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Implementation of Artificial Intelligence and Deep Learning for Optimizing Sustainable Agricultural Production

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ABSTRACT

This study aims to explore the application of Artificial Intelligence (AI), deep learning technologies, and machine learning approaches for optimizing sustainable agricultural production, particularly in agricultural price forecasting. Using a Systematic Literature Review approach, this research collects and analyzes literature indexed in Scispace, Google Scholar, DOAJ, and Scopus published between 2014 and 2024. The findings indicate that AI, deep learning, Support Vector Machine (SVM), and Relevance Vector Machine (RVM) technologies hold significant potential in improving operational efficiency, food security, and forecasting accuracy in the agricultural sector. These technologies can support various aspects of agriculture, including agricultural price forecasting, crop yield prediction, plant disease detection, and more efficient natural resource management. However, the implementation of these technologies still faces several significant challenges, such as inconsistent data quality, high implementation costs, ethical issues related to data usage, and infrastructure limitations in rural areas. This study concludes that while these technologies offer considerable potential, their successful implementation depends heavily on addressing these challenges and developing policies that support the sustainable adoption of technology in the agricultural sector.

Keywords : *Artificial Intelligence; deep learning; SVM; RVM; agricultural price forecasting; sustainable agricultural production; food security.*

ABSTRAK

Penelitian ini bertujuan untuk mengeksplorasi penerapan Kecerdasan Buatan (AI), teknologi pembelajaran mendalam, dan pendekatan pembelajaran mesin untuk mengoptimalkan produksi pertanian berkelanjutan, khususnya dalam peramalan harga pertanian. Dengan menggunakan pendekatan Tinjauan Pustaka Sistematis, penelitian ini mengumpulkan dan menganalisis literatur yang diindeks di Scispace, Google Scholar, DOAJ, dan Scopus yang diterbitkan antara tahun 2014 dan 2024. Temuan menunjukkan bahwa teknologi AI, pembelajaran mendalam, Support Vector Machine (SVM), dan Relevance Vector Machine (RVM) memiliki potensi signifikan dalam meningkatkan efisiensi operasional, ketahanan pangan, dan akurasi peramalan di sektor pertanian. Teknologi ini dapat mendukung berbagai aspek pertanian, termasuk peramalan harga pertanian, prediksi hasil panen, deteksi penyakit tanaman, dan pengelolaan sumber daya alam yang lebih efisien. Namun, implementasi teknologi ini masih menghadapi beberapa tantangan signifikan, seperti kualitas data yang tidak konsisten, biaya implementasi yang tinggi, masalah etika terkait penggunaan data, dan keterbatasan infrastruktur di daerah pedesaan. Studi ini menyimpulkan bahwa meskipun teknologi-teknologi ini menawarkan potensi yang cukup besar, keberhasilan implementasinya sangat bergantung pada penanganan tantangan-tantangan ini dan pengembangan kebijakan yang mendukung adopsi teknologi secara berkelanjutan di sektor pertanian.

Kata Kunci : Kecerdasan Buatan; Pembelajaran Mendalam; SVM; RVM; Peramalan Harga Pertanian; Produksi Pertanian Berkelanjutan; Ketahanan Pangan.

INTRODUCTION

Sustainable agriculture plays a crucial role in addressing increasingly complex global challenges, such as population growth, climate change, and the rising demand for food. As the population continues to grow rapidly, global food requirements increase, while at the same time, natural resources are limited, and environmental conditions worsen [1]. Therefore, agricultural systems must not only meet the growing demand for food but also maintain ecological balance and minimize negative environmental impacts. Innovation in agricultural technology is essential to optimize food production more efficiently and sustainably, without depleting natural resources or damaging the environment [2]. This includes the implementation of environmentally friendly methods, the use of efficient technologies, and the prudent management of natural resources to support long-term sustainability.

The role of technology in transforming the agricultural sector is highly significant, particularly with the implementation of automation, the Internet of Things (IoT), and smart sensors, which have enhanced efficiency and productivity in various regions worldwide. These technologies enable more accurate land monitoring and management, reduce excessive resource use, and minimize waste. Automation allows agricultural processes to be carried out more quickly and precisely, while IoT and smart sensors provide real-time data that assist farmers in making more informed decisions to improve crop yields and minimize risks. These technological innovations are key to enhancing the resilience and efficiency of the agricultural sector amidst the global challenges faced today [3].

The ability of Artificial Intelligence (AI) and Deep Learning (DL) to analyze big data in the agricultural sector is crucial, particularly for identifying weather patterns, monitoring plant health, predicting crop yields, and optimizing input usage [4]. These technologies enable the processing and analysis of large volumes of data to generate deeper and more accurate insights, which in turn assist farmers in making more informed and efficient decisions. By leveraging AI and DL, predictions related to weather changes and plant conditions can be made more accurately, while the use of inputs such as water, fertilizers, and pesticides can be optimized to enhance agricultural yields sustainably [5].

