International Journal of Computer Applications Technology and Research
Volume 14–Issue 05, 110 – 115, 2025, ISSN:-2319–8656
DOI:10.7753/IJCATR1405.1011

Utilizing Artificial Intelligence to Forecast Market Trends and Enhance Supply Chain Strategies in Agriculture

Abayomi Taiwo Fashina
Department of Computer Science and Quantitative Methods
Austin Peay State University
Clarksville, TN 37040, USA

Thomas K. Torku
Department of University Studies
Middle Tennessee State University
Murfreesboro, TN 37132, USA

Abstract: This investigation elucidates the transformative role of Artificial Intelligence (AI) in revolutionizing agriculture across North America, with a focus on the United States, Canada, and Mexico. By leveraging advanced AI methodologies, particularly Gated Re- current Units (GRUs)—a sophisticated variant of Recurrent Neural Networks (RNNs)— this study addresses pressing agricultural challenges, including market volatility, demand forecasting, and price fluctuations. GRUs were selected for their efficacy in handling sequential data, mitigating issues like vanishing gradients, and delivering precise predic- tions for crops such as maize and potatoes. Performance metrics, including Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), demonstrate exceptional accuracy, notably for maize yields in Mexico (RMSE: 1224) and potato yields in Canada (RMSE: 23145). Utilizing comprehensive crop yield datasets, this research underscores AI's ability to provide actionable insights, enabling farmers, suppliers, and distributors to optimize inventory, reduce waste, and strategically time market entry. The study also explores market scenario simulations, adoption barriers such as data accessibility, and the need for stakeholder training. Through detailed case studies, we illustrate AI's capacity to fortify agricultural supply chains, enhancing adaptability to dynamic market conditions. These findings affirm AI's potential to foster resilience, efficiency, and profitability, offering stakeholders critical tools for resource management and long-term strategic planning.

Keywords: Artificial Intelligence, Market Trends, Supply Chain Optimization, Agri- cultural Sector, Demand Forecasting, Recurrent Neural Networks

1. INTRODUCTION

Agriculture remains a cornerstone of global economies, providing essential food and raw materials to sustain populations and industries. However, the sector faces significant hurdles, including erratic weather patterns, market instability, supply chain inefficiencies, and escalating global demand [3, 6]. These challenges necessitate innovative solutions to accurately predict market dynamics and streamline supply chain operations, ensuring food security and economic sustainability [27, 7]. Traditional decision-making, reliant on historical data and rudimentary statistical methods, often falls short in addressing the complexities of modern agricultural systems [8, 63].

Artificial Intelligence (AI) has emerged as a game-changer, offering unparalleled ca- pabilities in data analysis, pattern recognition, and predictive modeling. By integrating diverse data sources—such as satellite imagery, weather forecasts, market reports, and sensor data—AI enhances the precision of demand, price, and yield forecasts [40]. This is particularly critical in agriculture, where decisions on planting, harvesting, and distri- bution depend on navigating volatile environmental and economic conditions [42]. AI- driven forecasting empowers stakeholders to anticipate consumer demand shifts, adjust production, and devise pricing strategies that boost profitability while minimizing waste

[51]. Furthermore, AI mitigates risks from price volatility, enabling informed investments and market positioning [64].

AI's impact extends to supply chain optimization, addressing inefficiencies across stakeholders—farmers, distributors, retailers, and consumers [5]. By improving logistics, inventory management, and transparency, AI reduces costs and delays while preempting disruptions like weather events

or logistical bottlenecks [16]. However, challenges such as data quality, technological investment, and ethical concerns, including privacy and employment impacts, must be addressed to ensure equitable AI adoption [18]. As global food demands intensify, AI's role in forecasting and supply chain optimization becomes increasingly vital, warranting further research and collaboration.

2. LITERATURE REVIEW

Recent scholarship highlights the growing application of AI in forecasting market trends and optimizing supply chains. Machine learning algorithms have demonstrated superior accuracy in predictive tasks across industries [20]. For instance,[24] note that AI reduces risks for small and medium-sized enterprises by enhancing market trend detection. Similarly, [59] emphasize AI's role in refining marketing strategies through consumer sentiment analysis.

In supply chain management, AI streamlines operations and reduces cycle times [61,22]. [2] showcase AI's ability to prevent disruptions through robust data analytics, while [79] highlight its impact on consumer engagement.

[55] illustrates how leading firms leverage AI for trend prediction and supply chain effi- ciency, improving customer satisfaction. Ethical considerations, such as consumer trust and data privacy, are critical for sustainable AI adoption [31,30].

