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IMPLICATIONS OF NEURAL NETWORK AS A DECISION-MAKING TOOL IN MANAGING KAZAKHSTAN'S AGRICULTURAL ECONOMY

Abstract

This study investigates the application of Artificial Neural Networks (ANN) in forecasting agricultural yields in Kazakhstan, highlighting its implications for economic management and policy-making. Utilizing data from the Bureau of National Statistics of the Republic of Kazakhstan (2000-2023), the research develops two ANN models using the Neural Net Fitting library in MATLAB. The first model predicts the total gross yield of main agricultural crops, while the second forecasts the share of individual crops, including cereals, oilseeds, potatoes, vegetables, melons, and sugar beets. The models demonstrate high accuracy, with the total gross yield model achieving an R-squared value of 0.98 and the individual crop model showing an R value of 0.99375. These results indicate a strong predictive capability, essential for practical agricultural and economic planning. The study extends previous research by incorporating a comprehensive range of climatic and agrochemical data, enhancing the precision of yield predictions. The findings have significant implications for Kazakhstan's economy. Accurate yield predictions can optimize agricultural planning, contribute to food security, and inform policy decisions. The successful application of ANN models showcases the potential of AI and machine learning in agriculture, suggesting a pathway towards more efficient, sustainable farming practices and improved quality management systems.

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1. INTRODUCTION

In the era of rapid technological advancement, instruments dependent on artificial intelligence, especially neural networks, are becoming crucial in decision-making across different sectors of economic activity. With the growing challenges regarding food security and the changing climate, it is essential to accurately forecast agricultural yields to ensure economic and food stability. This allows for effective management and informed economic decision-making to minimize the risk of food-related crises, optimize supply chains, and promote sustainable agricultural practices and economic growth.

This is particularly important for countries where agriculture plays a significant role in the economy. Kazakhstan is a nation with considerable agricultural capabilities, particularly in the realm of crop production. The country encounters the task of optimizing its resources to achieve maximum efficiency and promote sustainable development (Suieubayeva et al., 2022). The population of Kazakhstan is slightly more than 20 million people in November 2023. The proportion of rural inhabitants stands at almost 38%, the share of employment in agriculture, forestry, and fisheries is 5,56%. In 2022, the agricultural sector of Kazakhstan experienced significant growth exceeding the national GDP growth rate of 3.3%. As of the end of 2022, the official estimate for Kazakhstan's Gross Domestic Product (GDP) was approximately $512 billion in purchasing power parity (PPP) terms (Bureau of National Statistics of Kazakhstan, 2022). As of 2021, the total value of Kazakhstan's agricultural output was approximately USD 8.4 billion. The agricultural sector accounted for about 5.1% of Kazakhstan's economic production in 2021. Wheat is the country's largest crop by acreage, accounting for 80% of grain production, but Kazakhstan also produces barley, cotton, sunflower seeds, and rice. For 2023, Kazakhstan exported 13.2 million tons of grain and flour in grain equivalent. The total sown area for agricultural production in Kazakhstan reached 23.4 million hectares in 2023. Furthermore, in 2022, Kazakhstan saw a significant increase in its agricultural trade with the European Union, with the turnover of agricultural products reach $995.5 million. The country has been focusing on exporting a variety of products to the EU, including flax, wheat, rapeseed, processed cereals, and fish products, with an emphasis on expanding trade and economic partnership. The gross production output in the agricultural, forestry, and fisheries sectors in 2022 amounted to 9.5 trillion tenge, indicating a significant 9.1% rise compared to the previous year. It provides a solid foundation for ensuring food security of the entire country (Duisenbekova & Daniłowska, 2021). Importantly, it should be noted that the food security of the country relies on various factors and should be ensured through the coordinated efforts of governmental bodies authorized to regulate diverse sectors of the economy. This situation underscores the critical role of management science in formulating and implementing effective strategies. Management theories and practices, particularly in the realm of public administration and strategic planning, become instrumental in this context. They provide the necessary tools and frameworks for decision-makers to optimize resource allocation, enhance supply chain efficiency, and foster sustainable agricultural practices. By integrating principles of management science, such as systems thinking, stakeholder analysis, and adaptive management, Kazakhstan can not only maintain but also enhance its food security while adapting to changing economic and environmental conditions (Levin et al., 2023).

