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Intellectual Capital in Agribusiness: Integrating Digital Solutions for Sustainable Development

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Abstract

This article explores the integration of digital solutions to enhance the sustainable development of agribusiness through the activation of the introduction of intellectual capital. The analysis is carried out taking into account various factors affecting yields, such as soil type, fertilizer use, market prices, employee education level, product demand, and automation level. The level of automation, the use of geographic information systems, access to big data, and hours of employee training were chosen as factors of intellectualization. Random forest, ARIMA, SARIMA, and LSTM models were used to predict yields. The data were taken from the statistical portals of Armenia and Georgia (137 observations). The results of the study show that the LSTM model demonstrated the best prediction accuracy with an average absolute error of 8.30 and a standard error of 102.47. The random forest model showed an average absolute error of 24.87 and a standard error of 828.23, while the ARIMA and SARIMA models did not show significant results. The study revealed significant correlations between digital solutions characterizing the level of intellectual capital in agricultural enterprises and agricultural land productivity, including the level of automation and access to big data. Analysis was also conducted on the impact of intellectual capital on the sustainability of agribusiness, including the impact of the level of education and training hours of employees. It is concluded that the integration of innovative technologies, such as big data and automation, contributes to improving the efficiency of agricultural production.

Keywords: intellectual capital, agribusiness, sustainable development, digital solutions, yield forecasting, random forest, ARIMA, SARIMA, LSTM, big data, automation, agriculture

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Интеллектуальный Капитал в Агробизнесе: Интеграция Цифровых Решений для Устойчивого Развития

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Аннотация

Данная статья исследует интеграцию цифровых решений для повышения устойчивого развития агробизнеса через активизацию внедрения интеллектуального капитала. Анализ проводится с учетом различных факторов, влияющих на урожайность, таких как тип почвы, использование удобрений, рыночные цены, уровень образования работников, спрос на продукцию и уровень автоматизации. В качестве факторов интеллектуализации выбраны уровень автоматизации, использование геоинформационных систем, доступ к большим данным и часы обучения работников. Применены модели Random Forest, ARIMA, SARIMA и LSTM для прогнозирования урожайности. Данные взяты со статистических порталов Армении и Грузии (137 наблюдений). Результаты исследования показывают, что модель LSTM продемонстрировала наилучшую точность предсказаний со средней абсолютной ошибкой 8.30 и среднеквадратичной ошибкой 102.47. Модель Random Forest показала среднюю абсолютную ошибку 24.87 и среднеквадратичную ошибку 828.23. В то время как модели ARIMA и SARIMA не показали значимые результаты. В процессе исследования были выявлены значимые корреляции между цифровыми решениями, характеризующими уровень интеллектуального капитала на агропредприятиях, и урожайностью сельскохозяйственных угодий, включая уровень автоматизации и доступ к большим данным. Также проводится анализ влияния интеллектуального капитала на устойчивость агробизнеса, включая влияние уровня образования и часов обучения работников. Сделаны выводы о том, что интеграция инновационных технологий, таких как большие данные и автоматизация, способствует повышению эффективности агропроизводства.

Ключевые слова: интеллектуальный капитал, агробизнес, устойчивое развитие, цифровые решения, прогнозирование урожайности, Random Forest, ARIMA, SARIMA, LSTM, большие данные, автоматизация, сельское хозяйство

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1. Introduction

Research on intellectual capital in agribusiness is aimed at analysing the importance of digital technologies and intangible assets in creating efficiency. In terms of economic aspects, we can highlight the importance of knowledge, skills, and innovation in improving efficiency and productivity. The human capital of skilled workers, the structural capital of processes in the organization, and the relational capital obtained from networks and partnerships contribute to the formation of intellectual potential among agricultural producers (Scafarto et al., 2016; Zaytsev et al., 2020).

Automation, big data analysis, geographic information systems (GIS), and other digital solutions help transform traditional farming practices into new forms of management while increasing the efficiency of business operations. Digital technologies make it possible to increase the return on control and management of agribusiness, creating conditions for increasing yields, reducing losses, and increasing the quality of resource use. Integration of digital solutions is necessary to solve problems related to resource reduction and the need to adapt new agricultural practices (Balaji and Mamilla, 2023; Shirokov et al., 2023; Zaytsev et al., 2024).

