_k) = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{3}$$

where, $correct\_intervals(oper_k)$ are the intervals in which the predicted operations match the ground truth, and $predicted\_intervals(oper_k)$ are the intervals classified as $oper_k$. $ground\_truth\_intervals(oper_k)$ are the intervals whose truth operations are $oper_k$, and $time(\cdot)$ is calculated as the sum of the time costs for all the considered intervals.

3　Results and discussion

3.1　Experimental setup

In the present study, three models were selected as the learning instances of ChatGPT for processing real agricultural machinery trajectory data: DBSCAN, decision tree (DT), and random forest (RF) models. For the former two models, there are already public methods available from literature. The last model represents a new attempt to verify whether ChatGPT can complete the work using existing algorithms only if it understands the predefined task; that is, there is no associated task document for the algorithm provided for ChatGPT. Simultaneously, we also deployed these models locally for comparison to evaluate the effectiveness of the proposed prompt guide.

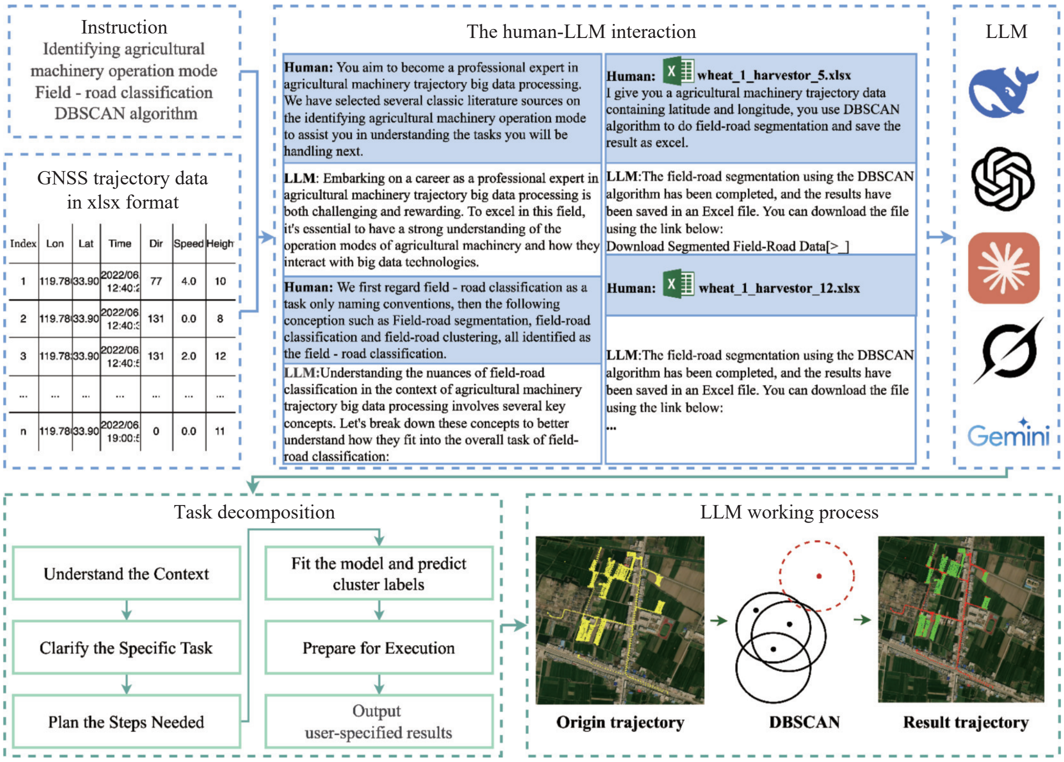


Figure 2 Illustration of a GPT-4.0 chat interface interaction

3.2 Method evaluation results

Tables 1 and 2 summarize the performance of the three models in recognizing agricultural machinery operation modes under both prompted and unprompted conditions. Trajectory processing models refer to the algorithm executed by ChatGPT, field operation trajectory represents the trajectory produced by agricultural machinery operating in the field, and road driving trajectory denotes the trajectory of agricultural machinery on the road, and three evaluation metrics are reported in Section 2.4. As shown in Table 1, RF w/ ChatGPT achieved the best results on one data sample (Sample 03), with an F1-score of 98.06%, and DT w/ ChatGPT obtained the competitive results on data samples 01 (96.79%) and sample 02 (99.55%). This indicates that the proposed prompt engineering can guide the ChatGPT to effectively tackle the operation mode identification task of agricultural machinery.

Then, it is evident that the difference between the results of the three models implemented by ChatGPT and the locally deployed models is minimal. These results demonstrate that the non-expert can complete agricultural machinery operation mode identification through the proposed prompt engineering, and can obtain results that approximate the locally deployed model.

In addition, Figure 3 and Figure 4 illustrate the processed trajectory-mapped remote sensing image. Most of the processed trajectories can be classified under the corresponding map background, which effectively illustrates that the large prediction model can be used to complete the agricultural machinery operation