The implementation of artificial intelligence (AI) and deep learning (DL) faces several challenges, primarily arising from data-related issues, technological gaps, and resource constraints [6]. A major obstacle is the limited access to high-quality, labeled data, which is crucial for training effective models. Acquiring such data is often expensive and time-consuming, particularly in remote areas where technological infrastructure may be inadequate [7]. Moreover, the demand for specialized expertise further complicates the situation, as many organizations struggle to find skilled professionals capable of navigating the complexities of AI technologies [8]. Additionally, the high costs associated with AI implementation may discourage small and medium-sized enterprises from adopting these technologies, exacerbating existing disparities in technological advancement [9]. Overcoming these challenges requires collective efforts to improve data accessibility, enhance infrastructure, and develop talent in the AI field.

The integration of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) into sustainability practices plays a crucial role in advancing the Sustainable Development Goals (SDGs) by improving resource efficiency, reducing waste, and mitigating environmental impacts . These technologies enable industries to optimize operations through predictive analytics, which enhances energy efficiency and minimizes waste, thereby promoting circular economy practices (Rane et al., 2024). AI-driven solutions support real-time monitoring of carbon emissions and waste across supply chains, allowing organizations to make informed adjustments that improve sustainability while also generating cost savings. Moreover, the convergence of AI with green management principles fosters operational excellence and resource optimization, resulting in significant improvements in sustainability metrics [10]. Additionally, innovative DL approaches utilize Earth observation data to tackle environmental challenges, such as air quality monitoring and precision agriculture, thereby contributing to the advancement of the SDGs across multiple sectors [11]. In sum, the strategic implementation of these technologies is essential for achieving comprehensive sustainability objectives.

Recent studies have examined the application of Artificial Intelligence (AI) and deep learning in agriculture, particularly in the context of commodity price prediction. Deep learning models have demonstrated considerable potential in forecasting agricultural commodity prices, outperforming traditional methods when handling large datasets [12]. Neural network models, including both Machine Learning and Deep Learning approaches, have been applied in precision agriculture for tasks such as classification, clustering, estimation, and forecasting [13]. The Long Short-Term Memory (LSTM) algorithm has been utilized to predict food commodity prices, achieving a Root Mean Square Error (RMSE) of 79.19%. Furthermore, Artificial Neural Networks have been employed to predict staple food prices in Jakarta, with accuracy rates ranging from 78% to 82% for different commodities [14]. Although these studies indicate progress in the application of AI in agriculture, there is still a need for more accurate and relevant commodity price prediction models to address existing research gaps.

The aim of this research is to develop an agricultural commodity price prediction system based on Relevance Vector Machine (RVM) that provides more accurate and reliable results compared to conventional methods. This study also seeks to compare the performance of RVM with other methods such as linear regression and Support Vector Machine (SVM) in terms of prediction accuracy, model reliability, and data utilization efficiency. Through this research, it is hoped that a more optimal method for predicting agricultural commodity prices will be identified, ultimately benefiting stakeholders in the agricultural sector by enabling

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more informed and data-driven decision-making.

METHOD

This study aims to explore the application of the Relevance Vector Machine (RVM) as a machine learning method for developing price prediction systems for agricultural commodities. Additionally, the research seeks to identify factors influencing the effectiveness of price predictions using RVM, compare its advantages with traditional methods such as linear regression and Support Vector Machine (SVM), and evaluate its potential to enhance efficiency and accuracy in agricultural price forecasting [15]. The findings of this study are expected to contribute to the development of more reliable price prediction technologies, support strategic decision-making in the agricultural sector, and provide recommendations for future research.

The literature for this study was obtained through systematic searches of academic databases, including Scopus, Dimensions, and Google Scholar. Keywords such as "Relevance Vector Machine," "price prediction system," and "agriculture" were used to retrieve relevant studies. The search focused on publications between 2014 and 2024 to ensure alignment with recent advancements in price prediction technology. The collected literature was then screened based on inclusion criteria, such as publications in reputable journals or proceedings, studies discussing the application of RVM in agriculture, and articles providing empirical data or comparative analyses. Exclusion criteria were applied to studies that solely discussed theoretical concepts without practical applications or employed other methods without referencing RVM.

Following the literature screening, relevant data were extracted for further analysis. The information collected included research methods, contexts of RVM application, factors influencing price predictions, and performance evaluations of RVM compared to other methods [16]. The data were analyzed descriptively and thematically to identify patterns, trends, and key findings related to the use of RVM in developing agricultural price prediction systems. The analysis also involved visualizations using software such as VOSviewer to illustrate keyword relationships, and descriptive statistics processed with R-Studio to strengthen data interpretation. The findings from this analysis were used to formulate strategic recommendations for stakeholders in the agricultural sector.