Management of agriculture in Kazakhstan plays a crucial role in boosting the efficiency of crop production, which constituted approximately 61% of the country's agricultural output in 2022 (National Statistics Bureau of Kazakhstan, 2022b).

The prediction of crop yield is imperative in managing food security challenges, particularly in the backdrop of global climate change (Wing et al., 2021). Accurate crop yield predictions have a significant role in supporting farmers' informed economic and managerial decisions. These predictions also contribute to global efforts aimed at preventing hunger and ensuring food security (Zhao et al., 2018).

The drive to develop more precise methods of crop yield forecasting leads to innovations at the intersection of plant sciences and data analysis, which will continue in the future. Most of the scientists predicted the yields of various crops using traditional econometric models. The majority methods in the studies were linear and multiple regression (Ansarifar et al., 2021; Conradt, 2022; Murugan et al., 2020; Rai et al., 2022; Sellam & Poovammal, 2016), and exponential weighted moving average (Annamalai & Johnson, 2023; Booranawong & Booranawong, 2017; Kim et al., 2020). However, the most widespread method used by scientists in forecasting crop yields was autoregressive integrated moving average (ARIMA) (Dharmaraja et al., 2020; Fan et al., 2016; Hemavathi & Prabakaran, 2018; Alani & Alhiyali, 2021; Lwaho & Ilembo, 2023; Rathod et al., 2018; Rathod et al., 2017; Senthamarai Kannan & Karuppasamy, 2020). Yu Arkhipova & Smirnov (2020) predicted crop yields in Russia by using econometric models such as the traditional least squares regression model and the truncated sample regression model. Yun & Gramig (2022) used regression modelling (non-spatial panel regression) of corn yield in US counties using weather and site characteristics as independent variables. Okorie et al., (2023) conducted yield forecasting of major crops (banana, plantain, beans, cassava, coffee, sorghum, potato, sweet potato, maize, rice, sugarcane, wheat, millet and cotton seed) in East African countries (Burundi, Kenya, Somalia, Tanzania, Uganda and Rwanda) using an ARIMA model. Also, this ARIMA approach was used in the research by Sharma et al. (2018) that projected maize production in India.

Some researchers have tried to predict Kazakhstan's crop yields (Islyami et al., 2020; Nhu et al., 2023; M. Sadenova et al., 2023). The most common variables in these studies consist of NDVI vegetation index and meteorological data on mean temperature, precipitation, soil moisture and wind speed. Romanovska et al. (2023) has developed a successful model based on weather and yield statistics from Kazakhstan to simulate regional wheat yields 2 months before the crop is harvested (R^2 value from 0.86 to 0.73). Their findings made it clear that among climatic variables, the most important for wheat production in Kazakhstan are average precipitation and its distribution. Moreover, high minimum temperatures are a major risk for wheat growth. M.A. Sadenova et al. (2021) carried out modelling of spring crop yields using meteorological data on temperature, precipitation, moisture deficit and MODIS satellite spectroradiometer data. Their results indicate that the 0.70 correlation coefficient between actual and predicted spring wheat yields regarding the model demonstrates its robustness to changes in meteorological conditions affecting spring crop yields.

Econometric models are powerful tools for understanding and predicting agricultural outcomes, but they do have limitations. They rely on the quality and availability of data, and they often assume that past relationships between variables will continue into the future, which may not always be the case, especially under conditions of climate change or major shifts in agricultural practices.

In recent years, there has been a growing interest among researchers in applying artificial neural networks to papers rather than using traditional econometric models.