Table 1 Overall performance of wheat datasets

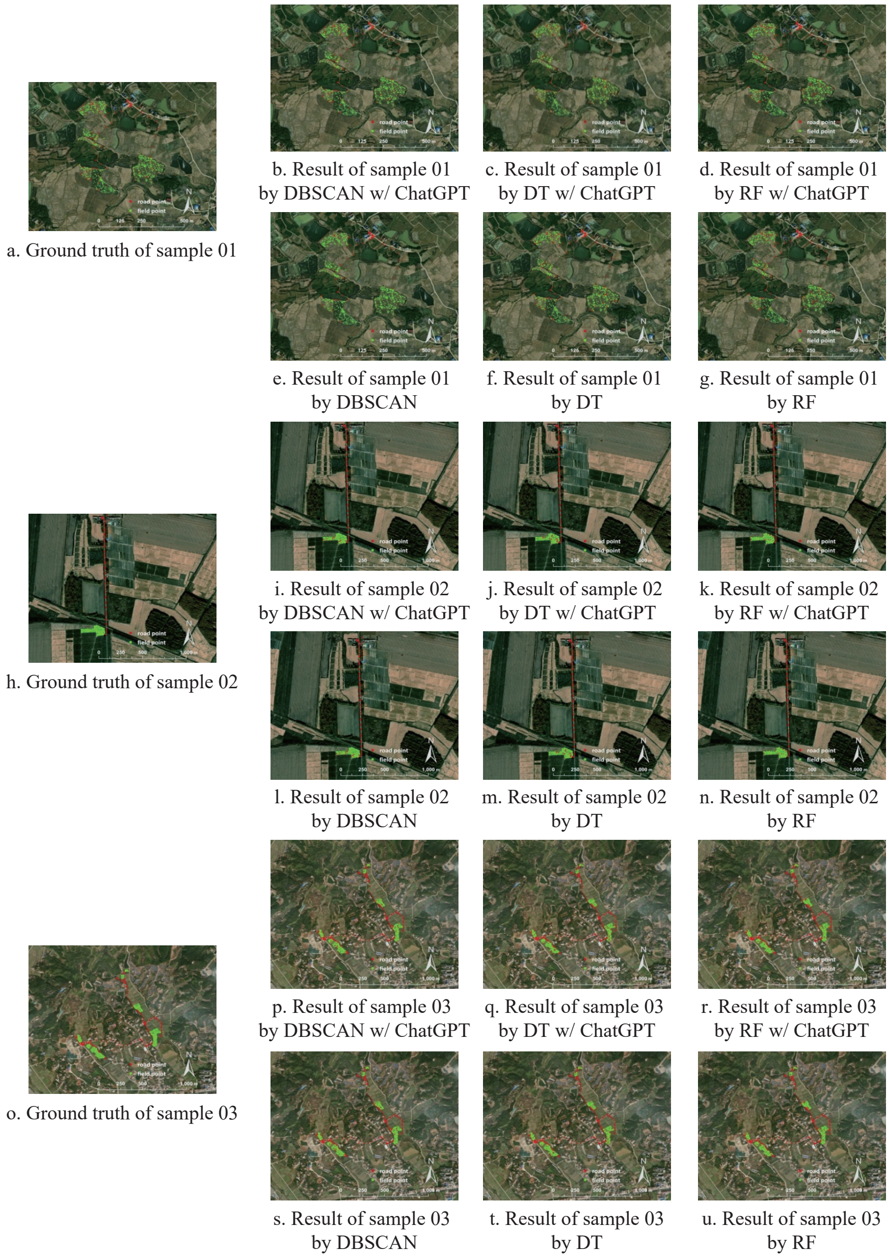
Sample index	Trajectory processing models	Field operation trajectory			Road driving trajectory			All trajectory		
		F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall
01	DBSCAN	98.3623	96.9589	99.8070	58.6667	92.4369	42.9687	78.5145	94.6979	71.3878
	DT	99.6362	99.4446	99.8284	93.1174	96.6386	89.8437	96.3768	98.0416	94.8361
	RF	99.9464	99.9356	99.9571	99.0215	99.2156	98.8281	99.4839	99.5756	99.3926
	DBSCAN w/ ChatGPT	97.9565	97.7578	98.1560	61.2576	63.7130	58.9843	79.6070	80.7354	78.5702
	DT w/ ChatGPT	99.6790	99.4662	99.8927	93.9024	97.8813	90.2343	96.7907	98.6738	95.0635
	RF w/ ChatGPT	99.8285	99.7857	99.8713	96.8503	97.6190	96.0937	98.3394	98.7024	97.9825
02	DBSCAN	98.3534	96.7602	100	94.6996	100	89.9328	96.5265	98.3801	94.9664