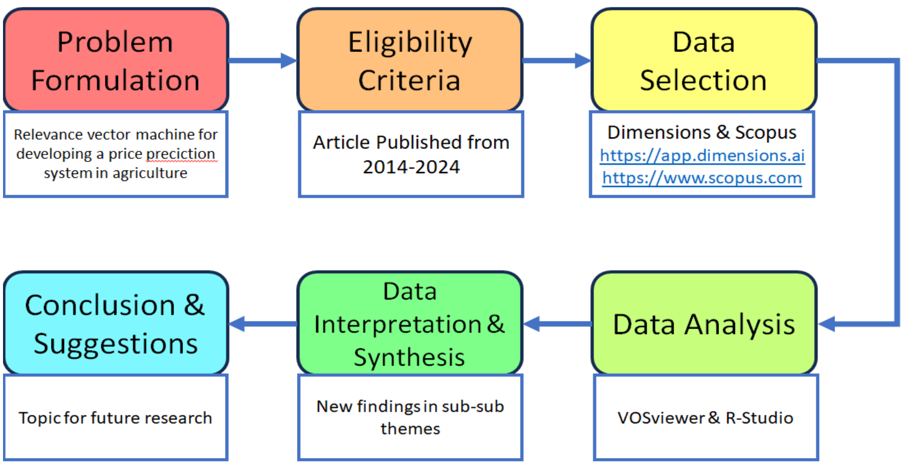

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Figure 1. Research Procedure

The research procedure is outlined in Figure 1. As illustrated, the study is conducted through several stages: problem formulation, establishing eligibility criteria, data selection, data analysis, interpretation and synthesis of findings, and conclusion drawing. The problem formulation stage is crucial for narrowing the scope of discussion to the application of the Relevance Vector Machine (RVM) for developing a price prediction system in agriculture. Eligibility criteria are determined to filter data relevant to the topic, using keywords such as "Relevance Vector Machine," "system development," and "agricultural price." Subsequently, data is selected from the Dimensions and Scopus databases, applying filters to include only publications from the last 10 years (2014–2024). The collected data is then imported into VOSviewer software to visualize the relationships between keywords and themes in the research. Additionally, R-Studio is employed for more in-depth descriptive statistical analysis and data exploration, such as calculating theme frequencies and conducting trend analysis. The visualizations and analytical results from VOSviewer and R-Studio are interpreted to identify key variables in the application of RVM for developing agricultural price prediction systems. These results are then used to formulate key findings and discuss their theoretical and practical implications. Finally, the researcher formulates conclusions and provides recommendations for future research on related topics.

RESULT AND DISCUSSION

Results of Data Selection

The search conducted in the Dimensions database initially yielded 114,283 entries relevant to the research topic. Following the application of eligibility criteria, 7,426 articles were identified as relevant and met the inclusion standards. Among these, 5,544 were journal articles, while 1,882 were conference proceedings. The distribution of data based on publication year is illustrated in Figure 2, which highlights the progression of research on curriculum management in modern Islamic boarding schools over the past 10 years. This distribution underscores trends and research dynamics within the specified time frame, providing insight into the development of studies in this area.

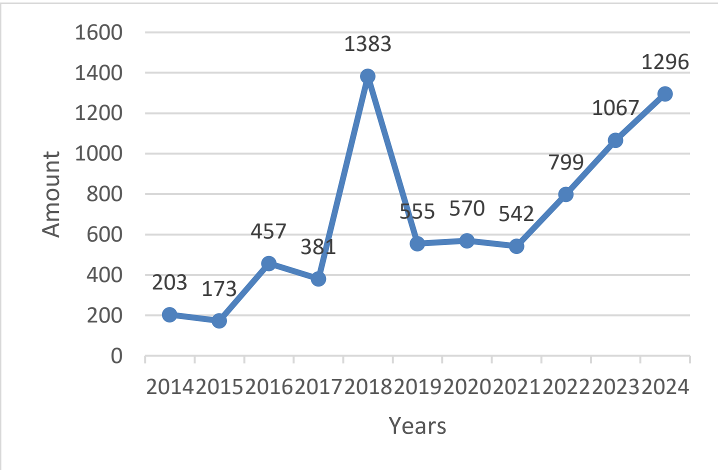

Figure 2. Publications in each year

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The trend in research publication numbers from 2014 to 2024 exhibits significant fluctuations. In 2014, the number of publications was recorded at 203, followed by a decrease to 173 in 2015. However, a significant increase occurred in 2016, with publications rising to 457, before experiencing a slight decline to 381 in 2017. A sharp surge took place in 2018, with publications reaching 1383, marking the highest peak during this period. Following this peak, the publication numbers sharply declined to 555 in 2019 and stabilized relatively in 2020 with 570 publications, followed by a further slight decrease to 542 in 2021. The trend showed an upward trajectory again in 2022, with publications reaching 799, and continued to rise sharply in 2023 to 1067. Finally, in 2024, the number of publications further increased to 1296, indicating a significant upward trend and potential for continued research development in the years to come. This graph reflects a non-linear growth pattern, where peaks and declines may be associated with external factors, such as increased attention to specific topics or shifts in global research dynamics.