The use of machine learning (ML) models exceeds traditional econometric models in several ways when it comes to predicting crop yields.

There are known studies on the application of artificial neural networks in crop yield forecasting. Guo & Xue (2014) predicted wheat yields in Australia using ANN where plantation area, rainfall and temperature data were used as variables. Other researchers conducted short-term forecasting of cotton yield in Turkey where they used ANN for the study (inputs were - cumulative rainfall indices, drought indices, cumulative heat units, vegetation indices, land surface water index) (Yildirim et al., 2022). Scientists (Dahikar & Rode, 2014) predicted the yield of crops (cotton, sugarcane, soybean, jawar, bajara, maize, wheat, rice, peanut) using ANN where the parameters were soil type, pH, nitrogen, phosphate, potassium, organic carbon, calcium, magnesium, sulphur, manganese, copper, iron, depth, temperature, rainfall, moisture.

There are studies on the application of neural networks for crop forecasting in Kazakhstan. M. Sadenova et al. (2023) applied the method of neural networks to predict yields of cereals, legumes, oilseeds and fodder crops in East Kazakhstan and found that for prediction in the model is possible using indicators of vegetation index NDVI and average temperature, surface soil moisture and wind speed. Beisekenov et al. (2021) evaluate the potential of using a machine learning model for forecasting soy crop yields in Kazakhstan.

The adaptability of Artificial Neural Networks (ANNs) to a range of environmental and chemical parameters, including but not limited to temperature, precipitation, soil composition, and vegetation indices, as well as the integration of data pertaining to fertilizer application, positions these networks as robust tool in the domain of agricultural yield prediction. This adaptability is primarily due to capacity of ANNs to process and analyze large datasets with complex, non-linear relationships, a characteristic that is particularly pertinent in the context of agricultural environments where multiple variables interact in a dynamic manner. The application of ANNs in this field facilitates a more precise and comprehensive approach to yield prediction, thereby offering a significant advancement over traditional forecasting models. This enhancement is largely attributed to the ability of ANNs to continuously learn and adapt to new data, thereby refining their predictive accuracy over time. Consequently, the integration of ANNs in agricultural forecasting models presents a valuable and versatile approach, potentially leading to more informed decision-making processes in agricultural management and policy formulation.

In this study, the authors present an innovative approach based on the utilization of artificial neural networks (ANN) for forecasting the volume of major agricultural crop yields in Kazakhstan. To achieve this, five key input parameters were identified as variables for predicting overall yields of major agricultural crops. Application of ANN in this research aids in understanding predicted the gross yields of major agricultural crops in the next 3 years, yielding precise results. This distinguishes this study from others. The outcomes hold potential benefits both for farmers (regulating the cultivation of primary agricultural crops) and government entities (managing stockpiles of primary agricultural crops, ensuring food security).

2. MATERIALS AND METHODS

Data from the Bureau of National Statistics of the Republic of Kazakhstan 2023 were used to create the ANN model. The five most important parameters that affect the annual yield were used as input data: average annual temperature, average annual precipitation, total consumption of mineral fertilizers, total consumption of fertilizers organics and total pesticide consumption. Historical data from the Office of National Statistics spanning 21 years (2000-2021) was also examined in the study. Data on climatic conditions presented in the Figure 1. The agrochemical factors employed in the research are displayed in Figure 2. Meanwhile, Figure 3 presents data on the annual gross yield categories.