The purpose of this article is to investigate the integration of digital solutions to increase the sustainable development of agribusiness through the introduction of intellectual capital. This study aims to analyse the impact of various factors on yield, including soil type, fertilizer use, market prices, employee education, product demand, and automation levels. The following methods are used to achieve these goals:

- collection and analysis of statistical data from the statistical portals of Armenia and Georgia
- application of predictive models for yield analysis and forecasting
- correlation analysis to identify significant relationships between digital solutions and productivity
- analysis of the significance of the impact of intellectual capital on the sustainability of agribusiness

The object of this research is the agricultural enterprises of Armenia and Georgia that use digital solutions and intellectual capital in their activities to support strategies aimed at achieving sustainable development. The subject of this study is the factors influencing crop yields, their relationship with intellectual capital, and digital solutions in agribusiness. The research uses predictive models such as random forest, ARIMA, SARIMA, and LSTM.

2. Literature Review

Intellectual capital is the basis for the development of many economic sectors, including agro-industrial production, where the integration of intellectual achievements, primarily digital solutions, is the basis for increasing the sustainability of agribusiness. In the context of agribusiness, intellectual capital includes components that affect the yield and overall development of agricultural enterprises. Table 1 presents the main components of intellectual capital, as well as highlighting aspects that can affect the modelling of intellectual capital in agribusiness (Edvinsson and Malone, 1997; Sveiby, 1997).

Table 1. Components of intellectual capital in agribusiness

Component of intellectual capital	**Definition**	**Example in the context of a business model**
Human capital	Knowledge, skills, and experience of employees	Level of education of employees, hours of training
Structural capital	Organizational processes and innovations	Level of automation

Relational capital	Networks and communications, access to information and technology	Access to big data

The efficiency of using intellectual capital and its impact on the sustainable growth of agribusiness can be investigated with a focus on optimizing processes and using human capital to increase productivity. Digital transformation to improve the sustainable value of products and services of agri-food systems can significantly improve the efficiency of supply chains, reducing gaps in access to information and resources, especially for small producers (Balaji and Mamilla, 2023; Silva et al., 2022). The impact of intellectual capital on the profitability of agribusiness companies has shown that structural capital and human capital have the main impacts (Ovechkin et al., 2021).

By analysing the various components of intellectual capital, including human, structural, and relational capital, it is possible to identify their impact on companies' financial performance. In practice, researchers note that the impact of management measures on changing the structure of intellectual capital contributes to the growth of productivity and competitiveness of companies. In this context, it is necessary to ensure the development of new approaches for assessing and managing intellectual capital in various sectors of the national economy, including the agro-industrial sector (Pedro et al., 2018; Xu and Liu, 2020). It is proposed to identify the contribution of intellectual capital to several key indicators of agribusiness (Table 2).

Table 2. Impact of intellectual capital on key agribusiness indicators

Key indicator	**Human capital**	**Structural capital**	**Relational capital**
Productivity	High level of knowledge and skills	Process optimization, use of new technologies	Access to advanced data and information
Financial profitability	Increased productivity	Reduced costs through automation	Improved market positions
Sustainability and environmental friendliness	Efficient use of resources	Introduction of environmentally friendly technologies	Strengthening ties with environmental organizations
Competitiveness	Innovative management methods	Product quality improvement	Expanding market relations

The focus on the components of intellectual capital in the context of their role in ensuring sustainable development makes it possible to form models for managing the processes of intellectualization. A particularly clear manifestation of intellectual capital is positively noted for small and medium-sized enterprises, where investment in human and structural capital contributes to improving the competitiveness of companies. At the same time, depending on the size of the business and the scope of economic relations, it is possible to adapt various methods for evaluating intangible assets and intellectual capital (Gołacka et al., 2020; Osinski et al., 2017). Consequently, it is possible to develop and apply methods for evaluating and managing intellectual assets, including analysing digital solutions that affect the performance of agribusiness entities.

Digital solutions are being actively implemented in the economic management of agribusiness, ensuring the rationalization of management processes at different levels. To achieve these goals, many enterprises attract financing, which makes it possible to activate innovative processes in agro-industrial production. At the state level, the issues of financing innovative processes in the agricultural sector are strategically important (Dumanska, 2018a, 2018b). These aspects define the role of intellectual capital in the strategy of ensuring economic security, emphasizing the formation of potential for managing intellectual resources in the context of achieving sustainable economic development and national security. To a large extent, it is necessary to use methods and tools that can be used to analyse and improve socioeconomic indicators (Rodionov et al., 2020; Zhogova et al., 2020). This study analyses the digital solutions presented in Table 3.

