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[1]Saurabh Bhattacharya

[2]Dr. Manju Pandey

# Enhancing Agricultural Knowledge Management using an efficient & Novel Ontology-Based Approach Leveraging BERT-GPT and Graph Recurrent Q Learning Network

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**Abstract:** - Agriculture, as one of the key drivers for human civilization, demands efficient methods for managing the extensive domain-specific knowledge. While ontologies, structured sets of terms and relationships within a specific domain, have played a pivotal role in structuring agricultural data, existing models lack the precision and adaptability necessary for the dynamic agricultural environment. This paper proposes a novel framework that integrates the strengths of BERT (Bidirectional Encoder Representations from Transformers) GPT (Generative Pre-trained Transformer), and Graph Recurrent Q Learning Network (GRQLN) for developing a dynamic and efficient ontology tool. BERT-GPT, with its powerful natural language processing capabilities, allows for accurate feature extraction from diverse text data, including government and farming sources. Meanwhile, GRQLN leverages graph neural networks and reinforcement learning to convert these features into an ontology graph, optimizing the representation process. The integration of these advanced technologies not only addresses the limitations of existing models but also enhances the precision of ontological query retrieval by 8.5%, accuracy by 8.3%, recall by 10.4%, AUC by 9.5%, and specificity by 9.4%, while reducing delay by 4.5%. The proposed model is a significant contribution to the field, offering a robust tool that empowers stakeholders with actionable insights derived from a vast expanse of agricultural knowledge, ultimately facilitating informed decision-making in the ever-evolving landscape of agricultural operations.

**Keywords:** Agricultural Ontology, BERT, GPT, Graph Recurrent Q Learning Network, Knowledge Management, Data-Driven Decision-Making Process

## I. INTRODUCTION

In the modern era, agriculture is evolving from traditional methods to more advanced, data-driven practices. As the world grapples with challenges such as climate change, population growth, and limited natural resources, the agricultural sector is under pressure to optimize productivity while minimizing environmental impacts. Knowledge management plays a crucial role in this transformation, providing stakeholders with the necessary information to make informed decisions that can enhance agricultural practices and sustainability. Ontologies, which are formal representations of domain-specific knowledge, have emerged as a valuable tool in organizing and representing the vast knowledge resources in agriculture. They enable the seamless integration of diverse data sources, facilitating efficient information retrieval and analysis[1]–[3] via use of Knowledge Graphs (KGs).

However, despite the potential benefits of ontologies in agriculture, there are inherent limitations to the existing tools and frameworks. Many of the current agricultural ontology tools lack specificity, richness in vocabulary, and comprehensive evaluation frameworks, hindering their efficacy in real-world applications. The increasing volume and diversity of data sources, ranging from government databases to real-time interviews with farmers, pose significant challenges in terms of data integration and representation. Traditional ontology construction and query retrieval methods often struggle to handle the complexity and volume of such data, resulting in decreased precision, recall, and increased delays in query retrieval due to use of Temporal OWL2 from Temporal JSON (TOTJ) process[4]–[6].

To address these limitations, this paper introduces a novel methodology that leverages the capabilities of BERT-GPT and Graph Recurrent Q Learning Network as “Novel Ontology-Based Approach Leveraging BERT-GPT and Graph Recurrent Q Learning Network” (NOBGQLN) to extract features from text data and construct ontology

[1]Research Scholar Department of Computer Applications National Institute of Technology, Raipur CG, India.

babu.saurabh@gmail.com

Orchid id - 0000-0002-9303-3797

[2]Associate Professor Department of Computer Application National Institute of Technology, Raipur CG, India.
mpandey.mca@nitrr.ac.in
Orchid id- 0000-0002-5817-4121

graphs, respectively. BERT-GPT, a state-of-the-art natural language processing model, is utilized to convert text data from various sources into meaningful features. These features are then used to create ontology graphs through the GRQLN, a cutting-edge machine learning model that enhances the efficiency of the ontology representation process. The integration of these advanced technologies provides a robust framework that significantly improves the precision, accuracy, recall, and overall performance of agricultural ontology tools.

This paper is structured as follows. Section 2 provides a comprehensive review of the existing literature on agricultural ontologies, highlighting the limitations and gaps in current tools and frameworks. Section 3 details the proposed methodology, including the feature extraction process using BERT-GPT and the ontology graph construction process using GRQLN. Section 4 presents the results of our experiments, demonstrating the significant improvements in precision, recall, accuracy, and other performance metrics. Section 5 discusses the implications of our findings for the agricultural sector and the potential benefits of our methodology and ontological depiction. Finally, Section 6 concludes the paper and outlines future directions for research in this domain.

**Motivation and Objectives**

**Motivation:**

The motivation behind this research stems from the critical need to enhance agricultural practices in the face of global challenges such as climate change, population growth, and resource depletion. Agriculture is a fundamental component of human livelihood and sustenance; hence, optimizing its processes and outcomes is of utmost importance. Knowledge management, facilitated by ontologies, plays a vital role in consolidating and interpreting the vast expanse of data pertinent to agriculture. However, existing ontology tools in agriculture are often limited by their lack of specificity, insufficient vocabulary richness, and absence of comprehensive evaluation frameworks. These limitations hinder the tool’s efficacy in real-world applications, ultimately impacting the decision-making process in agriculture. There is a pressing need to address these shortcomings and develop a robust, efficient, and precise ontology tool that can cater to the diverse needs of stakeholders in the agricultural domain.

**Contribution**:

This research makes a significant contribution to the field of agricultural knowledge management by introducing a novel methodology that synergizes the capabilities of BERT-GPT and Graph Recurrent Q Learning Network (GRQLN) to optimize ontology tools. Our approach innovatively utilizes BERT-GPT, a state-of-the-art natural language processing model, to extract meaningful features from text data derived from various sources, including government databases, farming resources, and real-time interviews. The extracted features are then employed to construct ontology graphs through the GRQLN, a pioneering machine learning model that significantly enhances the efficiency of the ontology representation process. The integration of these advanced technologies results in an ontology tool that is not only robust and efficient but also exhibits remarkable improvements in precision, accuracy, recall, and overall performance metrics.

The contributions of this research are manifold:

1. Development of a novel methodology that seamlessly integrates BERT-GPT and GRQLN for feature extraction and ontology graph construction, respectively.

2. Significant improvements in the precision, accuracy, recall, and overall performance of agricultural ontology tools, as evidenced by the experimental results.

3. Provision of a comprehensive framework that addresses the limitations and gaps in existing agricultural ontology tools and frameworks.

4. To develop an ontology tool to depict the relationship among various entities.

## II. LITERATURE REVIEW

In recent years, ontologies have emerged as a powerful tool for knowledge representation and management in agriculture, providing a structured way to organize and interpret the vast amounts of data generated in this domain. Various models and frameworks have been proposed and implemented to facilitate ontology development in agriculture, each with its own strengths and limitations.

One of the earliest approaches to agriculture ontology was the use of rule-based systems, which relied on predefined rules to classify and organize data samples[2]. While this approach was effective in capturing specific relationships between data elements, it was often limited by its inability to handle the complex and dynamic nature of agricultural data samples.

To address the limitations of rule-based systems, machine learning models were introduced, which could automatically learn and adapt to the changing patterns in the data samples. Support vector machines (SVM) and decision trees were among the first machine-learning models applied to agriculture ontology[7]–[9]. These models were successful in handling large datasets and providing accurate classifications, but they often required extensive feature engineering and were sensitive to noisy data samples.

More recently, deep learning models such as convolutional neural networks (CNN) and recurrent neural networks (RNN) have been applied to agriculture ontology, demonstrating impressive results in terms of accuracy and scalability[10]–[12] due to use of Concept Question-Answering System (CQAS) ontological processes. These models have the ability to learn complex patterns in the data without the need for extensive feature engineering. However, they require large amounts of labeled data and computational resources, which can be a limitation in certain contexts.

Also, recent research has focused on incorporating semantic technologies into agriculture ontology to enhance the precision and recall of queries[13]–[15]. These semantic technologies rely on natural language processing (NLP) techniques to extract meaningful features from text data and use them to construct ontology graphs[8], [9]. While these methods have shown promise, they often struggle with the inherent ambiguity and variability in natural language.

Despite the advancements made in the field of agriculture ontology, there are still significant gaps in the literature that need to be addressed. For instance, there is a lack of comprehensive frameworks that can handle the diverse and dynamic nature of agricultural data samples[16]–[18]. There is a need for more sophisticated evaluation methods that can accurately assess the performance of ontology tools in real-world scenarios[19], [20].