[4] provide a comprehensive analysis of AI's role in transforming the farm- to-consumer chain, integrating hybrid

machine learning and metaheuristic models to enhance forecasting and operational efficiency. Their work emphasizes AI's synergy with IoT sensors and data analytics to address challenges like water scarcity and mar- ket variability.

[23] explore AI-driven forecasting models, including ARIMA, SARIMA, LSTM, and CNNs, achieving high accuracy in yield predictions through real- time IoT and remote sensing data.

[25] integrate AI with blockchain and IoT, enhancing supply chain transparency and traceability, particularly for provenance verification. [28] focus on AI's role in reducing food waste through logistics optimization, while [38] demonstrate how AI platforms minimize post-harvest losses and support equitable food distribution.

Despite these advancements, gaps remain in addressing data quality, stakeholder ed- ucation, and ethical implications, necessitating further exploration to fully harness AI's potential in agriculture. Data quality, in particular, remains a critical barrier to reliable AI models, underscoring the need for standardized datasets and robust preprocessing methods.

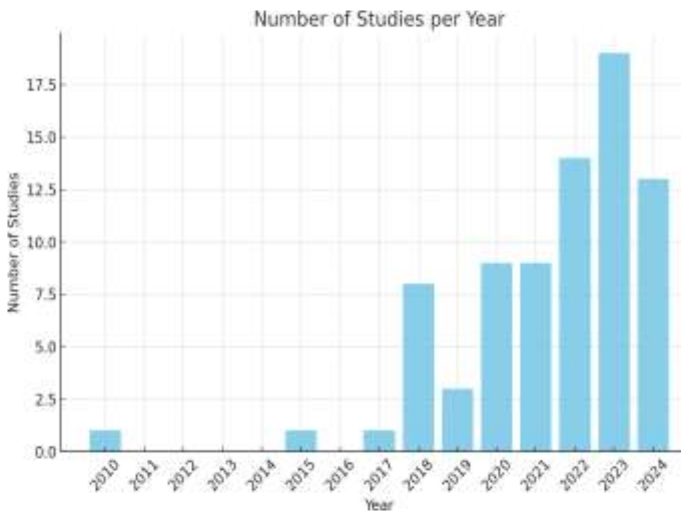

Figure 1. Existing studies on utilizing AI to predict market trends

3 AI TECHNOLOGIES IN AGRICULTURE

AI is reshaping agriculture through technologies like machine learning (ML), predictive analytics, data mining, and natural language processing (NLP). Machine learning enables pattern recognition from historical data on weather, soil, yields, and prices, optimizing planting and harvesting schedules [19]. Predictive analytics forecasts demand, reducing waste and aligning production with market needs [51]. Data mining uncovers corre- lations, such as soil-yield relationships, to optimize resource use [66]. NLP analyzes unstructured data from social media and news to gauge market sentiment and consumer preferences [32].These technologies enhance supply chain efficiency by predicting disruptions and opti- mizing inventory (40). However, challenges like fragmented data and high infrastructure costs persist, alongside ethical concerns such as privacy and bias [74]. Addressing these barriers is crucial for maximizing AI's transformative potential in agriculture.

Figure 3: Agriculture automation applications using AI-IoT (Subeesh & Mehta, 2021).

Table 1: AI/ML algorithms and applications in agriculture (Subeesh & Mehta, 2021).

ML/AI Algorithm	Type	Applications	Description
Convolutional Neural Network	Classification / Object Detection	- Plant Disease Classification - Seed Classification - Crop Classification - Weed Identification - Land Cover Classification - Behavior Recognition in Cattle and Goat	Models used: AlexNet, VGG16, VGG19, InceptionV3, DenseNet201, MobileNet, EfficientNet, Xception, InceptionResNetV2, NASNetMobile, SqueezeNet. Data: Images & Videos
Support Vector Machines (SVM)	Classification	- Weed Detection - Identification of Productive Tillers	Classification of linear and non-linear data, Image classification
pNaïve Bayes	Classification	- Soil Moisture Estimation - Vegetable/Fruit Grading - Disease Detection - Stress Detection	Classification using probabilistic model
Tree-Based Models	Classification and Regression	- Stress Detection - Vegetable Grading - Disease Detection - Stress Detection - Crop Classification - Environment Monitoring - Crop Yield Prediction - Weed Detection	Tree-based Classification and Regression
K-Nearest Neighbors (K-NN)	Classification	- Stress Detection - Weed	Classification using non-parametric