Distribution of Research in Several Countries

The researcher then conducted an investigation into the distribution of publications across several countries. Figure 3 demonstrates that the topic of Relevance Vector Machine for the development of price prediction systems in modern Islamic boarding schools has been extensively researched and collaborated on across various countries around the world, including China, Australia, the USA, Canada, Germany, Denmark, Bangladesh, India, Spain, and Austria.

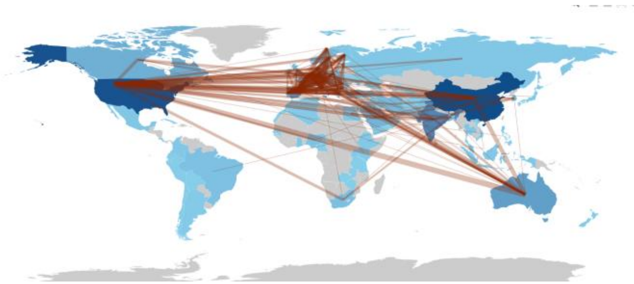

Figure 3. Countries' Collaboration World Map

The image depicts a global network of connections, with lines indicating various interactions between countries. The darker blue regions, particularly in North America and China, highlight key nodes in the network. The network lines, shown in orange, represent the flow of data or collaborations between these countries and others across the globe. The intensity of the lines suggests varying levels of connection strength, with major hubs like the United States, China, and parts of Europe forming central points of activity. The map appears to emphasize global connectivity, where countries in North America, Asia, and Europe are significantly involved in exchanges, likely reflecting a global trend of cooperation or data-sharing in research, trade, or other collaborative efforts. The flow lines are more concentrated around these regions, indicating stronger, more frequent interactions, while areas in Africa and South America are less connected, with fewer lines indicating weaker or less frequent connections. This visualization likely reflects the global distribution of activities such as academic research, international trade, or geopolitical interactions over a specific period, showing the major players in global exchange networks.

Table 2. Most Cited Countries

Country	TC	Average Article Citations
CHINA	4007	48.30
AUSTRALIA	2377	69.90
USA	1908	50.20
CANADA	1599	84.20
GERMANY	1229	61.50
DENMARK	988	164.70
BANGLADESH	964	120.50
INDIA	895	24.20
SPAIN	825	35.90
AUSTRIA	762	76.20

Denmark and Bangladesh exhibit exceptionally high average citations per article, with values of 164.70 and 120.50, respectively. This suggests that, despite their relatively lower publication output compared to countries such as China and Australia, the quality or relevance of articles from Denmark and Bangladesh is considered more significant by the global academic community. In other words, articles from these countries tend to receive greater individual attention from researchers worldwide. Meanwhile, China leads in total citations (4007) but has a lower average citation per article (48.30). This indicates that while China's publication output is exceptionally high, the impact of each individual article, on average, is smaller compared to countries with higher average citation rates such as Denmark, Bangladesh, and Canada (84.20).

Other countries like Australia (69.90) and Austria (76.20) also demonstrate strong performance in research quality, with relatively high average citation rates. In contrast, India, while having a significant number of publications, shows a lower average citation per article (24.20), reflecting that although its publication productivity is high, the impact of its research is not as pronounced as in countries with higher average citation rates. Thus, this data suggests that research success is not solely determined by publication productivity but also by quality, relevance, and impact, as measured by the average citations per article.

Network Visualization of Data

Furthermore, researchers visualized all research results using VOSviewer to see the research variables and the relationship between variables. The visualization results are as shown in Figure 5.