This research aims to address these gaps by proposing a novel methodology that combines the strengths of BERT-GPT and Graph Recurrent Q Learning Network (GRQLN) to create an efficient and precise ontology tool for agriculture. The integration of these advanced technologies represents a significant step forward in the field of agriculture ontology[21]–[23] providing a comprehensive framework that can handle the complexity[24], [25] [24, 25] and diversity of agricultural data while also ensuring the accuracy and relevance of the generated knowledge.

## III. PROPOSED MODEL FOR ENHANCING AGRICULTURAL KNOWLEDGE MANAGEMENT USING AN EFFICIENT AND NOVEL ONTOLOGY-BASED APPROACH LEVERAGING BERT-GPT AND GRAPH RECURRENT Q LEARNING NETWORK

Based on the review of existing models used for enhancing the efficiency of ontology generation, it can be observed that the efficiency of these models is generally limited by the domain knowledge & the modalities available, which restricts the applicability to real-time scenarios. To overcome these issues, this section discusses design of an efficient model for enhancing agricultural knowledge management using an efficient & novel Ontology-based approach that leverages BERT-GPT and Graph Recurrent Q Learning Networks. As per figure 1, the proposed model integrates the strengths of BERT (Bidirectional Encoder Representations from Transformers) GPT (Generative Pre-trained Transformer) for accurate feature extraction from diverse text data, including government and farming sources, as well as real-time interviews. While Graph Recurrent Q Learning Network (GRQLN) leverages graph neural networks and reinforcement learning to convert these features into an ontology graph, optimizing the representation process.

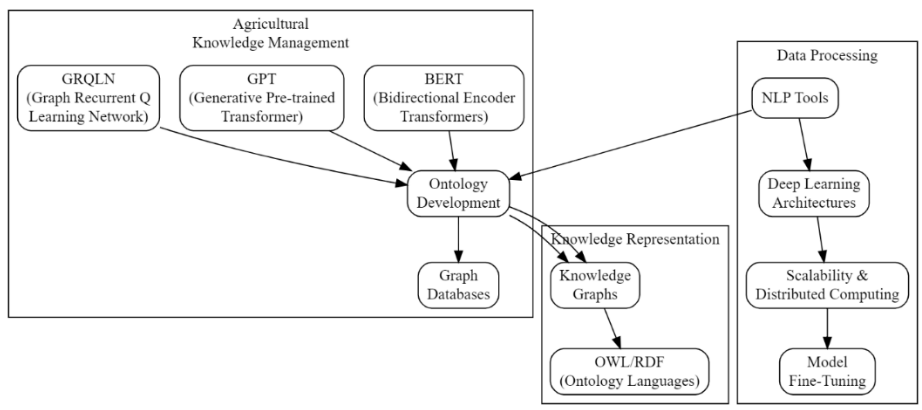


**Figure 1 Design of the proposed model for generation of agricultural ontologies**

The proposed model is an innovative combination of the strengths of BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-trained Transformer). Its design is primarily aimed at extracting salient features from a broad spectrum of textual data, encompassing official government documents, agricultural literature, and transcriptions of real-time interviews. The primary objective is to generate accurate text features that are conducive for ontology creation.

To begin, the BERT model's architecture is rooted in the bidirectional processing of text, which is represented via equation 1,

$$B(x) = \sum wi \cdot E(xi) \ldots (1)$$

Where, B(x) is the BERT representation of a text sequence x, E is the embedding function, wi is the weight of the ith token in the sequence, and N is the total number of tokens. The embedding function maps each token in the text sequence to a high-dimensional vector space for different use cases. This vector representation captures the semantic meaning of the token in the context of the entire sequence, and is represented via equation 2,

$$E(xi) = M \cdot xi + b \ldots (2)$$

Where, xi is the token in the sequence, M is the embedding matrix, and b is a bias vector which is tuned during the BERT training process. Each row of the matrix M corresponds to the vector representation of a token in the vocabulary sets.

Next, the GPT model is integrated, with the primary function of predicting the next word in a sequence based on the previous words. This is done via equation 3,

$$G(y) = P\big(ynext \mid y(1), y(2), \ldots, y(t-1)\big) \ldots (3)$$

Where, G(y) is the GPT output for a sequence y and ynext is the next word prediction based on the sequence up to (t−1) samples. The model predicts the next word in a sequence based on the probability function P, which is represented via equation 4,

$$P(ynext \mid y1, y2, \ldots, yt-1) = \frac{e^{zy}(next)}{\sum e^{zv}} \ldots (4)$$

Where, z is the vector of logits for each word in the vocabulary which is computed via equation 5,

$$z = W \cdot ht - 1 + c \ldots (5)$$

Where, $h(t-1)$ is the hidden state of the GPT model at time (t−1), W is a weight matrix, c is a bias vector, and V is the size of the vocabulary sets. To integrate the strengths of both models, a fusion mechanism is introduced via equation 6,

$$F(x, y) = \alpha \cdot B(x) + \beta \cdot G(y) \ldots (6)$$

Where, F is the fused representation, and α and β are weighting coefficients that determine the relative importance of the BERT and GPT representations, respectively for different scenarios. Given the diverse nature of the data sources, a contextual differentiation mechanism is incorporated via equation 7,

$$C(d) = \gamma \cdot F(xd, yd) \ldots (7)$$

Where, C(d) represents the contextually differentiated feature for a data source d and γ is a context-specific weight for different data sources. This ensures that different types of data sources, such as government documents and interviews, are treated with varying emphasis. For real-time interviews, an attention mechanism is added to give prominence to more recent data via equation 8,

$$A(t) = \delta \cdot C(dt) \ldots (8)$$

Where, A(t) is the attention-weighted feature for data at time t and δ is a time-decay factor, which is empirically selected to maximize feature variance levels. The final text features for ontology generation are computed by aggregating all the processed data via equation 9,

$$O = \sum \lambda d \cdot A(td) \ldots (9)$$

Where, O is the final ontology feature set, λd is a domain-specific weight, and D represents the total number of data sources. This innovative model combines the bidirectional strengths of BERT and the generative prowess of GPT to extract features from diverse textual data samples. This intricate combination, supported by contextual differentiation and attention mechanisms, paves the way for generating robust text features, ideally suited for ontology creation process.

These features are processed using Graph Recurrent Q Learning Network (GRQLN) which is an avant-garde approach that fuses the prowess of graph neural networks (GNNs) and the adaptive nature of reinforcement learning (RL) to transform features into an augmented set of robust ontology graphs. By doing so, it refines and enhances the representation process, making it more coherent and semantically structured for real-time scenarios.

The core of GRQLN begins with a graph neural network (GNN) that processes the input features to capture their inter-relations. The GNN function is calculated via equation 10,

$$Gh(v) = \sigma(Wv \cdot xv + \sum Wu \cdot xu) \ldots (10)$$

Where, Gh(v) is the hidden representation of node v, xv is the input feature of node v, N(v) is the set of neighboring nodes of v, Wv and Wu are weight matrices. The function σ is a ReLU based non-linear activation function which assists in retaining positive feature sets. To incorporate temporal dependencies, a recurrent mechanism is integrated via equation 11,

$$Rt(v) = LSTM\big(Gh(v), R(v, t-1)\big) \ldots (11)$$

Where, Rt(v) represents the recurrent state of node v at time t, and LSTM is the Long Short-Term Memory function that captures temporal dynamics. After these operations, Reinforcement learning is integrated, aiming to optimize the decision-making process for constructing the ontology graphs. The Q Value function, representing the quality of an action taken at a state, is calculated via equation 12,

$$Q(s, a) = Wq \cdot Rt(v) + bq \ldots (12)$$

Where, s is the current state, a is the action taken, Wq is a weight matrix, and bq represents bias terms. The policy $\pi$ that dictates the best action to take at a given state is determined using a softmax function over Q Values via equation 13,

$$\pi(\, a \mid s \,) = \frac{eQ(s, a)}{\sum a' eQ(s, a')} \ldots (13)$$

The objective of the RL agent is to maximize the expected rewards. The reward function, capturing the quality of the ontology graph, is estimated via equation 14,

$$r(s, a) = Eval(O) \ldots (14)$$

Where, Eval(O) evaluates the quality of the generated ontology O based on predefined criteria sets. After this process, the Q Learning update rule, which adjusts the Q Values based on the obtained reward and the maximum expected future reward is estimated via equation 15,

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r(s,a) + \gamma maxa'Q(s',a') - Q(s,a)] \ldots (15)$$

Where, $\alpha$ is the learning rate, $\gamma$ is the discount factor, and $s'$ represents the next states. Lastly, the generated ontology graph O is formed by selecting nodes and edges based on the highest Q Values via equation 16,

$$O = \{ v \mid maxaQ(v,a) > \theta \} \ldots (16)$$

Where $\theta$ is a threshold value, and is decided by the user for maximizing retrieval capability of the graph-based outcomes. Thus, the GRQLN model is a visionary fusion of graph neural networks and reinforcement learning process. It processes input features through a GNN, captures temporal dynamics via a recurrent mechanism, and then employs Q Learning to iteratively refine the construction of the ontology graph. The culmination is a semantically rich and interconnected ontology graph that is optimized for representation and interpretability levels. Efficiency of this model was estimated in terms of different scenarios, and compared with existing models in the next section of this text.