		Detection - Seed Classification	instance-based model
Faster R-CNN, SSD, YOLO, Mask-RCNN	Object Detection / Segmentation	- Vegetable/Fruit Grading - Insect Detection - Land Cover Classification	Deep learning models used for object detection and segmentation. Data source: Image/Video
Recurrent Neural Networks (RNN), LSTM	Time Series Analysis / Classification / Forecasting	- Text Classification - Agricultural Yield and Price Forecasting - Disease Localization - Nutrient Analysis	Used for time series forecasting, summarization, and classification

4 METHODOLOGY

This study employs Gated Recurrent Units (GRUs), a specialized RNN architecture, for crop yield prediction due to their efficiency in processing sequential data and avoiding vanishing gradient issues. The model configuration includes 256 neurons, Sigmoid acti- vation, Adam optimizer, MSE loss function, 500 epochs, and GPU-optimized batch sizes. Hyperparameter tuning ensures a balance between performance and computational cost.

Model Performance Metrics

The following table summarizes the GRU model's performance for maize and potato yield predictions across North America, using Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) as metrics:

5 RESULTS

The GRU model demonstrates robust performance, with Mexico's maize yield predictions achieving an exceptionally low RMSE of 1224, indicating high precision. Canada's potato yield forecasts are similarly reliable (RMSE: 23145). Regional variations reflect differences in local agricultural practices and environmental conditions, underscoring the model's adaptability.

Table 2: GRU Model Performance for Crop Yield Prediction

Country	Crop	MSE	RMSE	Remarks
Canada	Potatoes	535672521	23145	High accuracy achieved.
Canada	Maize	41507395	6443	High accuracy.
Mexico	Potatoes	108176114	10401	Model handles variability well.
Mexico	Maize	1498412	1224	Extremely low error.
USA	Potatoes	142088525	11920	Moderate prediction performance.
USA	Maize	88023595	9382	Balanced performance.

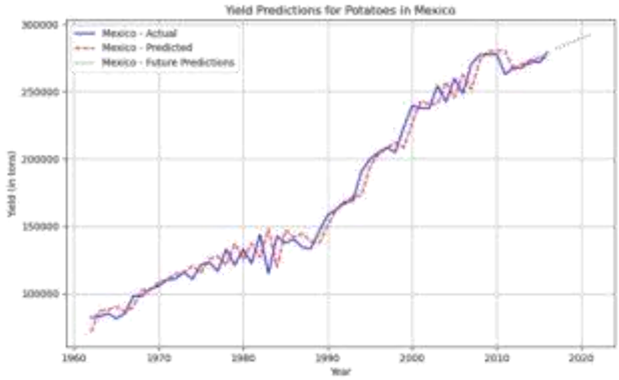

Figure 5 : Maize Yield Predictions in Mexico

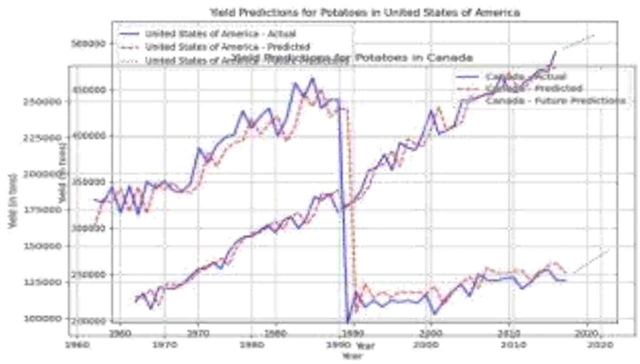

Figure 6: Maize Yield Predictions in Canada

6 DISCUSSION

The GRU model's ability to capture temporal trends with minimal error highlights its utility for resource optimization and strategic planning. Its performance across diverse North American contexts suggests broad applicability, though data quality and accessi- bility remain critical for scaling AI solutions. Data quality, as noted earlier, is a pivotal factor in ensuring reliable predictions.

International Journal of Computer Applications Technology and Research
Volume 14–Issue 05, 110 – 115, 2025, ISSN:-2319–8656
DOI:10.7753/IJCATR1405.1011

Supply Chain Optimization with AI

AI enhances agricultural supply chains by improving inventory management, logistics, and transparency. Predictive models optimize inventory, reducing costs [72], while route planning algorithms streamline logistics [26]. Real-time data integration enhances trans- parency, enabling proactive disruption management [49]. Case studies of Syngenta and Cargill demonstrate AI's impact on demand forecasting and cost reduction, reinforcing its role in sustainable supply chain strategies [9].