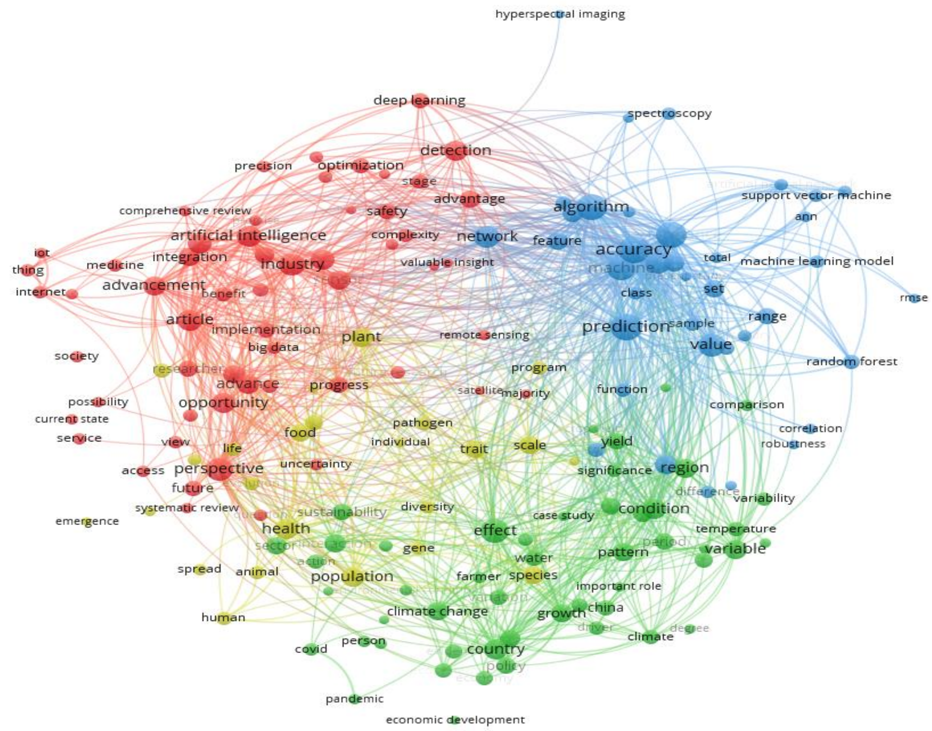

Figure 5. Network Visualization Of Modern Boarding School Curriculum Management.

Figure 5 is a network visualization of all variables studied over the past 10 years and depicts four different color clusters: green, red, yellow, and blue. The interpretation is as follows.

1. The red cluster in this visualization highlights keywords closely related to artificial intelligence (AI) and its applications across various domains, particularly in modern industry and technology. Dominant keywords such as artificial intelligence, deep learning, detection, network, optimization, precision, and industry underscore the pivotal role of AI as a foundational element in driving efficiency, innovation, and system integration across multiple industrial sectors. The implementation of AI not only focuses on enhancing accuracy and process optimization but also addresses safety concerns through early detection mechanisms and data-driven decision-making. Additionally, keywords like review and advancement reflect the ongoing scientific exploration and development of AI, fostering the discovery of new methodologies to address future industrial challenges. The integration of AI with complementary technologies, such as deep learning, offers significant potential for improving productivity and delivering innovative solutions to navigate the increasing complexity of modern systems.
2. The blue cluster in this visualization focuses on algorithms, accuracy, and prediction, with particular emphasis on the application of machine learning methods in data analysis. Key terms such as accuracy, algorithm, prediction, feature, range, value, and support vector machine highlight the importance of methodological approaches in ensuring the precision of predictive outcomes through systematic data processing. Connections between keywords like

machine learning model and random forest indicate that machine learning techniques have become a central strategy for enhancing predictive performance, both for numerical and complex datasets. Methods such as support vector machine and random forest play a crucial role in pattern recognition, data classification, and maximizing predictive value through efficient computational processes. This approach not only improves accuracy but also addresses the complexity and variability of data features across diverse application scenarios, positioning machine learning as a robust and adaptive solution for data-driven problem-solving in the era of advanced technology.

3. The green cluster in this visualization highlights themes related to population dynamics, environmental effects, agriculture, and economic development. Keywords such as health, population, species, region, condition, growth, scale, and climate change reflect a research focus on understanding the impact of environmental changes on ecosystems, regional economic growth, and food security. The presence of terms like pandemic and economic development underscores the relevance of these studies to pressing global challenges, such as economic crises and public health issues. Research in this area often explores the interconnectedness of environmental sustainability, agricultural productivity, and human well-being, emphasizing the need for strategies to mitigate the adverse effects of climate change on regional populations and economies. Additionally, topics such as species diversity, resource management, and the condition of agricultural systems illustrate a comprehensive approach to achieving sustainable development goals while addressing challenges posed by population growth, climate variability, and global health crises.
4. The yellow cluster in this visualization highlights opportunities and progress within agricultural and industrial systems, emphasizing the potential for development and innovation. Keywords such as opportunity, progress, implementation, uncertainty, plan, and future reflect a strong focus on sustainability and the challenges surrounding the implementation of new technologies in these sectors. The term uncertainty points to the complexities and risks associated with technological adoption, while plan and progress suggest the strategic steps required to overcome these obstacles and achieve future advancements . Additionally, keywords like food and pathogen underscore the critical role of research in addressing food security challenges, particularly in combating crop diseases and ensuring the resilience of agricultural systems. This cluster suggests a forward-looking approach that balances the pursuit of innovation with the need to mitigate risks, creating opportunities for sustainable growth in agriculture and industry while tackling pressing global issues related to food production and distribution.