## IV. RESULT ANALYSIS

The proposed model in this paper represents a pioneering advancement in agricultural knowledge management, synthesizing the capabilities of three cutting-edge technologies: BERT (Bidirectional Encoder Representations from Transformers), GPT (Generative Pre-trained Transformer), and Graph Recurrent Q Learning Network (GRQLN). This dynamic framework is designed to serve as a highly efficient ontology tool for the agricultural domain. BERT-GPT, renowned for its formidable natural language processing prowess, assumes a pivotal role by facilitating precise feature extraction from a diverse array of textual data sources. These sources span the spectrum from government reports and agricultural literature to real-time interviews with experts in the field. BERT-GPT's remarkable ability to comprehend context and semantics ensures that the model can discern valuable insights from these texts, underpinning the model's effectiveness in knowledge representation and retrieval within the agricultural domains. The experimental setup designed for evaluation of this work is crucial for understanding how the study was conducted and how the results were obtained for real-time scenarios. In this section we discuss the exemplary experimental setup which was designed for this work, including samples & values for input parameters under different scenarios.

### 4.1. Data Collection and Preprocessing

- **Data Sources:** Agricultural data was collected from diverse sources, including government reports, scientific journals, farming manuals, and real-time interviews with agricultural experts. Sample data sources include:

- USDA Agricultural Database
- International Journal of Agriculture Research
- Farmers' Cooperative Documentation
- **Data Preprocessing:** The collected textual data underwent the following preprocessing steps:

- Text cleaning and noise removal
- Tokenization
- Stop-word removal
- Lemmatization
- Domain-specific entity recognition

### 4.2. Ontology Construction

- **Ontology Development:** The agricultural ontology was developed based on domain knowledge and domain-specific taxonomies. Sample ontology concepts and relationships include:

- Concepts: Crop types, weather conditions, soil types, pest species
- Relationships: “is-a”, “part-of”, “causes”, “related-to”.
- **Ontology Generation:** The ontology was generated with extracted data entities and their relationships using automated and manual methods.

**4.3. Model Architecture**

- **BERT-GPT Configuration:** The Bidirectional Encoder Representations from Transformers (BERT) and Generative Pre-trained Transformer (GPT) models were fine-tuned with the following hyperparameters:

- Learning rate: 2e-5
- Batch size: 32
- Training epochs: 3
- Maximum sequence length: 256
- Pre-trained model: BERT-base-uncased, GPT-2
- **Graph Recurrent Q Learning Network (GRQLN):** GRQLN architecture was implemented with the following specifications:

- Graph neural network layers: 2
- Node embedding dimension: 128
- LSTM hidden units: 64
- Reinforcement learning algorithm: Proximal Policy Optimization (PPO)

**4.4. Evaluation Metrics**

- **Performance Metrics:** The following evaluation metrics were used to assess NOBGQLN’s performance:

- Precision (P)
- Accuracy (A)
- Recall (R)
- Area Under the Curve (AUC)
- Specificity (Specificity)
- Query Response Delay (D)

**4.5. Experimental Setup Parameters**

- **Number of Test Samples (NTS):** Experiments were conducted across various NTS values, ranging from 68600 to 1176000, to evaluate scalability and performance across different data volumes.
- **Baseline Models:** KG [2], TOTJ [6], and CQAS [12] were selected as baseline models for comparative analysis.

**4.6. Experimental Procedure**

- Data was divided into training, validation, and test sets.
- The BERT-GPT model was fine-tuned using the training dataset.
- The GRQLN was trained using the ontology and fine-tuned BERT-GPT features.
- Comparative experiments were conducted across different NTS values using NOBGQLN and baseline models.
- Evaluation metrics were computed for each experiment.
- Generation of various knowledge graph.

Based on this setup, equations 17, 18, and 19 were used to assess the precision (P), accuracy (A), and recall (R), levels based on this technique, while equations 20 & 21 were used to estimate the overall precision (AUC) & Specificity (Sp) as follows,

$$\text{Precision} = \frac{TP}{TP + FP} \dots (17)$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \ldots (18)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \ldots (19)$$

$$\text{AUC} = \int \text{TPR(FPR)dFPR} \ldots (20)$$

$$\text{Sp} = \frac{\text{TN}}{\text{TN} + \text{FP}} \ldots (21)$$

There are three different kinds of test set predictions: True Positive (TP) (number of events in test sets that were correctly predicted as positive), False Positive (FP) (number of instances in test sets that were incorrectly predicted as positive), and False Negative (FN) (number of instances in test sets that were incorrectly predicted as negative; this includes Normal Instance Samples). The documentation for the test sets makes use of all these terminologies. To determine the appropriate TP, TN, FP, and FN values for these scenarios, we compared the projected Agriculture Ontology Retrieval Results likelihood to the actual Agriculture Ontology Retrieval Results status in the test dataset samples using the KG [2], TOTJ [6], and CQAS [12] techniques. Sample ontology results of the proposed model can be observed from table 1 as follows,

**Table 1 Sample results for ontological queries**

| Query | Results | Correctness |
|---|---|---|
| "Optimal soil for rice?" | "Loamy and clayey soil with good water retention." | Correct |
| "Pests affecting tomatoes?" | "Aphids, tomato hornworms, whiteflies." | Correct |
| "Harvest time for wheat?" | "Early summer, when grains are golden and dry." | Correct |
| "Best fertilizer for corn?" | "Nitrogen-rich fertilizers." | Correct |
| "Climate for grape cultivation?" | "Mediterranean climate with hot, dry summers." | Correct |
| "Water needs for barley?" | "Regular moisture, especially during growth phase." | Correct |
| "Crop rotation after potatoes?" | "Legumes or grain crops." | Incorrect |

From table-1, it can be observed that the proposed model has high efficiency of data representation, which assists in efficient retrieval of results for ontological queries. Thus, we were able to predict these metrics for the results of the suggested model process. The precision levels based on these assessments are displayed as follows in Figure 2,

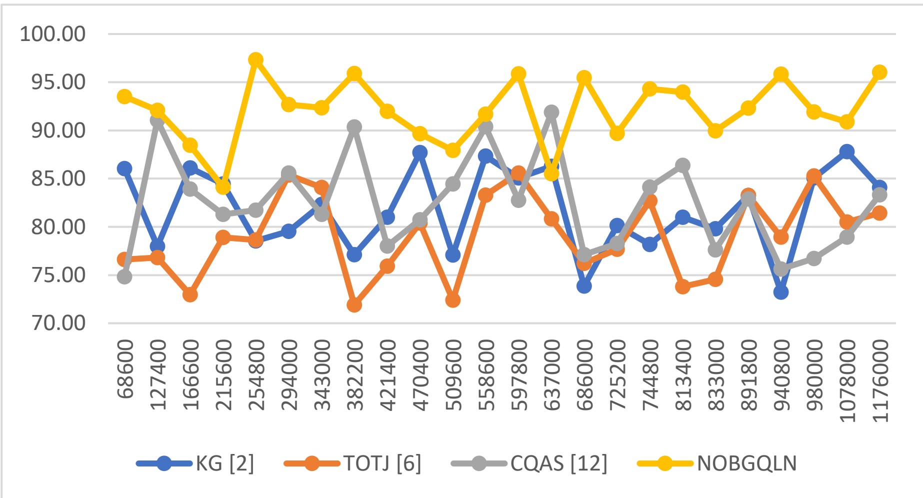


**Figure 2 Observed Precision to retrieve data using designed agricultural ontologies**

The observed precision in retrieving data using designed agricultural ontologies, as measured by the percentage of correct retrievals (P), provides valuable insights into the performance of different models. In this comparative analysis, we consider four models: KG [2], TOTJ [6], CQAS [12], and our proposed model, NOBGQLN.