Table 3. Digital solutions in agribusiness

Digital technology	Description	Example in the context of a data model of a mapping model
Big data	Analysis of large volumes of data for making informed decisions	Access to big data
Automation	Use of automated systems for process management	Automation level
Geographic information systems (GIS)	Spatial data collection, analysis, and visualization	Crop area optimization
Drones	Field condition monitoring and yield assessment	Precise crop control and management
Internet of Things (IoT)	A network of interconnected devices for data collection and exchange	Sensors for monitoring soil conditions and growth
Artificial intelligence (AI)	Using machine learning algorithms for data analysis and forecasting	Yield forecasting and risk management
Robotics	Using robots to perform agricultural tasks	Automated harvesters
Mobile applications	Applications for farmers that provide access to information and tools	Weather forecasting, inventory management, and task planning
E-commerce platforms	Online platforms for selling agricultural products	Direct sales to consumers, supply chain management
Chain	Distributed ledger technology for transparency and traceability	Traceability of product provenance and anti-counterfeiting

The researchers propose methods for improving the innovation management systems in the enterprises of the agro-industrial complex. In order to increase the efficiency of innovation implementation and improve management processes, one should turn not only to financing digital solutions but also to creating conditions for managing digitalization processes (Zinina and Tezina, 2016). The use of digital solutions can significantly improve the efficiency of agro-industrial processes, reduce gaps in access to information and resources, and improve interaction between participants in the agri-food chain. It is proposed to highlight the impact of digital solutions on intellectual capital in agribusiness (Table 4).

Table 4. Impact of digital solutions on intellectual capital in agribusiness

Digital technology	Human capital	Structural capital	Relational capital
Big data	Employee development	Improving data-driven decision-making	Strengthening partnerships through data exchange
Automation	Reducing physical workload	Improving process efficiency	Increasing productivity
Geographic information systems (GIS)	Technology training	Optimizing land use	Access to spatial data
Drones	Operator training	Field monitoring and management	Improving communication with service providers
Internet of Things (IoT) service providers	Improving technical literacy	Monitoring real-time conditions	Exchanging data between devices
Artificial intelligence (AI)	Training in new methods of analysis	Forecasting and optimization	Improving customer interaction
Robotics	Training in working with robotic systems	Automating routine tasks	Improving logistics links

These digital solutions and components of intellectual capital form the basis for improving the efficiency and sustainability of agricultural enterprises. At the beginning of the 21st century, it was noted that digital solutions and other intelligent aspects of farm management should be integrated in agriculture. In practice, this contributes to the development of small food enterprises. It is noted that various aspects of management, including organizational culture and access to technology, directly affect the implementation of innovations in small firms (Avermaete et al., 2003). To analyse the effectiveness of intellectual capital in agribusiness, it is acceptable to use econometric methods that take into account economic and technological factors that affect the productivity and sustainability of agribusiness entities. Based on digital solutions, it becomes possible to form networks of interaction between various participants in the agro-industrial sector to assess their impact on the operational, financial, and social indicators of enterprises (Asatryan et al., 2022; Rey et al., 2023).

3. Materials and Methods

Data from the statistical portals of Armenia and Georgia were used for the study. A total of 137 observations were collected, including a number of variables that affect crop yields (Table 5).

Table 5. Selected indicators for modelling

Variable	Description	Unit of measurement
Months	Observation period	Months
Crop_Yield	Yield	Currency/hectare
Precipitation	Precipitation	Millimetres
Soil_Type	Soil type	1, 2, 3
Fertilizer_Use	Fertilizer usage	Fraction (0–1)
Seed_Fertilizer_Cost	Cost of seeds and fertilizers	Currency
Market_Prices	Market prices for products	Currency
Education_Level	Level of education of employees	1, 2, 3
Demand	Demand for products	Index
Competition	Market competition	Share (0–1)
Farm_Workers	Number of agricultural workers	People
Automation_Level	Automation level	Share (0–1)
GIS_Usage	Usage of geographic information systems	Share (0–1)
Big_Data_Access	Access to big data	Share Data (0–1)
Training_Hours	Employee training hours	Hours

The selected variables allow us to assess the impact of various factors on crop yields and analyse the relationship between digital solutions, intellectual capital, and agribusiness sustainability.