	DT	99.8882	100	99.7767	99.6655	99.3333	100	99.7769	99.6667	99.8883
	RF	99.7772	99.5555	100	99.3243	100	98.6577	99.5508	99.7777	99.3288
	DBSCAN w/ ChatGPT	96.8648	93.9203	100	89.2193	100	80.5369	93.0420	96.9601	90.2684
	DT w/ ChatGPT	99.7762	100	99.5535	99.3333	98.6754	100	99.5548	99.3377	99.7767
	RF w/ ChatGPT	99.6648	99.7762	99.5535	98.9967	98.6667	99.3289	99.3307	99.2214	99.4412
03	DBSCAN	96.4038	94.7010	98.1689	32.2448	48.7654	24.0853	64.3243	71.7332	61.1271
	DT	96.4870	94.3121	98.7646	26.2443	50.8771	17.6829	61.3657	72.5946	58.2237
	RF	99.4065	99.0365	99.7793	91.3183	96.5986	86.5853	95.3624	97.8176	93.1823
	DBSCAN w/ ChatGPT	97.1287	94.4178	100	30.9278	100	18.2926	64.0283	97.2089	59.1463
	DT w/ ChatGPT	96.6318	94.3277	99.0514	27.0396	57.4257	17.6829	61.8357	75.8767	58.3671
	RF w/ ChatGPT	99.7468	99.5386	99.9558	96.3893	99.3527	93.5975	98.0680	99.4457	96.7767