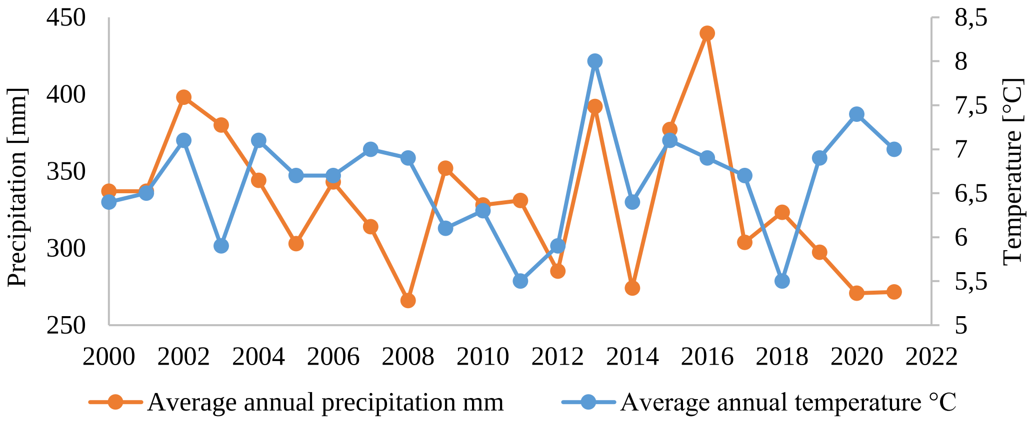

Fig. 1. Average annual temperature and average precipitation in Kazakhstan in the years 2000-2022

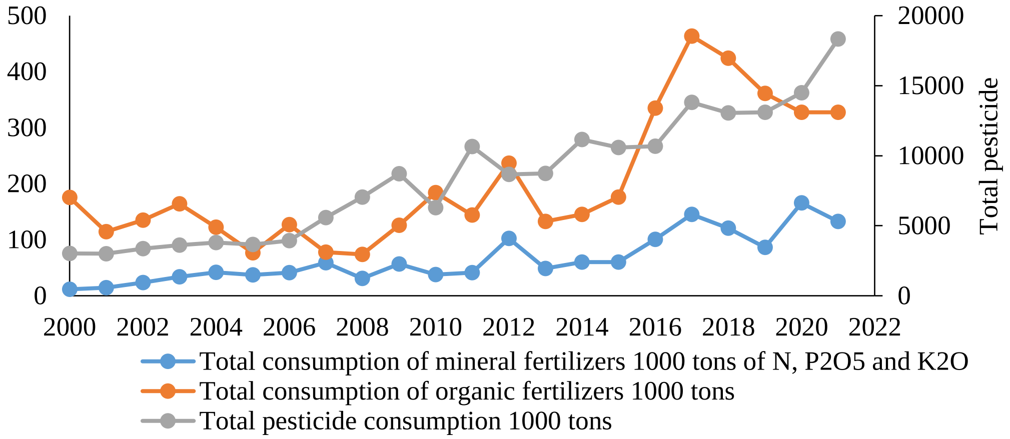

Fig. 2. Total consumption of mineral, organic fertilizers and pesticides in Kazakhstan in the years 2000-2022

