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Graph Neural Network-Based Forecasting of Nutritional Trends and Consumer Behavior in Health-Oriented Food Markets

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Abstract: ***This study presents a trend analysis framework based on Graph Neural Networks (GNNs) and Reinforcement Learning (RL), designed to process data from multiple sources, including social media, online shopping records, and nutrition databases. A BERT-GNN model is used to extract food-related topics and sentiment from online text, while a Transformer-based time series model analyzes changes in demand over time. The outputs are combined within an RL structure to support adaptive decision-making under varying market conditions. Compared with conventional approaches such as RNN and ARIMA, the proposed method improves prediction accuracy by 21.7%. The framework also proves effective in detecting rising interest in health-related food products, such as plant-based and probiotic items. These results suggest that the system can serve as a practical tool for anticipating consumption shifts and informing policy or supply chain responses in the food sector.***

Keywords: Food trend prediction; Graph neural network; Reinforcement learning; BERT; Transformer; Time series model; Market analysis.

1. INTRODUCTION

The food industry plays an important role in the global economy [1,2]. As the world population grows and living standards rise, the size of the food market continues to expand. According to data from Statista, the global food industry has grown at an average annual rate of 4.5% over the past decade [3]. By 2030, its total output is expected to exceed USD 10 trillion. However, behind this growth are several ongoing challenges [4]. Consumers are now paying more attention to food quality, safety, nutrition, and personalized choices. A report by Mintel shows that the organic food sector has grown by 8% annually in recent years [5]. The demand for functional foods has increased by 30% in just three years. These numbers reflect a clear change in consumer expectations [6]. At the same time, unstable economic conditions—such as price fluctuations of raw materials and frequent changes in global trade policies—have made it harder for companies to control costs and expand their markets [7,8]. Stricter food safety and environmental rules in many countries have increased compliance pressure [9]. For example, a new EU food regulation in 2022 added 20% more limits on additives [10]. As a result, many producers had to change their ingredients and processing methods. Artificial intelligence has been introduced in some food-related applications [11]. However, early machine learning methods could only handle simple patterns and were not suitable for the complex food market. Neural network models have improved performance to some extent, but they still struggle to capture the relationships among products and changing consumer behavior [12]. This study aims to overcome these problems by combining multiple AI techniques. In a competitive and fast-changing market, predicting what consumers will buy is essential. If companies understand future trends early, they can adjust production plans, manage resources better and cut costs [13]. They can also develop products that match new demands and improve their supply chain to avoid overstock and shortages. For example, one major food company used trend forecasting to enter the plant-based market early [14]. Its market share increased by 15% in one year.

Online platforms like social media and e-commerce have created new chances for analyzing the food market [15,16]. Every day, users post millions of comments about food, sharing their experiences and preferences. For example, Weibo sees over five million food-related discussions daily [17]. E-commerce platforms store large volumes of purchase records. One major platform handles billions of transactions each year [18]. These data are rich, diverse, and updated in real time. They offer a strong foundation for AI-based analysis. Graph Neural Networks (GNNs) are useful for analyzing data with complex relationships. In the food market, products may be substitutes or complements. Consumers also interact with food in many ways—by buying, reviewing, or recommending. GNNs can help detect these connections. Reinforcement Learning (RL) helps models learn to make decisions by interacting with changing environments. By combining GNNs and RL, it is possible to build a system that can respond to market changes and help businesses make better choices [19]. Social media data contain useful information about what people like or want [20]. But since the data are mostly unstructured text, traditional tools cannot process them well. Natural language processing tools like BERT can understand the meaning of such text and help extract food-related content. Transformer-based models, which use attention mechanisms, work well with time-series data [21]. They can find patterns over time and help forecast food demand. Many previous studies on food market analysis still have limitations [22]. They often use only one data source and ignore the value of combining social media, e-commerce, and nutrition data [23]. Their models do not fully describe the connections between foods or changes in consumer behavior. They also respond slowly to market changes. To solve these problems, this study builds a system that combines GNN, RL, BERT, and Transformer models. It uses multiple data sources and advanced modeling methods to predict food trends and analyze the market. The goal is to support smarter decisions in the food industry and promote sustainable growth.

2. METHODOLOGY

2.1 Data Collection

Data collection followed a clear and carefully designed plan. For social media data, a web crawler was used under each platform's data policies and legal rules. Filters such as topic tags, time range, and user activity were applied to ensure the data was both relevant and up to date. On Weibo, food-related posts and comments were selected using topic categories and popularity rankings. On Douyin, food videos were identified using video content tags and user engagement (likes and comments) [24]. On Xiaohongshu, food-related posts were filtered by keyword analysis and interaction counts to select high-quality entries [25]. For e-commerce data, we accessed the official API of a major platform to collect product information across 1,000 food items. The data included product names, prices, sales volumes, and user reviews. The data was sorted by food type and sales periods. To supplement this, nutrition information was collected from the USDA food database using a matching method. This ensured that nutrition data matched each food item and remained complete and accurate.

2.2 Data Preprocessing

Social media data were preprocessed using a combination of rule-based filtering and machine learning techniques [26]. Redundant entries, illegible content, and irrelevant hyperlinks were eliminated. Missing values were addressed through multiple imputation methods, which relied on similar food items and contextual information to estimate plausible replacements. For textual content, a word segmentation algorithm incorporating part-of-speech tagging and named entity recognition was applied to accurately identify word boundaries and semantic categories. Non-informative stop words were excluded, while domain-specific key terms were retained [27]. Subsequently, all data sources were integrated using a data alignment algorithm, with food names serving as the primary matching field. This process resulted in a comprehensive dataset linking social media, e-commerce, and nutrition-related information, which served as the foundation for subsequent model training.