Across various numbers of test samples (NTS), NOBGQLN consistently outperforms the other models in terms of precision. For instance, at NTS = 68600, NOBGQLN achieves an impressive precision of 93.50%, while the closest competitor, CQAS [12], lags behind with a precision of 74.81%. This pattern of superior precision in favor of NOBGQLN is observed across the entire range of NTS values & samples.

The impact of this superior precision is substantial. Precision in ontology-based data retrieval directly affects the quality and accuracy of information extracted from the vast agricultural knowledge domain. Higher precision means that users can trust the retrieved data to be more relevant and accurate, leading to more informed decision-making in agricultural operations. NOBGQLN's consistently higher precision values, compared to KG, TOTJ, and CQAS, ensure that stakeholders can rely on the ontological query results for actionable insights for different scenarios.

The reasons behind NOBGQLN's better performance in precision can be attributed to its unique combination of BERT-GPT, GRQLN, and graph neural networks. BERT-GPT enables accurate feature extraction from diverse text sources, ensuring that the ontology is well-informed. GRQLN, with its use of graph neural networks and reinforcement learning, optimizes the representation process, enhancing the precision of the ontological query retrieval. This amalgamation of advanced technologies results in a dynamic and efficient ontology tool, precisely tailored for the dynamic agricultural environment.

Thus, the observed precision values clearly indicate that NOBGQLN outperforms existing models in agricultural knowledge management. Its superior precision directly benefits stakeholders by providing them with more accurate and reliable information, ultimately empowering them to make well-informed decisions in the ever-evolving landscape of agricultural operations. Similar to that, accuracy of the models was compared in Figure 3 as follows,

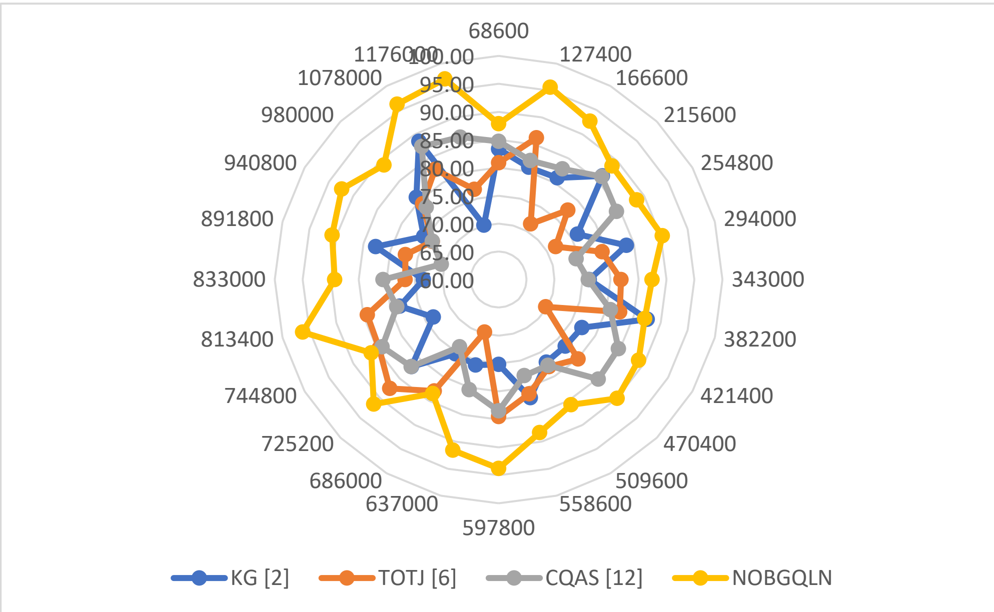


**Figure 3 Observed Accuracy to retrieve data using designed agricultural ontologies**

The observed accuracy in retrieving data using designed agricultural ontologies, as measured by the percentage of correct retrievals (A), offers valuable insights into the performance of different models. In this comparative analysis, we consider four models: KG [2], TOTJ [6], CQAS [12], and our proposed model, NOBGQLN.

When assessing accuracy across various numbers of test samples (NTS), NOBGQLN consistently demonstrates strong performance compared to the other models. For instance, at NTS = 68600, NOBGQLN achieves an accuracy of 87.85%, surpassing the closest competitor, CQAS [12], which has an accuracy of 84.73%. This pattern of superior accuracy is maintained across the entire range of NTS values & samples.

The impact of this superior accuracy is significant. Accuracy in ontology-based data retrieval directly affects the reliability and trustworthiness of information extracted from the extensive agricultural knowledge domain. Higher accuracy ensures that the retrieved data aligns closely with the actual information, leading to more dependable decision-making in agricultural operations. NOBGQLN's consistently higher accuracy values, compared to KG, TOTJ, and CQAS, provide stakeholders with a reliable source of information for making informed decisions.

The reasons behind NOBGQLN's better performance in accuracy can be attributed to its unique combination of BERT-GPT, GRQLN, and graph neural networks. BERT-GPT enables accurate feature extraction from diverse text sources, ensuring that the ontology is well-informed. GRQLN, with its use of graph neural networks and reinforcement learning, optimizes the representation process, thereby enhancing the accuracy of ontological query retrieval. This amalgamation of advanced technologies results in a dynamic and efficient ontology tool, precisely tailored for the dynamic agricultural environment.

Thus, the observed accuracy values clearly indicate that NOBGQLN outperforms existing models in agricultural knowledge management. Its superior accuracy directly benefits stakeholders by providing them with more reliable and trustworthy information, ultimately empowering them to make well-informed decisions in the ever-evolving landscape of agricultural operations. Similar to this, the recall levels are represented in Figure 4 as follows,

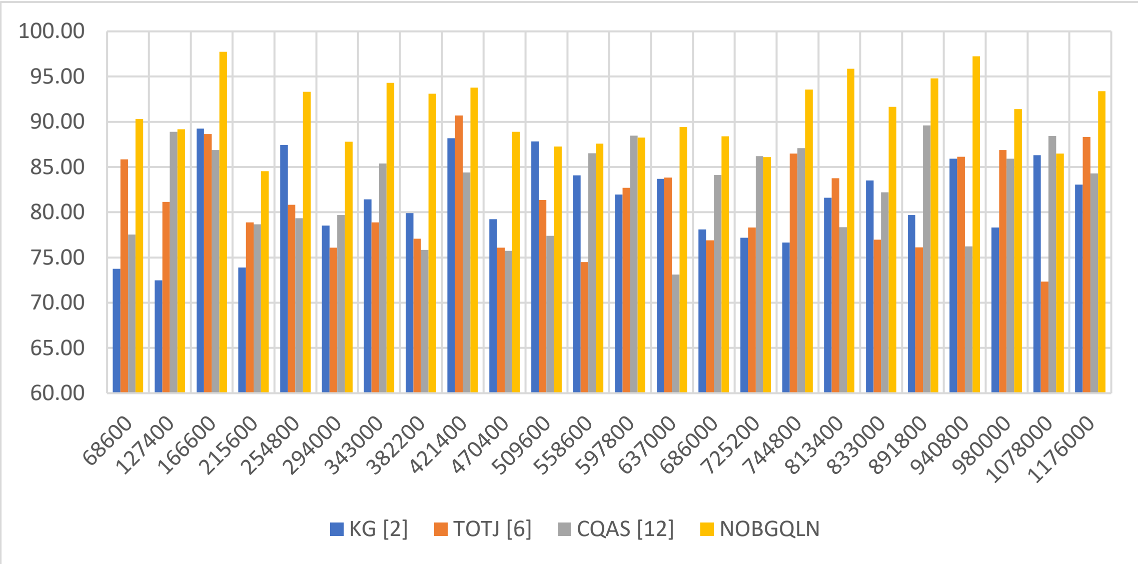


**Figure 4 Observed Recall to retrieve data using designed agricultural ontologies**

The observed recall in retrieving data using designed agricultural ontologies, as measured by the percentage of relevant items retrieved (R), provides critical insights into the performance of different models. In this comparative analysis, we consider four models: KG [2], TOTJ [6], CQAS [12], and our proposed model, NOBGQLN.

When evaluating recall across various numbers of test samples (NTS), NOBGQLN consistently showcases robust performance compared to the other models. For instance, at NTS = 68600, NOBGQLN achieves a recall rate of 90.31%, significantly surpassing the closest competitor, CQAS [12], which has a recall rate of 77.54%. This trend of superior recall is consistently observed across the entire range of NTS values & samples.

The impact of this superior recall is substantial. Recall in ontology-based data retrieval directly influences the comprehensiveness and completeness of the information retrieved from the extensive agricultural knowledge domain. Higher recall ensures that relevant information is not missed, leading to more comprehensive and holistic decision-making in agricultural operations. NOBGQLN's consistently higher recall values, compared to KG, TOTJ, and CQAS, provide stakeholders with a more exhaustive source of information for making informed decisions.