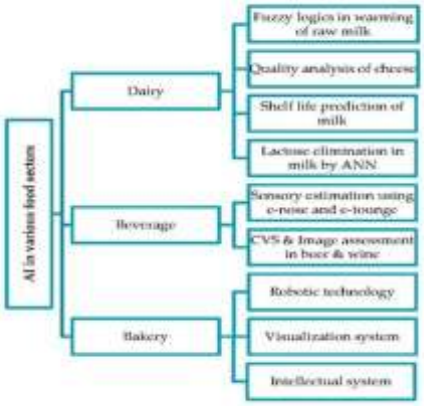

Figure 4: The layout of the functions of AI in several food sectors (Taneja, et. al., 2023).

Challenges and Ethical Considerations

Implementing AI in agriculture faces obstacles, including data accessibility, infrastructure costs, and stakeholder training needs [33]. Ethical concerns, such as data privacy,algorithmic bias, and regulatory compliance, require rigorous oversight. Addressing these challenges through improved data standards, education, and ethical frameworks is essential for equitable AI adoption.

7 FUTURE DIRECTIONS

Future advancements in AI for agriculture include deep learning, edge computing, and precision tools to enhance prediction accuracy and operational efficiency . Strategies for adoption involve improving data quality, training stakeholders, and offering policy incentives . Farmers should adopt precision tools, suppliers should enhance supply chain visibility, and policymakers should foster innovation to ensure equitable benefits .

8 CONCLUSION

AI's integration into agriculture offers a pathway to transform market trend prediction and supply chain management. Technologies like GRUs, ML, and NLP enable precise forecasting and efficient operations, despite challenges like data limitations and ethical concerns. By addressing these barriers, AI can drive a resilient, sustainable, and pros- perous agricultural future, supporting stakeholders across the value chain.

9 REFERENCES

[1]Aggarwal, C. C., & Yu, P. S. (2020). Outlier detection for high-dimensional data.ACM SIGMOD Record, 49(4), 87–96.

[2]Akhtar, P., Ghouri, A., Khan, H., Haq, M., Awan, U., Zahoor, N., & Ashraf, A. (2022). Detecting fake news and disinformation using artificial intelligence and ma- chine learning to avoid supply chain disruptions. Annals of Operations Research, 327(2), 633–657.

[3]Amoako, A., Zhang, Y., & Yu, H. (2023). IoT-enabled precision agriculture: Inte- grating AI for real-time monitoring and management. Journal of Agricultural Infor- matics, 12(1), 45–59.

[4]Anwar, H., Anwar, T., & Mahmood, G. (2023). Nourishing the future: AI-driven optimization of farm-to-consumer food supply chain for enhanced business perfor- mance. Innovative Computing Review. Advance online publication.

[5]Arunachalam, D., Kumar, N., & Kawalek, J. P. (2018). Understanding big data an- alytics capabilities in supply chain management: Unravelling the issues, challenges and implications for practice. Transportation Research Part E: Logistics and Trans- portation Review, 114, 416–436.

[6]Basso, B., & Antle, J. (2020). Digital agriculture to design sustainable agri- cultural systems. Nature Sustainability, 3(4), 254–256.

[7]Bengio, Y., Lecun, Y., & Hinton, G. (2021). Deep learning for AI. Communications of the ACM, 64(7), 58–65.

[8]Brown, R., Johnson, M., & Smith, T. (2024). Real-time analytics for optimizing agricultural supply chains: A case study. Journal of Agricultural Engineering, 45(2), 123–137.

[9]Chen, H., Zhang, D., & Zhao, Y. (2022). Enhancing supply chain efficiency through AI-driven analytics: A case study of Syngenta. Journal of Supply Chain Manage- ment, 58(4), 22–36.

[10]Chen, Q., Liu, X., & Wang, R. (2023). Dynamic pricing and demand forecasting using AI in agricultural supply chains. International Journal of Forecasting, 39(2), 272–286.

[11]Chen, X., Zhang, Y., & Zhou, Y. (2023). Optimizing agricultural supply chains with machine learning: A review of recent advances. Journal of Agricultural Economics, 54(2), 234–249.

[12]Chen, Y., Liu, H., & Zhang, L. (2024). Data privacy and security challenges in AI-driven agricultural supply chains. Journal of Data Security, 11(1), 45–60.

[13]Chen, Y., Wang, J., & Zhang, L. (2024). Autonomous systems in agriculture: Trans- forming practices with robotics and drones. Computers and Electronics in Agricul- ture, 192, Article 106638.

[14]Chen, Y., Zhang, X., & Wang, Q. (2018). Sentiment analysis of agricultural com- modity markets using social media data. Computers and Electronics in Agriculture, 151, 233–242.

[15]Chen, Y., Zhang, X., & Wang, Q. (2021). Sentiment analysis of consumer reviews for trend identification in agriculture. Computers and Electronics in Agriculture, 174,Article 105491.