The Role of Artificial Intelligence and Deep Learning in Modern Industry

Artificial Intelligence (AI) and Deep Learning have made significant contributions across various industrial sectors, particularly in detection, optimization, and security [17]. In terms of detection, AI technology enables the rapid and accurate processing of large-scale data to identify patterns, anomalies, or

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potential risks [18]. For example, in the healthcare industry, AI is utilized to detect diseases through the analysis of medical imaging, such as X-rays or MRIs, thereby enhancing diagnostic efficiency. Similarly, in the manufacturing sector, deep learning facilitates the detection of defects or damages in products with high precision, minimizing losses caused by substandard goods and improving overall quality control [19].

Furthermore, AI and deep learning play a crucial role in process optimization and enhancing security across diverse sectors [20]. In optimization, these technologies improve operational efficiency by predicting trends and analyzing real-time data, such as in supply chain management and energy resource management. Regarding security, AI contributes to the development of advanced cybersecurity systems capable of detecting suspicious activities and preventing digital threats [21]. In the transportation sector, AI drives the advancement of autonomous vehicles, which enhance road safety by reducing the risks associated with human error. Thus, the integration of AI and deep learning not only enhances productivity but also promotes sustainability and security in modern industries [22].

The implementation of Artificial Intelligence (AI) and Deep Learning has a significant impact across various industrial sectors, particularly in enhancing the accuracy and efficiency of detection, process optimization, and strengthening security systems. In the healthcare sector, AI facilitates faster disease detection, thereby accelerating diagnosis and patient treatment. In manufacturing, deep learning aids in detecting product defects with high precision, reducing waste in the production process. Additionally, AI plays a crucial role in optimizing resource utilization and risk management across sectors, as well as enhancing the protection of data and systems from cyber threats. Despite the numerous benefits these technologies offer, challenges in their implementation remain, particularly concerning the need for high-quality data, high costs, and ethical issues such as potential biases in automated decision-making. However, overall, research indicates that AI and deep learning hold significant long-term potential, particularly in terms of improving efficiency and reducing operational costs.

Algorithm and Machine Learning Techniques to Increase Prediction Accuracy

Support Vector Machines (SVM) play a pivotal role in predictive analysis by enhancing data accuracy through various innovative techniques. Hybrid models, such as the SVM-Naïve Bayes combination, have shown superior predictive performance compared to traditional algorithms, effectively addressing individual weaknesses while leveraging their strengths [23]. Additionally, intelligent SVM regression models have been developed to improve predictions of financial data, demonstrating increased accuracy and reduced interference from extraneous factors ("Financial Data Prediction Based on Intelligent Support Vector Machine Regression Model," 2023). Modifications to the SVM algorithm, including the implementation of multiple kernel learning, have also been shown to significantly enhance classification accuracy by integrating various kernel functions, thereby optimizing predictive capabilities (Ivanov, 2021; "Improving Support Vector

Machine Accuracy with Shogun's Multiple Kernel Learning," 2022). Furthermore, the use of mixed kernel functions in genome selection has outperformed traditional models, achieving notable improvements in both prediction accuracy and computational efficiency [24]. These advancements collectively underscore the versatility and efficacy of SVM in refining predictive analytics across diverse fields.

Support Vector Machine (SVM) plays a critical role in prediction analysis and improving data accuracy. As a supervised machine learning model, SVM is widely utilized for both classification and regression tasks. It works by finding the hyperplane that best separates data points of different classes or predicts continuous values in regression problems. One of the main advantages of SVM is its ability to handle high-dimensional data efficiently and provide accurate predictions, even in cases of complex data distributions. To enhance its predictive power, SVM has been combined with other techniques, such as hybrid models, which integrate SVM with algorithms like Naïve Bayes [25]. These hybrid models have demonstrated superior accuracy in prediction tasks by combining the strengths of each individual algorithm while mitigating their respective weaknesses. Additionally, modifications like multiple kernel learning (MKL) further enhance SVM's performance by incorporating different types of kernel functions, allowing the model to better capture the complexity of data and improve classification accuracy [26]. These advancements have made SVM a versatile tool for improving the accuracy and robustness of predictions across various domains, including finance, healthcare, and genomics.