3.1 Modelling

To achieve the goal of the study, predictive models were used that have unique characteristics and methods of data analysis (Table 6).

3.1.1 Random Forest

The random forest model is an ensemble machine learning method that uses multiple decision trees for predictions. Each tree is trained on a random subsample of data, and the final result is obtained by averaging the predictions of all trees.

Advantages:

- Resistance to overfitting

- Ability to work with a large number of attributes

- High accuracy of predictions

3.1.2 ARIMA

The ARIMA model is used for time series analysis and forecasting. It combines autoregression, integration, and moving average, which allows one to model data based on seasonal and time dependencies.

Advantages:

- Designed for time series analysis

- Takes into account seasonal fluctuations

3.1.3 SARIMA

The SARIMA model is an extension of the ARIMA model and includes additional parameters for analysing time series with a particularly pronounced seasonal component.

Advantages:

- Accounts for seasonal changes

- Suitable for data with strong seasonality

3.1.4 LSTM

The LSTM model is a type of recurrent neural network designed to work with sequential data and time series. LSTM is able to store long-term dependencies in data due to its memory cell architecture.

Advantages:

- Accounts for long-term dependencies

- High accuracy of predictions for time series

- Resistance to the problem of vanishing gradients

Table 6. Comparison of predictive models

Model	**Advantages**	**Disadvantages**	**Application examples**
Random Forest	High accuracy, resistance to overfitting	Lots of computing resources, complexity of interpretation	Yield factor analysis
ARIMA	Suitable for time series, seasonality	Limited application with non-linear dependencies	Demand forecasting
SARIMA	Accounting for seasonal changes	Difficulty in setting parameters	Yield forecasting with seasonality
LSTM	Accounting for long-term dependencies, high accuracy	Long learning time, the need for big data	Time series forecasting

The models selected for data analysis allow us to take into account and model complex relationships between variables that affect the yield of agribusiness. Their use allows us to make predictions with increased accuracy, which is the basis for making informed decisions.

4. Results and Discussion

4.1 Results of Predictive Models

4.1.1. Random Forest

The random forest model showed good results:

- Root mean square error (RMSE): 828.23

- Mean absolute error (MAE): 24.87

This model effectively takes into account many factors (Figure 1) that affect yield and can be useful for analysing the relationships between variables. The constructed model takes into account parameters for hyperparametric modelling, which allows initializing the random forest model and searching for the best parameters using GridSearchCV.