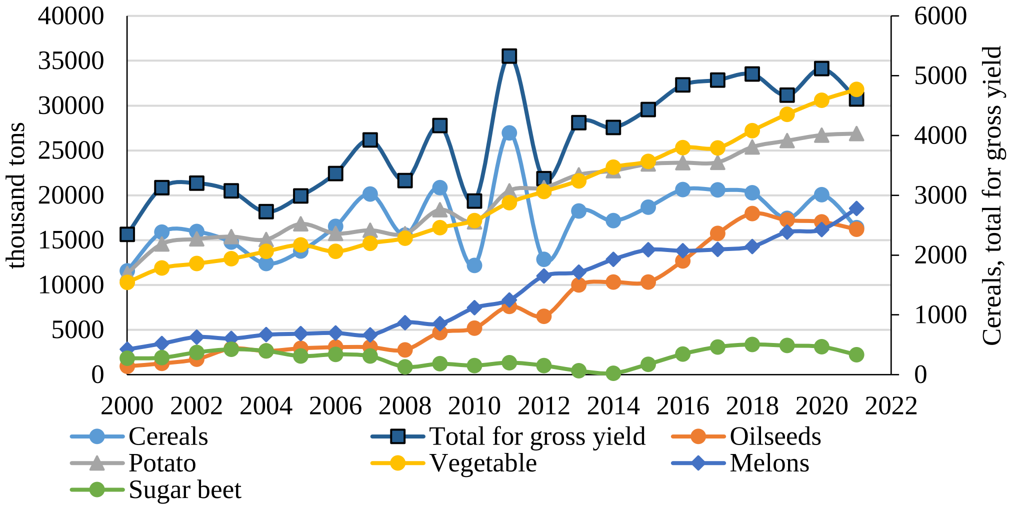

Fig. 3. The annual gross yield of the main agricultural crops

For the modelling of artificial neural networks (ANN) the Neural Net Fitting library from the MATLAB software package was employed. During the research two distinct models were developed. The baseline model aimed to predict the total gross yield of main agricultural crops (in thousands of tons) for the subsequent three years. The second model focused on forecasting the share of individual crops for the upcoming three years. The categories of crops considered for this modelling included: cereals (including rice) and legumes (by weight after processing), oilseeds, potatoes, vegetables of both open and closed ground, melons, and sugar beets (by weight after processing). Therefore, for the input data for a given year (t), the output data (pattern) were not assumed for this year, but for a point in time 3 years after this year for (t +3). During the training phase, a shallow neural network was employed, leveraging the Levenberg-Marquardt algorithm as the core learning algorithm. These networks featured one hidden layer. Through experimental methods, the neuron count in this layer was set between 2 and 15. The diagram of the neural network is shown in Fig. 4.

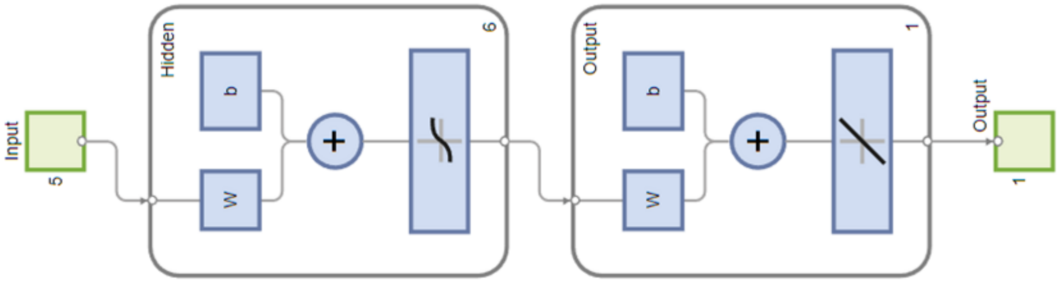

Fig. 4. The diagram of the neural network

For the training process, 20 sets of parameters were used. These were then split into training data constituting 80%, and validation data, accounting for the remaining 20%. Due to the limited amount of model data, test data was omitted.

To evaluate the quality of the neural network model for regression tasks, selected quantitative metrics were employed. These metrics are as follows:

– Mean Squared Error (*MSE*):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - y_i')^2 \tag{1}$$

where: n – the number of observations.
y_i – the real value.
y_i' – the predicted value.

This metric calculates the average of the squares of the differences between the observed and predicted values, emphasizing larger errors over smaller ones.

– Root Mean Square Error (*RMSE*):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i')^2} \tag{2}$$

The *RMSE* provides error magnitude in the same units as the target variable, offering insights into the spread of residuals.

– Mean Absolute Error (*MAE*):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}(|y_i - y_i'|) \tag{3}$$

MAE computes the average of the absolute differences between the forecasted and actual values, weighing all individual differences equally.

– Mean Absolute Percentage Error (*MAPE*):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - y_i'}{y_i}\right| x100 \tag{4}$$

Expressed as a percentage, *MAPE* gives the average error between predicted and observed values in relative terms.

– Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - y_i')^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{5}$$

R^2 shows the proportion of variance in the dependent variable that is predictable from the independent variable(s).