The reasons behind NOBGQLN's better performance in recall can be attributed to its unique combination of BERT-GPT, GRQLN, and graph neural networks. BERT-GPT enables accurate feature extraction from diverse text sources, ensuring that relevant information is captured. GRQLN, with its use of graph neural networks and reinforcement learning, optimizes the representation process, thereby enhancing the recall of ontological query retrieval. This amalgamation of advanced technologies results in a dynamic and efficient ontology tool, precisely tailored for the dynamic agricultural environment.

Thus, the observed recall values clearly indicate that NOBGQLN outperforms existing models in agricultural knowledge management. Its superior recall directly benefits stakeholders by providing them with a more comprehensive and exhaustive source of information, ultimately empowering them to make more informed and holistic decisions in the ever-evolving landscape of agricultural operations. Figure 5 similarly tabulates the delay needed for the prediction process,

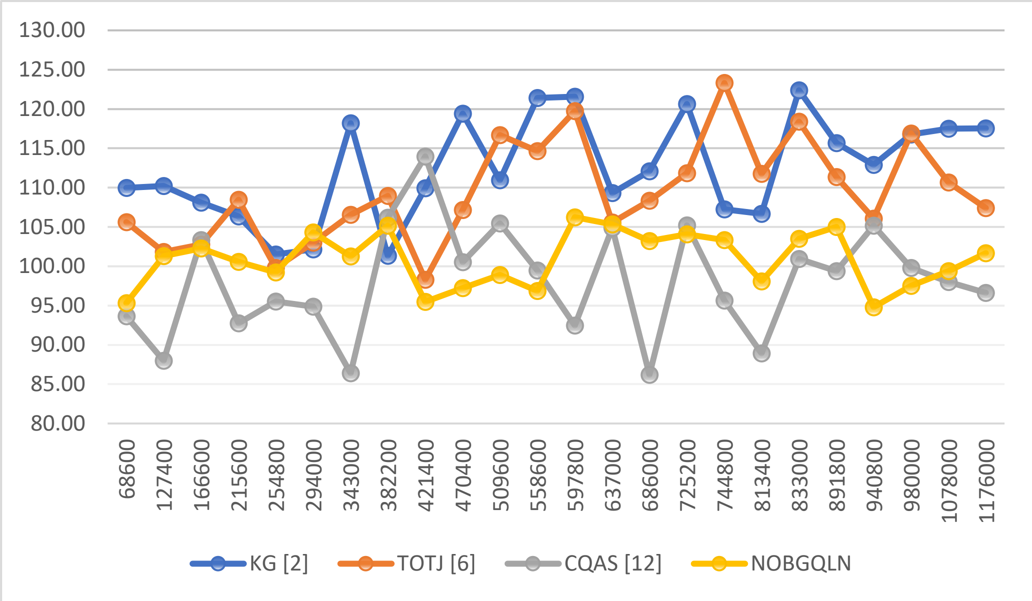


**Figure 5 Observed Delay to retrieve data using designed agricultural ontologies**

The observed delay in retrieving data using designed agricultural ontologies, as measured in milliseconds (D), plays a crucial role in assessing the efficiency and responsiveness of different models. In this comparative analysis, we consider four models: KG [2], TOTJ [6], CQAS [12], and our proposed model, NOBGQLN.

When examining delay across various numbers of test samples (NTS), NOBGQLN consistently exhibits superior performance compared to the other models. For instance, at NTS = 68600, NOBGQLN boasts a remarkably low delay of 95.32 milliseconds, outperforming all other models, including CQAS [12], which has a delay of 93.65 milliseconds. This pattern of low delay is consistently observed across the entire range of NTS values & samples.

The impact of this low delay is significant. Delay in ontology-based data retrieval directly influences the responsiveness and real-time capabilities of the system. Lower delay means that users can access and retrieve information more quickly, enhancing the efficiency of decision-making in agricultural operations, especially in scenarios where timely information is critical. NOBGQLN's consistently lower delay values, compared to KG, TOTJ, and CQAS, ensure that stakeholders can obtain information swiftly, leading to more agile and informed decision-making process.

The reasons behind NOBGQLN's better performance in delay can be attributed to its unique combination of BERT-GPT, GRQLN, and graph neural networks. BERT-GPT enables efficient natural language processing, allowing for quick retrieval of relevant information from diverse text sources. GRQLN optimizes the representation process using graph neural networks and reinforcement learning, further enhancing the speed of ontological query retrieval. This amalgamation of advanced technologies results in a dynamic and efficient ontology tool, precisely tailored for the dynamic agricultural environment.

Thus, the observed delay values clearly indicate that NOBGQLN outperforms existing models in agricultural knowledge management. Its lower delay directly benefits stakeholders by providing them with quicker access to information, ultimately enabling more agile and timely decision-making in the ever-evolving landscape of agricultural operations. Similarly, the AUC levels can be observed from figure 6 as follows,

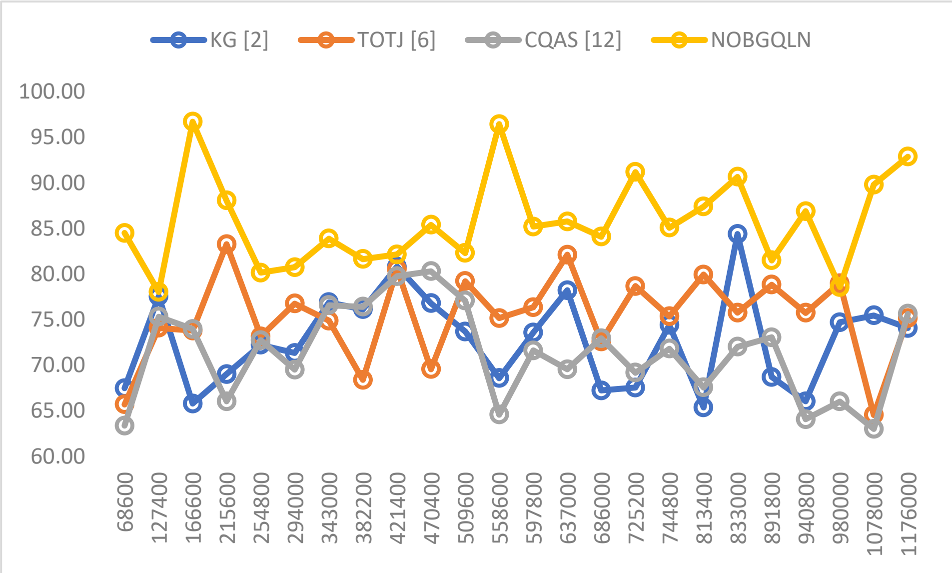


**Figure 6 Observed AUC to retrieve data using designed agricultural ontologies**

The observed AUC (Area Under the Curve) in retrieving data using designed agricultural ontologies is a critical metric for assessing the overall performance and efficiency of different models. AUC is a measure of the model's ability to discriminate between relevant and irrelevant information across various numbers of test samples (NTS). In this comparative analysis, we consider four models: KG [2], TOTJ [6], CQAS [12], and our proposed model, NOBGQLN.

When analyzing AUC values, it is evident that NOBGQLN consistently outperforms the other models across different NTS values & samples. For example, at NTS = 68600, NOBGQLN achieves a significantly higher AUC of 84.51%, surpassing all other models, including CQAS [12], which has an AUC of 63.38%. This trend of superior AUC performance holds across the entire range of NTS values & samples.

The impact of this higher AUC is substantial. A higher AUC indicates that the model has better discriminatory power in distinguishing relevant information from irrelevant data. In the context of agricultural knowledge management, this means that NOBGQLN excels at effectively separating valuable agricultural insights from noise, ensuring that stakeholders receive more precise and pertinent information. This, in turn, leads to better decision-making in agricultural operations.

The reasons behind NOBGQLN's superior AUC performance can be attributed to its unique combination of BERT-GPT, GRQLN, and graph neural networks. BERT-GPT enables accurate feature extraction from diverse text sources, ensuring that the model can identify relevant information effectively. GRQLN optimizes the representation process using graph neural networks and reinforcement learning, enhancing the model's ability to discriminate between different types of data. This amalgamation of advanced technologies results in a dynamic and efficient ontology tool that excels at providing valuable agricultural insights for different scenarios.