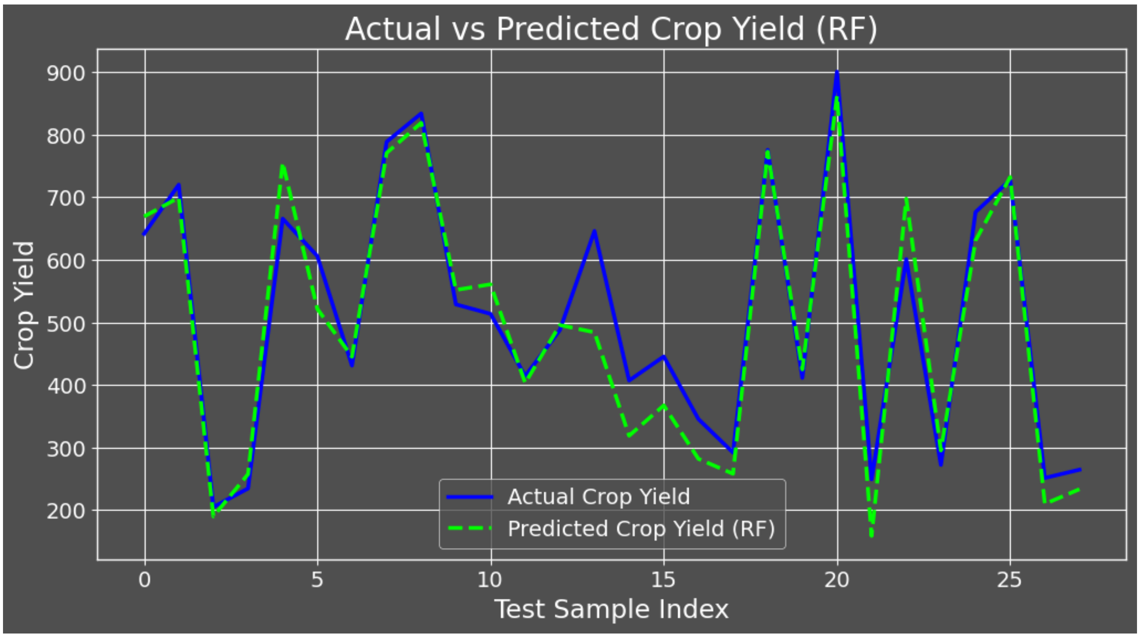

Figure 1. Random forest results

4.1.2. ARIMA

The ARIMA model did not show significant results:

- Root mean square error (MSE): 7810.76

- Mean absolute error (MAE): 80.94

This model did not allow us to identify significant results, which may be due to the high complexity and non-linearity of factors affecting yield (Figure 2).

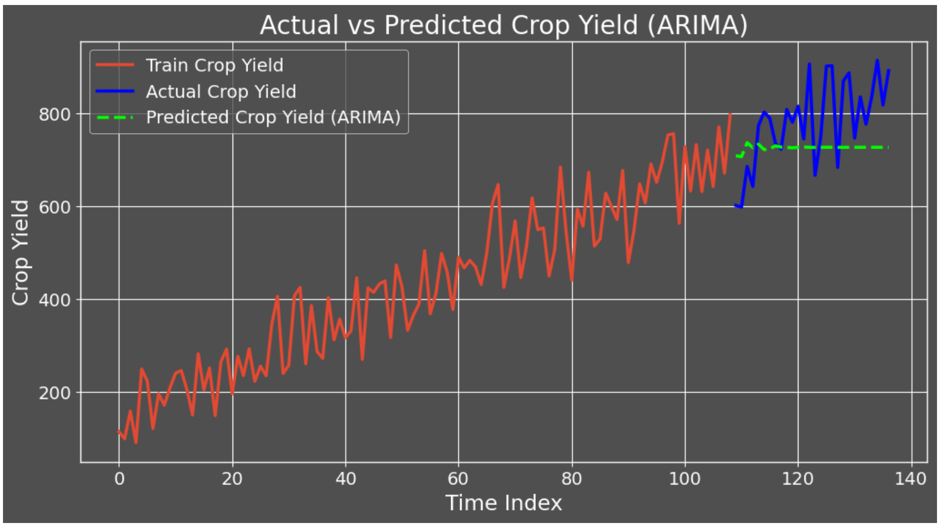

Figure 2. ARIMA results

4.1.3. SARIMA

The SARIMA model also did not show strong results:

- Root mean square error (MSE): 3126.34

- Mean absolute error (MAE): 46.19

This model, despite taking into account seasonal fluctuations, could not take into account all the factors affecting the yield (Figure 3).