– Correlation Coefficient (R):

$$R(y'.y^*) = \frac{cov(y.y')}{\sigma_{y'}\sigma_y} \quad R\epsilon < 0.1 > \tag{6}$$

where: σ_y – standard deviation of real data.

$\sigma_{y'}$ – standard deviation of predicted data.

The coefficient *R* measures the strength and direction of the linear relationship between two variables.

Utilizing these metrics, along with their mathematical definitions and variable explanations, ensures a comprehensive assessment of the model's performance. Their combined use aids in pinpointing both magnitude and direction of errors, making sure model inaccuracies are thoroughly grasped and addressed.

3. RESULTS

3.1. Modelling the total gross yield of main crops

Optimal modelling outcomes were attained with a network comprising 6 neurons. This conclusion was reached after 14 epochs. The training outcomes for this network are detailed in Table 2. The ANN (Artificial Neural Network) model created for predicting the total gross yield of main crops is very well fitted to the training data. High values of R (0.983) and R^2 (0.967) were obtained, which indicates the usefulness of the model. The optimal validation was achieved at the 8th epoch as illustrated in Figure 5. The model demonstrates high performance, as evidenced by the high R-squared values in both training (0.94) and validation (0.939) (Figure 6).

An R-squared value close to 1 suggests that the model explains a large portion of the variance in the data, indicating effective performance in both training and validation phases. The validation R-squared (0.939) closely mirrors the training R-squared (0.94) indicating that the model not only fits the training data well but also generalizes effectively to new, unseen data. This is crucial for practical application, suggesting reliable performance in real-world scenarios beyond the training and validation datasets.

Tab. 2. Optimal neural network training results with associated quality metrics

Training algorithm	Levenberg-Marquardt
Epoch	14
Performance	$5.54*10^{-23}$
Best validation performance	6228603.377 at epoch 8
Gradient	$6.66*10^{-8}$
R(all)	0.983
R^2	0.967
MSE	$1.698*10^{6}$
RMSE	$1.303*10^{3}$
MAE	933.72
MAPE	3.554

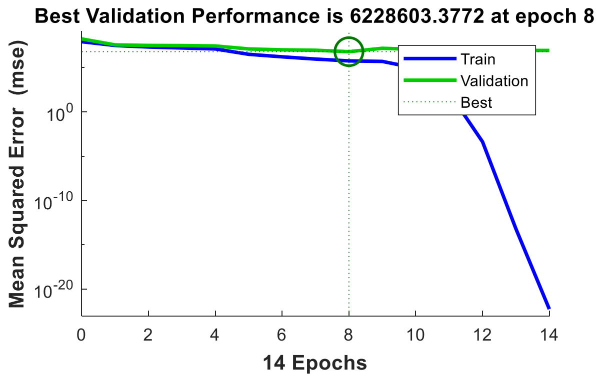

Fig. 5. Best Validation Performance for the total gross yield of main agricultural crops

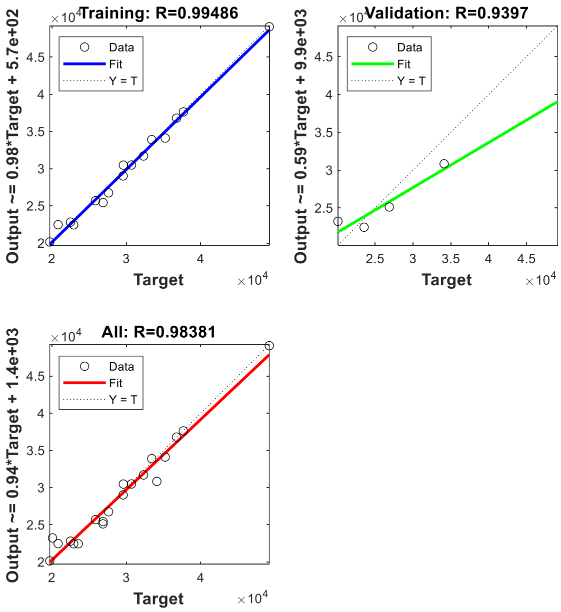

Fig. 6. ANN regression statistics for the total gross yield of main crops

The overall R-squared value of 0.98 points to the model's high accuracy across all the data it was trained and validated on, implying a strong linear relationship between the predictors and the total gross yield of the main crops.