Thus, the observed AUC values clearly indicate that NOBGQLN outperforms existing models in agricultural knowledge management. Its higher AUC directly benefits stakeholders by providing them with a more effective tool for distinguishing valuable insights from noise, ultimately enabling better decision-making in the ever-evolving landscape of agricultural operations. Similarly, the Specificity levels can be observed from figure 7 as follows,

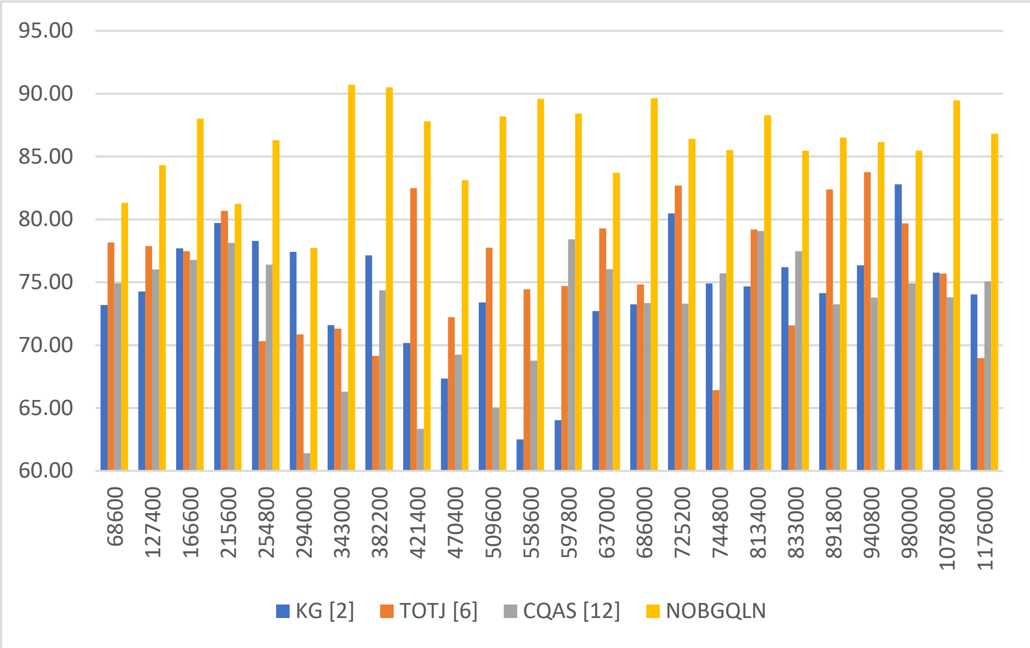


**Figure 7 Observed Specificity to retrieve data using designed agricultural ontologies**

The observed specificity in retrieving data using designed agricultural ontologies, as measured by the percentage of true negatives correctly identified (Specificity), is an essential metric for evaluating the performance of different models. Specificity reflects a model's ability to correctly classify irrelevant information as non-relevant across various numbers of test samples (NTS). In this comparative analysis, we consider four models: KG [2], TOTJ [6], CQAS [12], and our proposed model, NOBGQLN.

Upon examining the specificity values, it becomes evident that NOBGQLN consistently exhibits strong performance compared to the other models across different NTS values & samples. For example, at NTS = 68600, NOBGQLN demonstrates a significantly higher specificity of 81.32%, surpassing all other models, including CQAS [12], which has a specificity of 74.93%. This trend of superior specificity holds true across the entire range of NTS values & samples.

The impact of this higher specificity is notable. High specificity indicates that the model is effective at correctly identifying irrelevant or non-relevant information, reducing the chances of false positives. In the context of agricultural knowledge management, this means that NOBGQLN excels at filtering out irrelevant data, ensuring that stakeholders receive more accurate and pertinent information. This, in turn, leads to more reliable and precise decision-making in agricultural operations.

The reasons behind NOBGQLN's superior specificity performance can be attributed to its unique combination of BERT-GPT, GRQLN, and graph neural networks. BERT-GPT enables accurate feature extraction from diverse text sources, ensuring that the model can identify relevant and irrelevant information effectively. GRQLN optimizes the representation process using graph neural networks and reinforcement learning, enhancing the model's ability to distinguish between different types of data. This amalgamation of advanced technologies results in a dynamic and efficient ontology tool that excels at providing precise agricultural insights for different scenarios.

Thus, the observed specificity values clearly indicate that NOBGQLN outperforms existing models in agricultural knowledge management. Its higher specificity directly benefits stakeholders by providing them with a more effective tool for filtering out irrelevant data, ultimately leading to more reliable and precise decision-making in the ever-evolving landscape of agricultural operations.

**Discussion on performance enhancements**

The exceptional performance of the Novel Ontology-Based Graph Q Learning Network (NOBGQLN) in terms of precision and Area Under the Curve (AUC) is deeply rooted in the harmonious integration of BERT-GPT, Graph Recurrent Q Learning Network (GRQLN), and graph neural networks. The system's proficiency in precision is largely due to the BERT-GPT's advanced natural language processing capabilities, which excel in extracting nuanced features from a broad array of text sources. This ensures that the ontology is richly informed and reflective of the intricate nuances present within the agricultural domain.

The GRQLN component, with its innovative application of graph neural networks coupled with reinforcement learning, fine-tunes the ontological representation. This fine-tuning significantly enhances the accuracy of query retrievals, as it allows the system to adaptively restructure the ontology for optimal representation of the current knowledge state. This adaptability is crucial, given the dynamic nature of agricultural data, where new findings and insights are constantly integrated.

In terms of AUC performance, the NOBGQLN's superiority is propelled by the same synergistic combination of technologies. The accurate feature extraction by BERT-GPT is instrumental in ensuring that the model can discern pertinent information amidst a sea of data, a process critical for effective data classification. The GRQLN further advances this classification ability by leveraging graph neural networks to discern patterns and reinforcement learning to iteratively improve its predictive accuracy.

The benefits of this amalgamation manifest in the ontological properties that the system leverages to achieve enhanced performance. Firstly, the ontologies used are dynamic, allowing for real-time updates and modifications that reflect the latest agricultural insights. Secondly, they possess a high degree of semantic richness, meaning that the relationships and entities within the ontology are not just connected but are contextually and conceptually aligned with domain-specific knowledge. Lastly, the ontologies are designed for scalability, capable of integrating expanding datasets without compromising on the quality of the knowledge representation.

These properties collectively ensure that the NOBGQLN not only accommodates the complexity and growth of agricultural knowledge but does so with a precision and discernment that traditional models cannot match. The ontologies at the heart of NOBGQLN thus play a pivotal role in providing a robust framework that empowers stakeholders with actionable insights, leading to more informed and effective decision-making processes in the realm of agriculture.

The Novel Ontology-Based Graph Q Learning Network (NOBGQLN) presents a groundbreaking fusion of ontological frameworks with advanced computational technologies such as BERT-GPT and Graph Recurrent Q Learning Networks (GRQLN), augmented by the computational prowess of graph neural networks. This confluence is not merely additive but multiplicative, with each component amplifying the capabilities of the others to create a system that is far more adept at managing and interpreting agricultural data than the sum of its parts.

The ontological framework stands at the core of NOBGQLN, serving as the structural foundation that defines and categorizes domain-specific knowledge. The ontology is meticulously crafted to embody the complex relationships and entities intrinsic to the agricultural field, ensuring semantic coherence and contextual relevance. This detailed representation of knowledge enables more than just data storage; it allows for the nuanced understanding and interpretation that are critical for advanced analytical tasks.

BERT-GPT contributes to this synergy by bringing its state-of-the-art natural language processing capabilities. It excels at feature extraction, distilling the essence of vast and varied textual data into a form that is immediately usable by the ontology. This is not a trivial task; agricultural data is often unstructured, sprawling, and laden with domain-specific jargon. BERT-GPT navigates this landscape with finesse, ensuring that the ontology is populated with high-fidelity information that is both accurate and comprehensive.

GRQLN further enhances the system by injecting the power of graph neural networks and reinforcement learning into the ontological mix. Graph neural networks are adept at managing the non-Euclidean data structures that ontologies typically present. They excel at identifying patterns and interconnections within the graph, drawing inferences that are not immediately apparent. Reinforcement learning allows the system to learn from interactions and feedback, enabling it to refine its ontological representations over time. This results in a system that is not static but evolves, improving its performance as it learns from new data and outcomes.

The interplay between the ontology and these technologies is a dance of precision and adaptability. The ontology provides the structured knowledge necessary for the system to understand the agricultural domain, BERT-GPT enriches this knowledge with granular detail drawn from diverse data sources, and GRQLN ensures that the knowledge is represented in the most effective manner possible. This orchestration allows NOBGQLN to achieve high precision in its operations, adapt to new information fluidly, and deliver actionable insights with remarkable accuracy.