Table 2 Overall performance of paddy datasets

Sample index	Trajectory processing models	Field operation trajectory			Road driving trajectory			All trajectory		
		F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall
01	DBSCAN	88.6179	83.6852	94.1685	37.7778	55.7377	28.5714	78.2227	77.9709	80.7560
	DT	92.7639	91.7840	93.7650	70.2439	73.4694	67.2897	88.1654	88.0442	88.3588
	RF	94.0230	89.4967	99.0315	70.7865	94.0299	56.7568	89.1008	90.4570	90.0763
	DBSCAN w/ ChatGPT	88.4632	83.5969	94.0697	37.6485	55.6276	28.4965	78.1656	77.8676	80.6423
	DT w/ ChatGPT	92.5634	91.6245	93.6589	70.1653	73.3468	67.1638	88.0689	88.0367	88.2467
	RF w/ ChatGPT	94.0664	89.2466	98.9527	69.9565	94.0199	56.6237	89.0004	90.3765	89.1263
02	DBSCAN	85.6716	88.9922	82.5899	43.8596	38.2653	51.3699	78.4130	80.1860	77.1700
	DT	95.4128	93.6937	97.1963	71.4286	80.6452	64.1026	91.7157	91.6823	92.0949
	RF	96.1905	92.6606	100.0000	81.3953	100.0000	68.6275	93.2081	94.1400	93.6759
	DBSCAN w/ ChatGPT	85.5763	88.8524	82.4693	42.9655	38.1937	51.3564	78.3465	80.1975	77.1567
	DT w/ ChatGPT	95.3469	93.5672	97.0466	71.3492	80.6127	63.9953	91.6965	91.6652	91.9969
	RF w/ ChatGPT	96.0767	92.5637	99.9636	81.2994	100.0000	68.5376	93.1693	94.1665	93.6624
03	DBSCAN	90.8098	88.4752	93.2710	18.5484	24.2105	15.0327	81.7698	80.4355	83.4832
	DT	94.4024	92.8571	96.0000	49.3151	58.0645	42.8571	89.2426	88.8754	89.9183
	RF	96.2293	93.0029	99.6875	64.7887	95.8333	48.9362	92.2028	93.3654	93.1880
	DBSCAN w/ ChatGPT	90.7699	88.4696	93.2682	18.4369	24.2069	15.0317	81.7613	80.4297	83.4795
	DT w/ ChatGPT	94.3994	92.8546	95.9973	49.3111	58.0674	42.8514	89.2413	88.8699	89.8692
	RF w/ ChatGPT	96.2164	93.0019	99.6754	64.7731	95.8234	48.9354	92.2019	93.3245	93.1766

a. Ground truth of sample 01 in wheat datasets
b. Result of sample 01 by DBSCAN w/o ChatGPT
c. Result of sample 01 by DT w/ ChatGPT
d. Result of sample 01 by RF w/ ChatGPT
e. Result of sample 01 by DBSCAN
f. Result of sample 01 by DT
g. Result of sample 01 by RF
h. Ground truth of sample 02 in wheat datasets
i. Result of sample 02 by DBSCAN w/ ChatGPT
j. Result of sample 02 by DT w/ ChatGPT
k. Result of sample 02 by RF w/ ChatGPT
l. Result of sample 02 by DBSCAN
m. Result of sample 02 by DT
n. Result of sample 02 by RF
o. Ground truth of sample 03 wheat datasets
p. Result of sample 03 by DBSCAN w/ ChatGPT
q. Result of sample 03 by DT w/ ChatGPT
r. Result of sample 03 by RF w/ ChatGPT
s. Result of sample 03 by DBSCAN
t. Result of sample 03 by DT
u. Result of sample 03 by RF

Figure 3 Ground truth and agricultural machinery operation mode identification results in three trajectory samples of wheat datasets



a. Ground truth of sample 01
b. Result of sample 01 by DBSCAN w/ ChatGPT
c. Result of sample 01 by DT w/ ChatGPT
d. Result of sample 01 by RF w/ ChatGPT
e. Result of sample 01 by DBSCAN
f. Result of sample 01 by DT
g. Result of sample 01 by RF
h. Ground truth of sample 02
i. Result of sample 02 by DBSCAN w/ ChatGPT
j. Result of sample 02 by DT w/ ChatGPT
k. Result of sample 02 by RF w/ ChatGPT
l. Result of sample 02 by DBSCAN
m. Result of sample 02 by DT
n. Result of sample 02 by RF
o. Ground truth of sample 03
p. Result of sample 03 by DBSCAN w/ ChatGPT
q. Result of sample 03 by DT w/ ChatGPT
r. Result of sample 03 by RF w/ ChatGPT
s. Result of sample 03 by DBSCAN
t. Result of sample 03 by DT
u. Result of sample 03 by RF