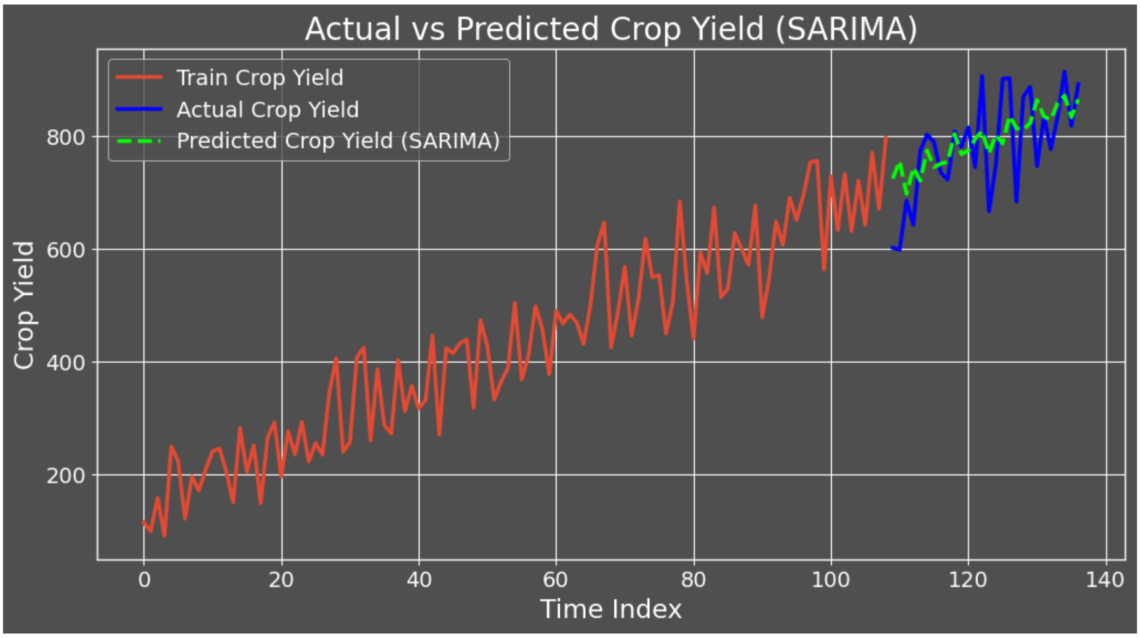

Figure 3. SARIMA results

4.1.4. LSTM

The LSTM model demonstrated high accuracy:

- Root mean square error (MSE): 102.47

- Mean absolute error (MAE): 8.30

This model showed the best results among all the models considered, as it was able to take into account long-term dependencies and nonlinear relationships between variables, taking into account the scaling inversion for the predicted values (Figure 4).

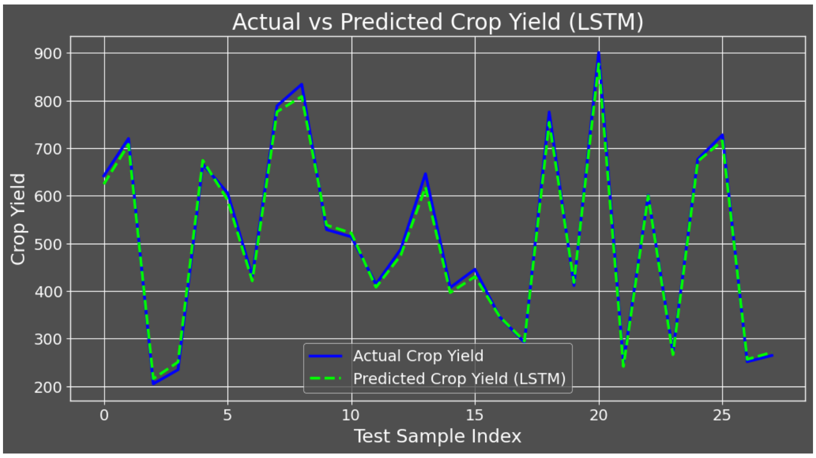

Figure 4. *LSTM results*

5. Discussion

5.1. Model Comparison

The results show that the LSTM model is the most effective for predicting yield revenues of agribusiness enterprises. The ability of the model to process sequential data and take into account complex time dependencies makes it important for conducting research in this area.

Mean absolute error (MAE) and mean square error (MSE) metrics were used to evaluate the predictions of various models. The results showed that the models have different degrees of accuracy in predicting yield (Table 7).

Table 7. Estimation of model accuracy

Model	MAE	MSE
Random forest	24.87	828.23
ARIMA	80.94	7810.76
SARIMA	46.19	3126.34
LSTM	8.30	102.47

The LSTM model showed the best results in comparison with other models, as it has low average absolute error and root mean square error, which indicates the reliability of this model in predicting the yield of agribusiness enterprises—that is, the efficiency of companies' activities. The random forest model showed good results but lost out to LSTM in terms of accuracy. ARIMA and SARIMA were not able to adequately cope with the task of predicting yield in this study.

5.2 Impact of Factors on Yield

Analysis of the significance of various factors affecting yield showed that the following factors have the most significant impact:

- A high level of automation leads to an increase in the efficiency of operations at agribusiness enterprises, which has a positive effect on yields

- Using big data for analysis and decision-making allows us to more accurately predict and optimize processes

- High-quality training of employees contributes to improving their skills, which, in turn, improves the results of their work

Figure 5 shows a graph of Shapley Additive Explanations values that reflects the impact of factors on the yield prediction model. SHAP values show how much each feature affects the model output.