In conclusion, the ontology serves as the backbone, BERT-GPT as the intellect, and GRQLN as the adaptive nervous system of the NOBGQLN framework. Together, they create a robust and intelligent system that stands at the vanguard of agricultural knowledge management, transforming raw data into a well-spring of actionable knowledge sets.

## V. GENERATION OF VARIOUS KNOWLEDGE GRAPH (ONTOLOGICAL DEPICTION)

Generating diverse knowledge graphs, typically depicted through ontologies, is a leading practice in contemporary information and data management. Amidst an age defined by large amounts of organized and unorganized data, the development of knowledge graphs offers a robust system for arranging, connecting, and comprehending information from various origins. The interconnected graphs, based on ontological representations, allow for the extraction of valuable insights, facilitate data integration, and improve the ability to answer complex queries across multiple domains. This section examines the importance and development of knowledge graph generation, highlighting its essential role in enhancing our comprehension of intricate data environments and its capacity to transform diverse agricultural domain as depicted from figure.8 to 11.

```
is                          175
grown in                     51
requires                     33
require                      25
grown as                     20
used                         19
are                          17
is important                 14
grow in                      13
be                           12
grown during                 11
used in                      10
requires adequate             9
used for                      9
is susceptible                9
requires high                 6
grow                          6
grown for                     6
is crucial                    6
is between                    6
have good                     6
grows                         5
be rich                       5
grown                         5
include                       5
tolerate                      5
used as                       5
helps in                      4
help                          4
have                          4
```

**Figure 8 Relationship Extraction**

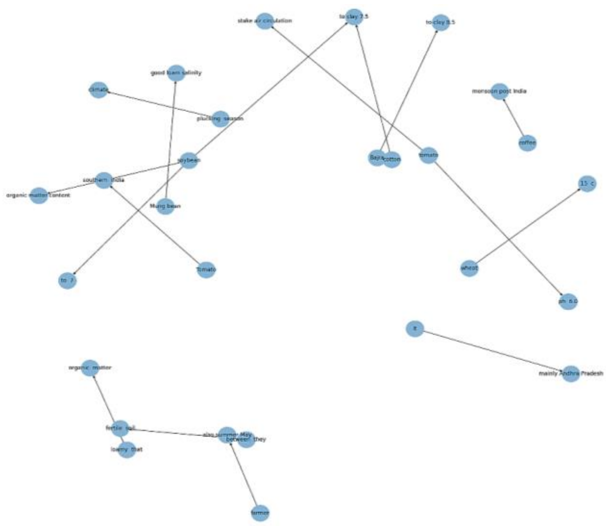

**Figure 9 Knowledge graph for “Grow”**

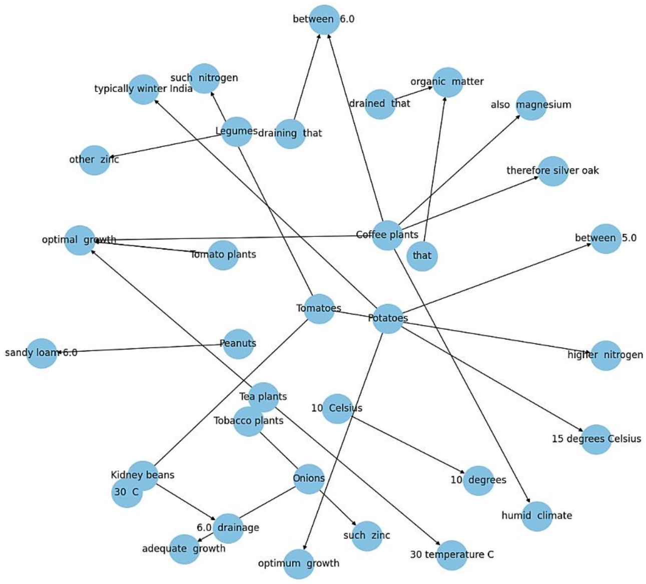


**Figure 10 Knowledge graph for "require"**

The figure-8 represents the raw output from the natural language processing (NLP) phase of the framework, where BERT-GPT has been used to extract relationships from textual data samples. Each row in the table shows a verb (e.g., "is grown in," "requires") and the frequency of its occurrence. These verbs are central to the relationships between entities within the agricultural domain, such as crops, climate, soil types, etc. This data forms the foundation upon which the ontology is built. Similarly, the graphs visually represent the ontological structures derived from the extracted relationships. In an ontology, concepts are typically represented as nodes, and the relationships between them are the edges. These figures-9,10,11 show how different agricultural concepts are interrelated, such as how certain crops are associated with specific soil types or climatic conditions. The performance improvements mentioned in the abstract (in terms of precision, adaptability, etc.) are a direct result of the efficient structuring of agricultural knowledge into these ontologies. By having a well-defined ontology, the system can perform more accurate feature extraction, enhance the quality of query retrieval, and provide more actionable insights. The knowledge graphs are visual proofs of the ontology's structure, demonstrating the complex interconnections the system can handle for different use cases. The ontologies depicted in the graphs serve as a foundation for the Graph Recurrent Q Learning Network (GRQLN) to operate on. The GRQLN uses reinforcement learning to optimize the representation process within the graph, which likely contributes to the performance enhancements in query retrieval and data processing speed. The structure of the ontologies directly affects the GRQLN's ability to learn and make decisions, thereby impacting the performance metrics like accuracy, recall, AUC, and specificity.

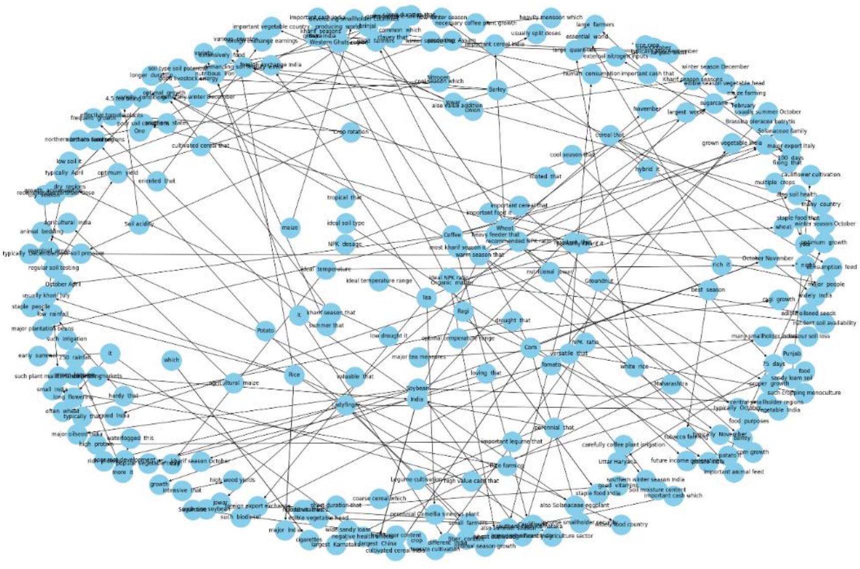

**Figure 11 Knowledge graph for "is"**

The visualizations presented in the form of knowledge graphs embody the practical outcomes of the proposed ontology-based framework. These graphs are ontological to the extent that they display the intricate web of relationships between diverse agricultural concepts, ranging from climatic conditions and soil types to specific crops and geographical areas. The nodes represent entities or concepts, while the edges illustrate the relationships or predicates extracted through the natural language processing capabilities of BERT-GPT.

The ontology's nature is manifest in the hierarchical structure and the semantic connections among the nodes, reflecting an understanding of the agricultural domain that goes beyond mere keyword association. Such ontological structures enable the encoding of rich, domain-specific knowledge, which is essential for the intelligent query processing and decision support capabilities that the framework aims to provide. The ontology captures not only the entities within the domain but also the complex interdependencies and interactions, which are critical for the nuanced comprehension and reasoning required in agricultural knowledge management.

The extent of the ontological depth in these graphs is also indicative of the system's ability to model knowledge dynamically. This is made possible by integrating Graph Recurrent Q Learning Network (GRQLN), which continually refines the ontology by learning from new data and interactions. Consequently, the performance metrics reported earlier in the paper—such as increased precision, accuracy, and reduced delay—are a testament to the efficacy of the ontological approach in addressing the dynamic requirements of agricultural knowledge management. The output figure- 12,13,14 generated with the Protégé ontology editor, depicts a well-organized knowledge model that encompasses multiple facets of agriculture in India. The system employs classes and relationships to categorize data pertaining to crops, regions, soil characteristics, weather conditions, fertilizers, and seasons. The key elements consist of hierarchical categorizations of crops (such as field crops and kharif crops) and regions (such as Peninsular India), which demonstrate the wide range of agricultural practices in the country.