2.3 Model Development

The BERT + GNN model was constructed using transfer learning. Initially, a pre-trained BERT model, trained on large-scale Chinese text data, was fine-tuned on food-related content. The model's hyperparameters were optimized to better align with the linguistic characteristics of the food domain [28]. The Graph Neural Network (GNN) component utilized a Graph Attention Network (GAT), consisting of three layers, each with eight attention heads. The attention mechanism enabled the model to assign varying weights to the links between nodes, thereby enhancing its understanding of the relationships between food items and user behaviors [29]. In the Transformer + GNN model, the Transformer section comprised six layers on both the input and output sides, with a hidden size of 512. Multi-head attention was applied to capture temporal patterns in food sales data. The output from the Transformer served as the input features for the GNN, which were passed between connected nodes to refine the prediction accuracy. For intelligent decision-making, a reinforcement learning model based on the Deep Q-Network (DQN) method was employed. The Q-network estimated the value of various actions under different system states. The learning rate was set to 0.001 to ensure stable training, while a discount factor of 0.99 was applied to prioritize long-term rewards. The model was trained by interacting with a simulated market environment, and its strategy was updated iteratively.

3. EXPERIMENTAL RESULTS AND DISCUSSION

3.1 Social Media Food Trend Analysis

Using the BERT + GNN model, social media data were analyzed to investigate consumer perceptions of health-related food products. In the case of "sugar-free beverages," approximately 75% of user comments expressed positive sentiment, with many users indicating that such products align with health-conscious lifestyles. These findings suggest that health-oriented food categories are gaining traction and becoming a focal point in consumer discourse. Topic popularity analysis further indicated a significant increase in interest surrounding plant-based foods. Over the past six months, the topic score for this category rose by 300%, establishing it as one of the most frequently discussed subjects in food-related social media. Based on the observed growth trend and user engagement levels, "probiotic fermented foods" are projected to become a prominent topic within the next three months. This form of trend forecasting offers practical value for the food industry by supporting forward-looking product planning and marketing strategy development. Additionally, it provides a useful framework for tracking shifts in consumer preferences over time. Compared with prior studies—such as Liu et al. [30], which employed a basic text analysis approach and reported only 60% sentiment classification accuracy with considerable latency in identifying emerging topics—the proposed BERT + GNN model demonstrated enhanced performance by combining contextual language understanding with graph-based relationship modeling. This integration contributes to improved accuracy and responsiveness in detecting evolving food trends.

3.2 Food Demand Forecasting

In the food demand prediction task, the Transformer + GNN model showed better performance than traditional methods. We compared it with the ARIMA model and a basic neural network. Our model achieved lower scores on two key error metrics: Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). Specifically, RMSE dropped by 30% compared to ARIMA and by 25% compared to the simple neural network. MAE dropped by 28% and 22%, respectively. These results show that the Transformer + GNN model better captures the changing patterns in food sales and gives more accurate predictions. This level of prediction accuracy is very helpful for real business use. It supports better decisions in production planning, inventory control, and supply chain management. It can help companies lower costs, respond faster to demand changes, and compete more effectively in the market. From a technical view, the ARIMA model uses repeating patterns in time series but cannot handle complex relationships. Simple neural networks often run into training problems when dealing with long sequences. The Transformer + GNN model avoids these issues. It uses attention to find key time steps and graph structure to improve learning between food items.

3.3 Intelligent Decision-Making

After a full round of training and testing, the learning model developed an effective decision strategy. In a test market environment, companies that followed the model's suggestions achieved better results. On average, their profit increased by 20% and their market share rose by 18% compared with those that used traditional decision-making methods. These results show that our intelligent decision model can respond well to market changes. It provides practical advice that companies can use. With this model, companies can make better choices in production, inventory, and marketing. This leads to more efficient use of resources and helps businesses stay competitive and grow in the long term. In similar conditions, that model increased profit by only 10% and market share by 12%. Our model, based on continuous learning, adjusts its decisions based on updated data and is more useful in real-world situations.

4. CONCLUSION

This study developed a food market analysis system based on graph neural networks. By combining data from social media, e-commerce platforms, and nutrition databases, and applying several modern modeling techniques, the system can predict food consumption trends with high accuracy. Test results showed that the system performed better than traditional models in key areas such as trend prediction, health food analysis, and demand forecasting. Accuracy improved by over 20%. These results can help food companies make better decisions in production and supply chain planning. The system can also assist public health departments in designing food-related policies that match consumer health needs. This study is one of the first to use GNN, reinforcement learning, BERT, and Transformer models together for this type of analysis. It builds food–consumer and product–product graphs to show how products relate to each other and how consumers behave. This improves the model's accuracy and decision-making ability. Companies can use this system to reduce risk and plan production and marketing more effectively. Policymakers can also use the results to guide public health planning and food education programs. Future work may focus on improving the model by testing new types of graph neural networks and attention-based methods. Data coverage can also be expanded to include economic trends, regional factors, and lifestyle data. In addition, building models for different regions or consumer groups can help provide more targeted suggestions and make the system more useful in real-world applications.

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