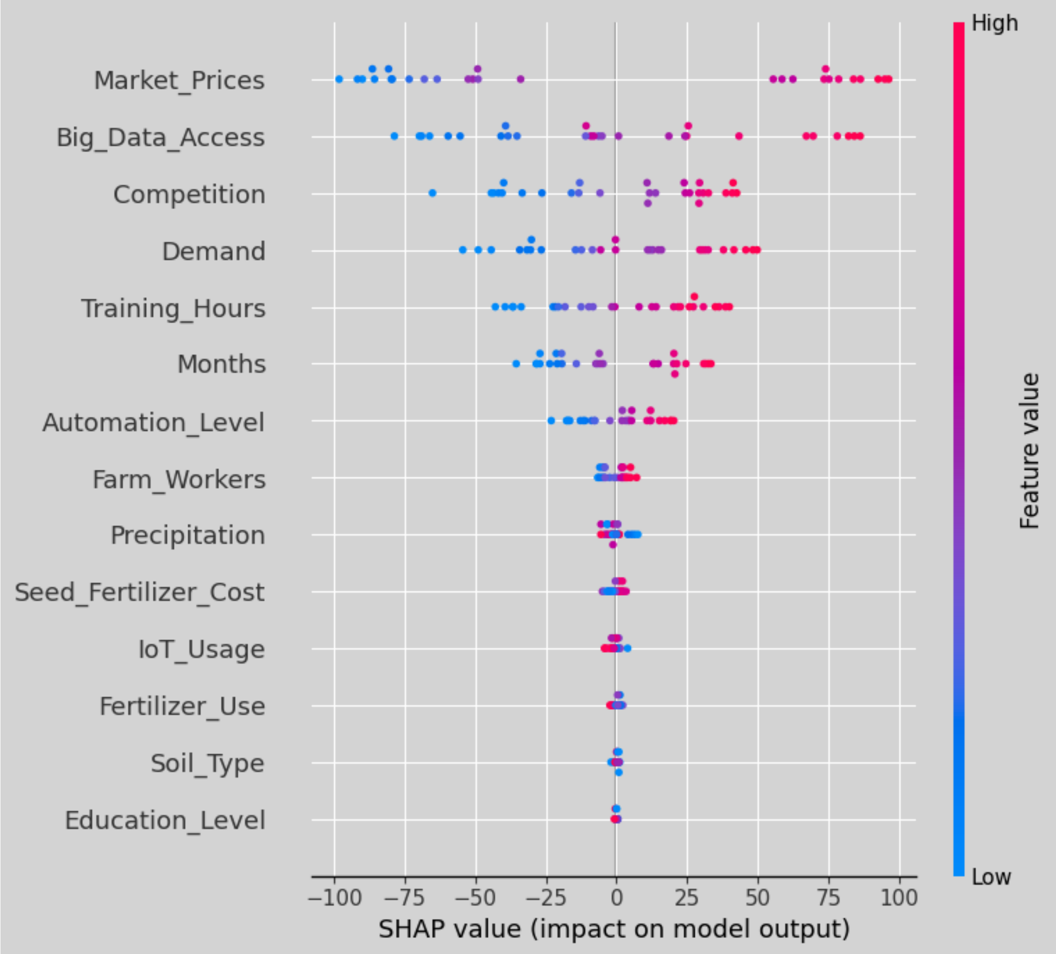

Figure 5. SHapley Additive exPlanations (SHAP) results

Key observations:

- Market_Prices – the impact of market prices on the yield prediction model is very positive, especially for high values of market prices (red dots).

- Big_Data_Access – Access to big data has a positive impact on model prediction, which highlights the importance of information and data in crop management.

- Competition and Demand factors have different effects on the model, which indicates a complex interaction between market conditions and the performance of agricultural enterprises.

- Training_Hours – Employee training hours have a positive impact on model prediction, which confirms the importance of human capital.

- Automation_Level – A high level of automation has a positive effect on the model's predictions, indicating the importance of technological equipment.

- Precipitation – precipitation show mixed effects, which may depend on specific climatic conditions and their impact on the crop.

- Education_Level – This has the least impact on the model's predictions.

- The SHAP value graph allows us to quantify the impact of various factors on the yield prediction model. Figure 6 shows a graph of the significance of traits that reflects the influence of the various factors on crop prediction. The graph shows the relative significance of each factor in the model used for analysis.