Given its high performance on both training and validation sets, this model appears ready for deployment in practical scenarios, assuming it has been adequately tested for all relevant conditions and potential biases.

Figure 7 presents forecasts for the total gross yield of primary agricultural crops for the years 2023 – 2025. The data indicates a steady increase in yield, yet with lower annual growth compared to previous years. It is noteworthy that the estimated rise for 2025 is substantial (39166.61), which could stem from various influences, such as advancements in agricultural technologies, improved plant genetics, enhanced resource management, alterations in farming practices, and climate variations impacting the duration of growing seasons and cultivation circumstances. This information has the potential to be highly relevant for agricultural planning, food policy, and economic strategies. It can also aid in predicting market trends and ensuring food security.

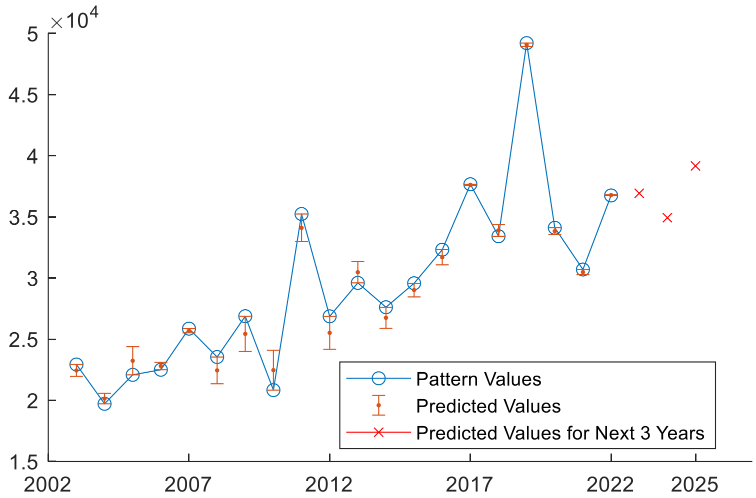

Fig. 7. Forecasts of the total gross yield of main agricultural crops from 2003 to 2025

3.2. Modelling the share of individual crops

The optimal modelling results were attained using a network with 7 neurons a conclusion derived after 13 epochs. The performance metrics for this specific network configuration are detailed in Table 3. Corresponding regression plots for training (R=0.993), validation (R=0.998), and the entire dataset (R=0.993) can be found in Figure 8. The value of R is 0.993, and R^2 is 0.999, which indicates a very strong correlation between the model's predictions and the actual values. This high level of correlation suggests that the model is highly accurate in forecasting the total gross yield of the main agricultural crops, reflecting its effectiveness in capturing the underlying patterns and trends in the data.

Tab. 3. Optimal neural network training results with associated quality metrics for the share of individual crops

Training algorithm	Levenberg-Marquardt
Epoch	13
Performance	$1.21*10^5$
Best validation performance	313795.406 at epoch 7
Gradient	$2*10^6$
R(all)	0.993
R^2	0.999
MSE	$4.949*10^5$
RMSE	533.51
MAE	318.57
MAPE	15.33