The integration of hybrid models, such as the SVM-Naïve Bayes combination, aims to enhance prediction accuracy by leveraging the unique strengths of each algorithm. In this case, SVM's strong classification capabilities are complemented by Naïve Bayes' probabilistic approach, helping to mitigate the weaknesses of each method. Additionally, the adaptation of SVM to regression tasks, particularly in financial data prediction, indicates its growing recognition as a tool capable of delivering more accurate forecasts in complex, real-world scenarios. The incorporation of multiple kernel learning (MKL) and mixed kernel functions further emphasizes SVM's adaptability and flexibility by using various kernel functions to capture intricate data patterns. These developments reflect a broader trend of improving SVM's versatility and predictive power across diverse fields. The research shows that SVM, with its ability to handle high-dimensional data and efficiently analyze complex datasets, remains an invaluable tool for predictive analytics. The use of hybrid models significantly enhances predictive performance by addressing the limitations of individual algorithms. However, the effectiveness of SVM in more intricate applications, such as financial data prediction, may still be constrained by data quality and quantity, as SVM requires large, high-quality datasets for optimal performance. Furthermore, while MKL and mixed kernel functions lead to notable improvements, they introduce computational challenges, including longer processing times and increased model training complexity, making these advanced techniques more resource-intensive.

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Environmental, Agricultural and Food Security Impacts in Economic Development

Climate change has a profound impact on agriculture, intensifying environmental challenges and posing significant risks to global populations and economies. Rising temperatures have led to decreased agricultural productivity, as soil conditions worsen and crops become more vulnerable to pests and diseases, resulting in reduced yields and economic losses. This decline in agricultural output threatens food security, particularly in nations heavily dependent on agriculture, and exacerbates issues such as biodiversity loss, food and water scarcity, and the spread of vector-borne diseases. Additionally, agricultural activities themselves contribute to climate change, with practices such as intensive farming and the use of agrochemicals leading to increased greenhouse gas emissions. The reciprocal relationship between climate change and agricultural practices highlights the urgent need for global cooperation and investment in sustainable, climate-resilient agricultural systems to mitigate these effects and promote long-term socio-economic stability [27].

Climate change has significant impacts on agriculture, food security, and global migration. The agricultural sector faces serious challenges due to changing rainfall patterns, increased occurrences of extreme weather events, and rising temperatures [28]. These changes threaten food production and may exacerbate poverty, particularly in rural areas. Rising sea levels also result in the shrinkage of agricultural land in coastal areas, forcing population displacement, as seen in the case of Kiribati. To mitigate the impacts of climate change, strategies for adaptation and mitigation are needed, including the development of climate-resistant crop varieties and the implementation of sustainable agricultural systems [29]. A holistic approach that incorporates biotechnical, socio-economic, and institutional aspects is essential for achieving sustainable agricultural development to meet global food demands.

The data indicates that climate change presents a significant challenge to both food security and agricultural sustainability, with rising temperatures and extreme weather events contributing to declines in agricultural productivity, particularly in developing nations that rely heavily on agriculture. This creates a vicious cycle, where agricultural practices exacerbate climate change, and climate change, in turn, further undermines agricultural output. Consequently, both climate change mitigation and adaptation strategies are crucial in addressing these challenges. The need for climate-resilient agricultural systems is more urgent than ever, as these systems can sustain food security and mitigate the socio-economic impacts of climate disruptions. While the research highlights the dual impacts of climate change on agriculture and food security, identifying key factors such as soil degradation, pest and disease proliferation, and the environmental costs of farming, it falls short in examining the practical challenges and costs associated with implementing these solutions on a global scale. Additionally, the studies do not fully explore the complex interplay of socio-economic factors and agricultural practices, which may limit the broader applicability and effectiveness of the proposed strategies in different regions.

Opportunities and Challenges for Implementing Technology in Agricultural Systems

The integration of technology within the food sector offers significant potential while simultaneously presenting substantial challenges, particularly in the areas of pathogen control and uncertainty. Digital technologies, such as artificial intelligence and data analytics, contribute to enhanced food security by optimizing supply chain monitoring and advancing smart agriculture practices. However, concerns related to accessibility and data security persist [30]. Likewise, food nanotechnology provides innovative solutions for improving food safety and quality, though public apprehension regarding the potential risks of nanomaterials remains a notable challenge [31]. Furthermore, advancements in electronics, including the Internet of Things (IoT) and sensors, promise to transform precision agriculture; nevertheless, the integration of these technologies faces considerable technical and operational obstacles. Non-traditional processing technologies, such as high-pressure processing and cold plasma, are effective in reducing foodborne pathogens while maintaining nutritional value, yet their widespread adoption is hindered by industry resistance and the need for a deeper understanding of their applications. Overall, while technological innovations offer considerable promise for improving food safety and quality, it is essential to address the uncertainties and public concerns associated with their implementation to ensure successful adoption [32].