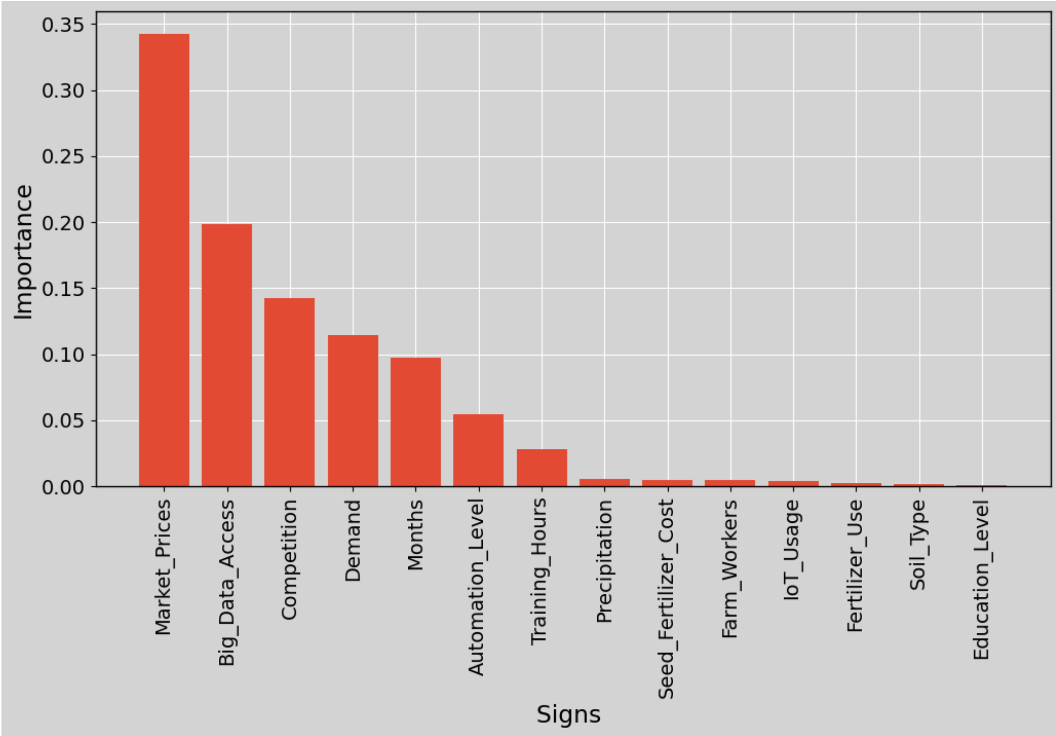

Figure 6. Feature significance graph

Key observations:

- Market_Prices has the highest significance (about 0.35).

- Big_Data_Access is the second most important factor (about 0.2020).

- Competition and Demand factors affect the model with high significance (about 0.15 and 0.12, respectively).

- Months and Automation_Level have a moderate impact, emphasizing the importance of seasonal changes and the level of automation in the production process.

- Training_Hours has a noticeable impact.

- Anticipation has some influence on the prediction of the model.

- The Seed_Fertilizer_Cost, Farm_Workers, IoT_Usage, Fertilizer_Use, Soil_Type, Education_Level factors are less significant than other factors but still contribute to the model.

6. Conclusion

The results of the study highlight the importance of intellectual capital in agribusiness. The level of education of employees and their training have a direct impact on the efficiency of using digital technologies and, consequently, on productivity. The integration of innovative technologies, such as big data and automation, helps to increase crop yields and improve the sustainability of agricultural production. Digital technologies contribute to the sustainable development of agribusiness. The use of big data allows agribusinesses to analyse information for decision-making, which helps optimize processes and reduce costs. Automation allows us to increase the efficiency of agricultural operations, reducing the impact of the human factor and increasing productivity.

The study showed that the use of LSTM models for predicting yield gains is the most appropriate (compared to the random forest, ARIMA, and SARIMA models). Significant correlations were found between digital solutions (level of automation, access to big data) and productivity. Thus, it is possible to develop some recommendations for agribusiness enterprises:

1. Strengthen training and professional development of agricultural workers to improve the efficiency of digital technologies use.

2. Implement and use big data to analyse and make informed decisions in agricultural production.

3. Increase the level of process automation to improve operational efficiency.

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