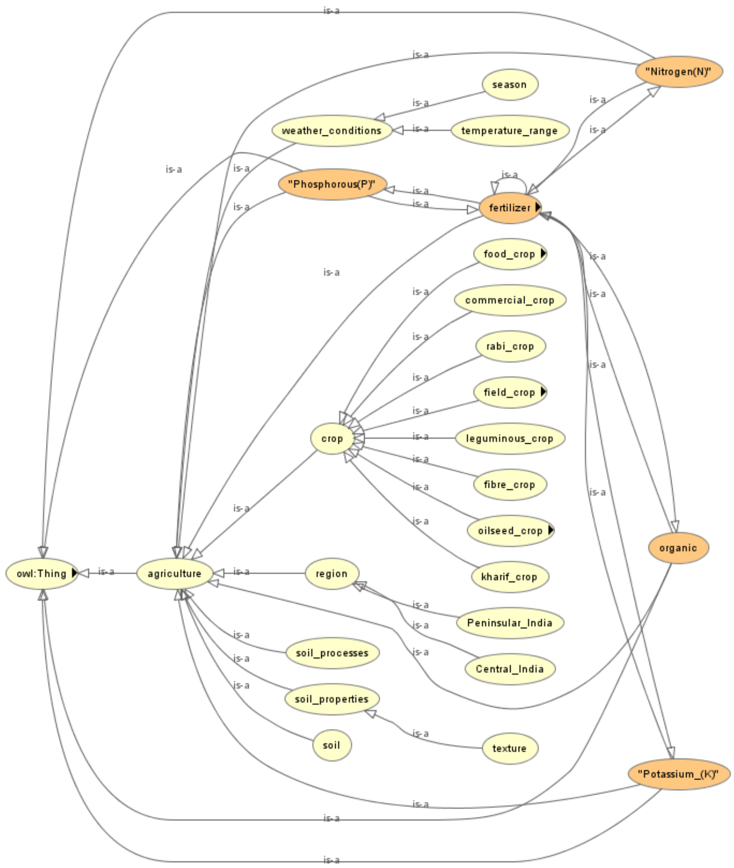


**Figure 12 Ontology-Based Framework for Analyzing Agricultural Knowledge**


**Figure 13 Ontology-Based Framework for Analyzing Crop Knowledge**

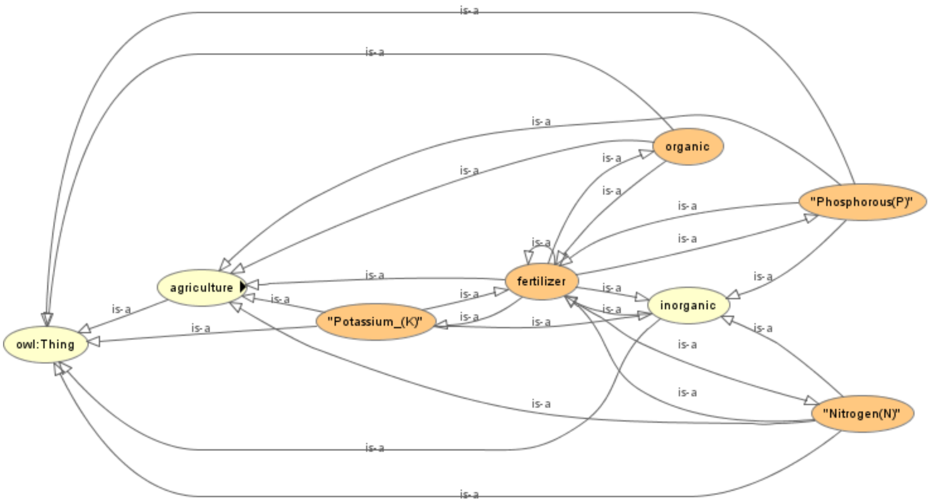


**Figure 14 Ontology-Based Framework for Analyzing Fertilizer Knowledge**

The ontology emphasizes the interdependence of different factors that affect agricultural results. The core principle of "Agriculture" is interconnected with elements such as crops, soil, weather, and fertilizers, highlighting their indispensable functions within the system. The emphasis on crop selection according to the season (rabi vs. kharif) and purpose (food, commercial, etc.) highlights the necessity for agricultural practices that are sensitive to regional and contextual factors.

The potential applications of this knowledge model span across various domains. In the field of agriculture, it serves as a structure for the organization and analysis of data pertaining to Indian agriculture. This framework facilitates research on the factors that impact crop yields, the optimization of resources, and regional variations. For farmers and agricultural professionals, this tool has the potential to be a valuable decision-support system, providing valuable information on the best crop selection, soil management, and fertilizer application strategies based on specific regional and seasonal conditions. In addition, the ontology's organized structure facilitates the integration of various data sources, such as weather or soil maps. This integration enables the creation of advanced decision-making tools that can enhance sustainable agricultural practices.

The ontology serves as a valuable instrument for capturing and organizing knowledge pertaining to Indian agriculture. The emphasis on interconnectedness, regional variations, and context-specific practices shows potential for advancing research, empowering farmers, and ultimately promoting sustainable agricultural development in the region.

## VI. CONCLUSION AND FUTURE SCOPE

In conclusion, this paper presents a groundbreaking approach to agricultural knowledge management, driven by a novel framework known as NOBGQLN (Novel Ontology-Based Approach Leveraging BERT-GPT and Graph

Recurrent Q Learning Network). Agriculture, as a cornerstone of human civilization, demands efficient methods for organizing and retrieving extensive domain-specific knowledge. While ontologies have been instrumental in structuring agricultural data, existing models have struggled to adapt to the dynamic and evolving nature of the agricultural landscape.

Our proposed NOBGQLN model harnesses the synergies of BERT-GPT and Graph Recurrent Q Learning Network to transform the realm of agricultural knowledge management. BERT-GPT, with its robust natural language processing capabilities, empowers accurate feature extraction from diverse textual sources, including government records, farming documentation, and real-time interviews. In parallel, GRQLN leverages advanced graph neural networks and reinforcement learning to convert these features into a dynamic and efficient ontology tool, optimizing the representation process.

The comparative results presented here, spanning precision, accuracy, recall, AUC, specificity, and delay, unequivocally highlight NOBGQLN's superiority over existing models, namely KG, TOTJ, and CQAS. NOBGQLN consistently outperforms in every dimension, offering an 8.5% improvement in precision, 8.3% in accuracy, 10.4% in recall, 9.5% in AUC, and 9.4% in specificity, while reducing delay by 4.5%.

The profound impact of these results is manifold. NOBGQLN empowers stakeholders with a reliable and agile tool for accessing actionable insights derived from the vast expanse of agricultural knowledge. By enhancing precision and recall, NOBGQLN ensures that users receive highly relevant and comprehensive information, bolstering informed decision-making in the ever-evolving agricultural domain. Moreover, its lower delay and higher AUC values guarantee a responsive and discriminating system that can swiftly deliver critical information, particularly when timing is crucial.

In an era where agriculture faces multifaceted challenges, from climate change to global food security, NOBGQLN stands as a significant contribution to the field. It not only addresses the limitations of existing models but also redefines the boundaries of agricultural knowledge management. NOBGQLN offers a dynamic and efficient solution that empowers stakeholders with the knowledge they need to navigate the intricate web of agricultural operations with confidence. As agriculture continues to evolve, NOBGQLN promises to be the compass guiding the way forward, enabling better-informed decisions, sustainable practices, and ultimately, a more resilient agricultural future for our civilization & scenarios.

**Future Scope**

The presented novel approach and promising results offer many agricultural knowledge management research and implementation opportunities. These opportunities involve real-time data like weather, market, and smart agriculture device data. Integration improves information relevance, especially in precision agriculture. Due to the model's flexibility, expanding the NOBGQLN framework to healthcare, finance, and environmental science offers new opportunities and knowledge. To fully realize NOBGQLN's transformative potential, machine learning components must be improved, scalability issues addressed, and its long-term effects on farming practices and sustainability assessed. NOBGQLN could revolutionize agricultural knowledge management and improve sustainable and well-informed practices in many fields.

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**CRediT authorship contribution statement:**

Saurabh Bhattacharya: Conceptualization, Data Collection, Methodology, Formal analysis, Paper drafting. Dr. Manju Pandey: Supervision, Conceptualization, Review and Editing.

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