Figure 4 Ground truth and agricultural machinery operation mode identification results in three trajectory samples of paddy datasets

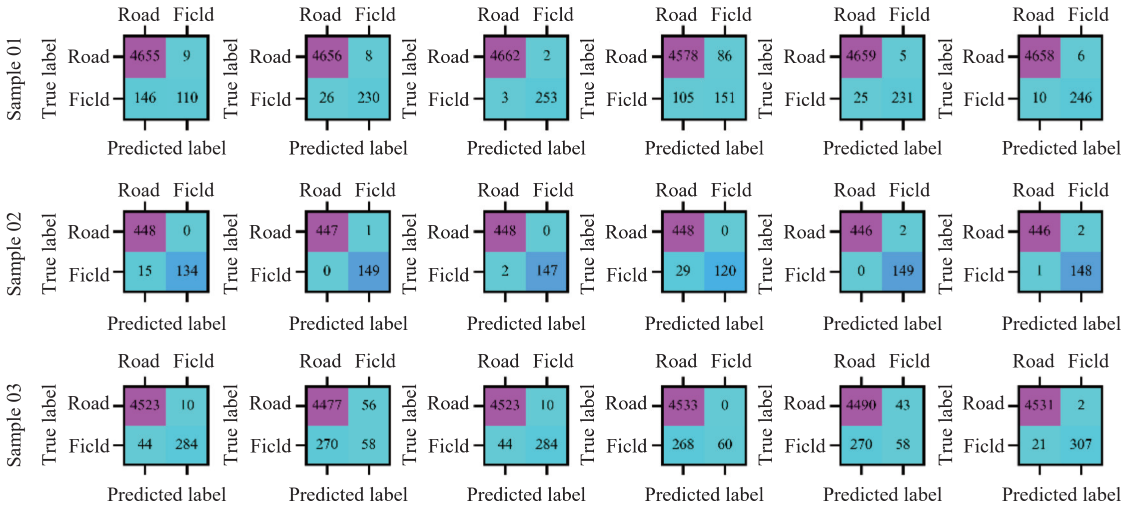
mode identification task. Figure 5 illustrates the confusion matrices corresponding to different models on three wheat trajectory samples.

3.3 Method analysis and discussion

In this section, we illustrate the findings and limitations of the study by analyzing the results. The experiment results show that the proposed prompt engineering can guide LLM to achieve relevant models to complete the operation mode identification of agricultural machinery, and the performance difference with locally deployed models is minimal. This demonstrates that agricultural professionals who lack computer expertise can obtain the necessary trajectory data at a lower cost. It avoids a series of tasks such as learning computer professional knowledge, learning coding, understanding, and developing/reproducing related models.

In addition, accurate identification via RF showed that LLM has strong learning ability and can use standard algorithms to autonomously complete related tasks on the premise of understanding the relevant tasks (standard refers to specific task documents that do not allow ChatGPT to learn the algorithm). This approach may provide a low-cost way to study related scientific topics from another perspective.