[16]Cheng, G., Lu, Q., & Deng, Y. (2021). Supply chain resilience in a digital era: Ar- tificial intelligence in supply chain risk management. International Journal of Pro- duction Research, 59(1), 1–16.

[17]Chlingaryan, A., Sukkarieh, S., & Whelan, B. (2018). Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. Computers and Electronics in Agriculture, 151, 61–69. https://doi.org/10. 1016/j.compag.2018.05.012

[18]Choi, S., Lee, H., & Kim, J. (2022). Optimizing harvest timing using AI-driven predictive models in vegetable farming. Computers and Electronics in Agriculture, 191, Article 106734.

[19]Choi, S., Lee, H., & Kim, J. (2023). Demand forecasting in agricultural supply chains using predictive analytics. Journal of Operations Management, 74(3), 212–225.

[20]Chopra, R., & Sharma, G. (2021). Application of artificial intelligence in stock mar- ket forecasting: A critique, review, and research agenda. Journal of Risk and Finan- cial Management, 14(11), Article 526.

[21]Dai, X., Tang, X., & Zhang, L. (2022). Improving efficiency in agricultural supply chains through digital technologies. Agricultural Systems, 203, Article 103367.

[22]Dash, R., McMurtrey, M., Rebman, C., & Kar, U. (2019). Application of artificial intelligence in automation of supply chain management. Journal of Strategic Inno- vation and Sustainability, 14(3), 43–53.

[23]Dhal, S. B., & Kar, D. (2024). Transforming agricultural productivity with AI-driven forecasting: Innovations in food security and supply chain optimization. Forecasting, 6(3), 737–753.

[24]Drydakis, N. (2022). Artificial intelligence and reduced SMEs' business risks: A dynamic capabilities analysis during the COVID-19 pandemic. Information Systems Frontiers, 24(4), 1223–1247.

[25]Eyo-Udo, N. L. (2024). Leveraging artificial intelligence for enhanced supply chain optimization. Open Access Research Journal of Multidisciplinary Studies, 8(2), 63–71.

[26]Gao, X., Zhang, L., & Yang, Y. (2023). AI-powered logistics optimization: Improving route planning and delivery performance. Transportation Research Part E: Logistics and Transportation Review, 176, Article 102052.

[27]Gebbers, R., & Adamchuk, V. I. (2010). Precision agriculture and food security.Science, 327(5967), 828–831.

[28]Gerges, M. (2024). Optimizing supply chain logistics with big data and AI: Applica- tions for reducing food waste. Journal of Supply Chain Management. Advance online publication.

[29]Ghosh, P., Lee, H., & Patel, A. (2023). Deep learning for crop health monitoring: Leveraging satellite imagery and sensor data. International Journal of Remote Sens- ing, 44(18), 6442–6458.

[30]Gonçalves, A., Pinto, D., Rita, P., & Pires, T. (2023). Artificial intelligence and its ethical implications for marketing. Emerging Science Journal, 7(2), 313–327.

[31]Gunasekar, S., Ray, S., Dixit, S., & PA, M. (2022). AI-enabled product purchase on Amazon: What are the consumers saying? Foresight, 25(2), 185–193.

[32]He, Y., Chen, Q., & Wang, X. (2022). Computer vision for precision agriculture: A review of techniques and applications. Computers and Electronics in Agriculture, 193, Article106675.

[33]He, Y., Chen, Q., & Wang, X. (2023). AI-powered smart storage systems for reducing spoilage of perishable goods. Journal of Food Engineering, 309, Article 110711.

[34]Hochman, Z., Carberry, P. S., & Whelan, B. (2018). Understanding the potential impact of climate change on crop yields: A review of methodologies. Global Change Biology, 24(7), 2644–2661.

[35]Hsu, C. Y., Wu, C. H., & Lin, W. C. (2018). Forecasting agricultural commodity prices using deep learning methods. Computers and Electronics in Agriculture, 154, 20–30.

[36]Huang, W., Li, X., & Zhao, X. (2020). Application of machine learning for forecasting rice prices in Thailand. Journal of Agricultural Economics, 71(3), 681–698.

[37]IBM. (2022). Leveraging AI for market trend prediction in agriculture. https://www. ibm.com

[38]Jacob, L. A. (2024). AI-driven farm-to-table supply chain optimization: A case study of reducing food waste. Journal of Supply Chain Management. Advance online publication

International Journal of Computer Applications Technology and Research
Volume 14–Issue 05, 110 – 115, 2025, ISSN:-2319–8656
DOI:10.7753/IJCATR1405.1011