The integration of digital technologies in agriculture presents substantial opportunities for enhancing food security, sustainability, and the livelihoods of farmers, yet it also introduces significant challenges [33]. Remote sensing and machine learning hold promise for more precise crop prediction, although challenges related to sampling and feature engineering must be addressed [34]. The potential for expanding agricultural activities in tidal swamp lands is notable, with innovations in water management, adaptive crop varieties, and agricultural machinery. However, infrastructure limitations, farmers' technological expertise, and insufficient institutional support continue to present barriers [35]. Nanotechnology applications in agriculture and food processing, such as fertilizers, antioxidants, and smart packaging, show promise in Indonesia. Nevertheless, challenges remain, including inadequate facilities, a lack of synergy among research institutions, limited human resources, and budget constraints. To foster the adoption of nanotechnology, policy efforts should focus on developing research networks, enhancing human resources, and promoting public-private partnerships [36].

The research highlights the transformative potential of emerging technologies in the food and agricultural sectors, emphasizing their capacity to enhance food security, sustainability, and efficiency. Digital technologies, particularly AI and data analytics, can optimize supply chain management and improve agricultural practices. However, challenges related to accessibility and data security necessitate stronger regulatory frameworks and infrastructure development to ensure broad, secure adoption. Similarly, while nanotechnology offers innovative solutions for food safety and quality, public concerns regarding safety and environmental risks must be addressed through targeted research and education. In agriculture, precision tools like remote sensing and machine learning show promise in improving crop prediction, but data quality and technical expertise issues still hinder their full potential. Furthermore, the utilization of underdeveloped agricultural lands, such as tidal swamps, faces challenges due to inadequate infrastructure and limited support for farmers. The research emphasizes the need for a collaborative environment, particularly for the development and adoption of nanotechnology in agriculture, advocating for strengthened research networks and public-private partnerships to overcome existing barriers.

Table 3. Comparison of RVM and SVM Performance in Agricultural Prediction Studies

Study	Case Study	Algorithm	Main Findings
Rana et al. (2024)	Agricultural commodity price prediction	SVM	Produced good prediction accuracy but required careful parameter tuning and larger training datasets.
Dong & Chen (2021)	Commodity forecasting	RVM	Achieved high forecasting accuracy with fewer support vectors and better model sparsity, reducing computational complexity.
Fissha et al. (2024)	Prediction modelling using dual-kernel RVM	RVM	Demonstrated improved prediction performance and stronger generalization ability through kernel optimization.
Nayak et al. (2015)	Machine learning prediction applications	SVM	Effective for nonlinear prediction problems but sensitive to kernel selection and parameter settings.
Comparative Synthesis	Agricultural forecasting	RVM vs SVM	RVM generally provides probabilistic outputs, uses fewer relevance vectors, and offers more interpretable uncertainty estimates, whereas SVM often requires more support vectors and higher computational resources.

Table 3 demonstrates a comparison between the performance of Support Vector Machine (SVM) and Relevance Vector Machine (RVM) in various prediction and forecasting studies relevant to the agricultural sector. The findings indicate that both algorithms are capable of producing accurate predictive models; however, they possess different strengths and characteristics. SVM is widely recognized for its robustness in handling nonlinear and high-dimensional data, making it effective for agricultural forecasting tasks. Nevertheless, its performance is often influenced by kernel selection and parameter tuning. In contrast, RVM offers several advantages, including a probabilistic prediction framework, fewer relevance vectors, lower computational complexity, and better model sparsity. These characteristics enable RVM to provide not only accurate forecasts but also uncertainty estimates that are valuable for agricultural decision-making under dynamic market and environmental conditions. Overall, the reviewed studies suggest that RVM has considerable potential as an alternative or complement to SVM for improving the accuracy, efficiency, and reliability of agricultural forecasting systems.

CONCLUSION

Based on the evaluation conducted, it can be concluded that technologies such as AI, deep learning, SVM, and other innovations hold significant potential to enhance operational efficiency, food security, and predictive accuracy across various sectors. However, challenges such as data quality, implementation costs, ethical issues, and infrastructure limitations remain substantial barriers to their widespread adoption. Furthermore, climate change exacerbates the challenges in the agricultural sector and food security, necessitating a more sustainable and adaptive approach to address these changes. A key gap identified is the lack of effective collaboration between research institutions, human resource development, and the implementation of policies that support large-scale technology adoption. Additionally, despite the considerable potential of these technologies, there is an urgent need to develop more efficient systems for handling large and high-quality datasets, as well as improving the infrastructure required to support their implementation.

An urgent research topic for the future is how to develop and implement AI and deep learning technologies in the context of sustainable agriculture and food security, with a focus on addressing challenges related to data quality and limited infrastructure. Furthermore, research on the integration of nanotechnology in agriculture and food processing, as well as studies on the development of policies that promote more inclusive and ethical technology adoption, are also critical to explore. Through these research efforts, it is expected that more applicable innovations can be achieved, widely accepted by society, and contribute to the sustainability of the agricultural sector and global food security.

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