The present study demonstrates the immense potential of the large language models for further advancements in various aspects. First, the large language model enhanced the natural language comprehension on technical or academic works for researchers, accelerating the speed of knowledge absorption and dissemination. Second, the research on this conversational interaction format allows for a more thorough presentation of work and eliminates a series of tasks such as setting up environments. Third, the large language model has proved its suitability to become an intelligent assistant for specific domains or industries, providing accurate and context-aware responses tailored to the needs of various fields. Fourth, this approach allows researchers to customize the behavior and responses of large language models based on their research preferences, thus enhancing the model specialization. Fifth, the guide does not require users to deploy large language models. Users can use the agricultural machinery trajectory to identify the operation mode simply by inputting prompts according to the guide. As large language models in the real world are gradually opened up (such as ChatGPT, which has opened API restrictions, Deepseek



Note: From left to right: the results generated by DBSCAN, DT, RF, DBSCAN with ChatGPT, DT with ChatGPT, RF with ChatGPT.

Figure 5 Confusion matrices for all models on three trajectory samples

and Claude, etc.), the guide is expected to further unleash its application potential. For users who lack a stable network environment, this article recommends using LLMs local deployment tools (such as Ollama) to deploy open source large-scale models, which can be used in an offline environment without API restrictions.

4 Conclusions

This note develops a low-cost workflow that uses prompt engineering to guide ChatGPT to autonomously construct a data-driven computational model of agricultural machinery trajectory operation modes from diverse formats and styles of the scientific literature. As an application result, this note provided a related comprehensive ChatGPT prompt guide based on agricultural machinery trajectory data. This guide allows researchers, regardless of their expertise, to effectively process their own agricultural machinery trajectory data by providing step-by-step instructions. In addition, the most striking result to emerge from the data is that even when ChatGPT does not explicitly learn the literature related to a specific algorithm such as RF, it can still employ this algorithm to accomplish the task after acquiring knowledge of the predefined objective. This approach may lead to the creation of new low-cost scientific research methodologies. However, due to the limitations of the capabilities of current large language models, it is difficult to rely on prompts to implement models that include complex training processes. Future work will focus on ongoing developments in large language models, with continuous refinement of related prompt engineering to better serve agricultural machinery trajectory data processing tasks. This research successfully demonstrated the potential of LLMs in the domain of agricultural research and contributed to further exploration of LLMs in agricultural sciences.

Acknowledgements

This research was financially supported by the National Natural Science Foundation of China (Grant No. 32301691), the National Key R&D Program of China and Shandong Province, China (Grant No. 2025YFE0103600 and 2021YFB3901300), the National Precision Agriculture Application Project (Grant No. JZNYYY001), the National Key R&D Program of China (Grant No. 2021YFD13000500, 2023YFB3904905 and 2022YFC3301605), the Project of Research and Demonstration of a Water Intelligent Monitoring System based on Domestic High-resolution Remote Sensing Multi-satellite Fusion (24-1-2-QLJH-7-GX).

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, ChatGPT was not involved in the writing process. It only served as a calculation component to process the agricultural machinery trajectory data according to the proposed prompt engineering.

Data availability statements

The datasets generated during the study are available at: https://github.com/Agribigdata/Field_road_dataset

[References]

[1] Wu C C, Li D, Zhang X, Pan J, Quan L, Yang L, et al. Application note: China's agricultural machinery operation big data system. Comput. Electron. Agric., 2023; 205: 107594.

[2] Donat M, Geistert J, Grahmann K, Bellingrath-Kimura S D D. Field path optimization to reduce headland and turning maneuvers at regional scales: automated detection of cultivation direction in the state of Brandenburg, Germany. Precision Agriculture, 2023; 24(5): 2126–2147.

[3] Kinoshita R, Rossiter D, van Es H. Spatio-temporal analysis of yield and weather data for defining site-specific crop management zones. Precision Agriculture, 2021; 22(6): 1952–1972.

[4] Zhai W X, Mo G Z, Xiao Y Z, Xiong X Y, Wu C C, Zhang X Q, et al. GAN-BiLSTM network for field-road classification on imbalanced GNSS recordings. Computers and Electronics in Agriculture, 2024; 216: 108457.

[5] Li D, Liu X, Zhou K, Sun R Z, Wang C T, Zhai W X, et al. Discovering spatiotemporal characteristics of the trans-regional harvesting operation using big data of GNSS trajectories in China. Computers and Electronics in Agriculture, 2023; 211: 108003.

[6] Zhai W X, Xiong X Y, Mo G Z, Xiao Y Z, Wu C C, Xu Z, et al. A Bagging-SVM field-road trajectory classification model based on feature enhancement. Computers and Electronics in Agriculture, 2024; 217: 108635.

[7] Zhai W X, Xu Z, Pan J W, Guo Z, Wu C C. A general image classification model for agricultural machinery trajectory mode recognition. Computers and Electronics in Agriculture, 2024; 227: 109629.

[8] Xiao Y Z, Mo G Z, Xiong X Y, Pan J W, Hu B B, Wu C C, et al. DR-XGBoost: An XGBoost model for field-road segmentation based on dual feature extraction and recursive feature elimination. Int J Agric & Biol Eng, 2023; 16(3): 169–179.

[9] Zhai W X, Xu Z, Liu J M, Xiong X Y, Pan J W, Chung S-O, et al. Feature deformation network with multi-range feature enhancement for agricultural machinery operation mode identification. Int J Agric & Biol Eng, 2024; 17(4): 265–275.

[10] Pan J W, Wu C C, Zhai W X. A hybrid genetic slime mould algorithm for

parameter optimization of field-road trajectory segmentation models. Information Processing in Agriculture, 2024; 11(4): 590–602.

[11] Chen Y, Li G Y, Zhang X Q, Jia J P, Zhou K, Wu C C. Identifying field and road modes of agricultural Machinery based on GNSS Recordings: A graph convolutional neural network approach. Computers and Electronics in Agriculture, 2022; 198: 107082.

[12] Poteko J, Eder D, Noack P O. Identifying operation modes of agricultural vehicles based on GNSS measurements. Computers and Electronics in Agriculture, 2021; 185: 106105.

[13] Huang J H, Liang S, Wu C C, Kou Z H, Chen Y. Evaluation system for agricultural machinery operation based on smartphone sensors. Applied Engineering in Agriculture, 2022; 38(2): 227–241.

[14] Li D, Liu X, Zhou K, Sun R Z, Wang C T, Zhai W X, et al. Discovering spatiotemporal characteristics of the trans-regional harvesting operation using big data of GNSS trajectories in China. Computers and Electronics in Agriculture, 2023; 211: 108003.

[15] Xiong X G, Yang J, Zhong R H, Dong J W, Huang J F, Ting K C, et al. Integration of harvester trajectory and satellite imagery for large-scale winter wheat mapping using deep positive and unlabeled learning. Computers And Electronics In Agriculture, 2024; 216: 108487.

[16] Qing J J, Deng X L, Lan Y B, Li Z K. GPT-aided diagnosis on agricultural image based on a new light YOLOPC. Computers and Electronics in Agriculture, 2023; 213: 108168.

[17] Tzachor A, Devare M, Richards C, Pypers P, Ghosh A, Koo J, et al. Large language models and agricultural extension services. Nature Food, 2023; 4(11): 941–948.

[18] Wang X L, Fang M, Zeng Z C, Cheng T. Where would i go next? Large language models as human mobility predictors. arXiv: 2308.15197, 2024. DOI: 10.48550/arXiv.2308.15197

[19] Zheng Z L, Zhang O F, Borgs C, Chayes J T, Yaghi O M. ChatGPT chemistry assistant for text mining and the prediction of MOF synthesis. Journal of the American Chemical Society, 2023; 145(32): 18048–18062.

[20] Xu J W, Tao R. Map reading and analysis with GPT-4V (ision). ISPRS International Journal of Geo-Information, 2024; 13(4): 127.

[21] Tao R, Xu J W. Mapping with chatgpt. ISPRS International Journal of Geo-Information, 2023; 12(7): 284.