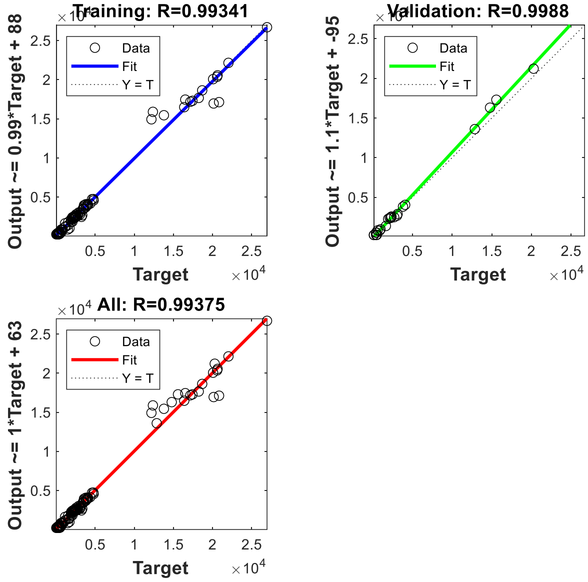

Fig. 8. ANN regression statistics for the share of individual crops

Figure 9 shows the Artificial Neural Network (ANN) regression statistics for the allocation of individual crops. These statistics present evidence that the ANN model is performing remarkably well in terms of regression to estimate the allocation of individual crops. The high values of R in both training and validation datasets suggest that the model not only fits the training data well, but also generalizes well to new data, which is crucial for a reliable predictive model. This suggests that the model is proficient in fitting the data it was trained on and is competent in making precise predictions on previously unseen data. This is vital for an efficient and feasible forecasting tool in agriculture.

Predictions for various crop categories are shown in Figure 7. The predictive outcomes demonstrate a commendably low error rate, falling below 10%. This assertion is further bolstered by an impressive regression coefficient, R=0.994.

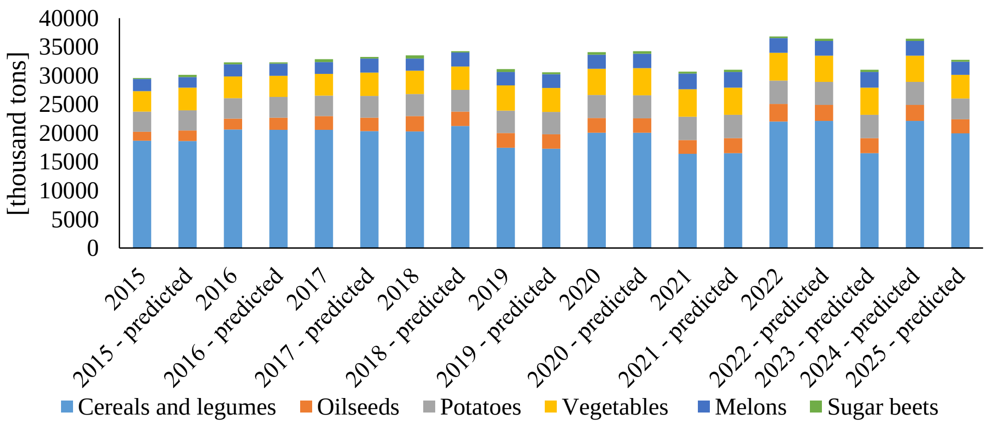

Fig. 9. Forecasts of the share of individual crops from 2003 to 2025

Analysis of data from 2000 to 2025 demonstrates a general augmentation in crop production, with certain fluctuations or downward trends. Cereals and legumes exhibited considerable variations with a maximum output in 2011 and minimum in 2000, while oilseeds observed a constant increase from 2000 until 2022. Potato production witnessed an increase until 2020, whereas the forecasts now indicate stabilization. Vegetables from both open and closed cultivation consistently grew till 2021, with a slight decline predicted in the subsequent years. Melons presented an overall increase, notably in 2021, and the forecasts suggest further fluctuations. After significant variations, sugar beet production is expected to stabilize. A continuation of the observed trends is suggested for the years 2023-2025.

The model developed, akin to the studies carried out by Guo & Xue (2014), Yildirim et al. (2022), Dahikar & Rode (2014), and M. Sadenova et al. (2023), employs a range of input data that is indispensable for precise yield prediction. These figures encompass climatic conditions, soil type, rainfall information, temperature, and other ecological factors that influence plant growth and development.

Additionally, presented model considers the characteristics of various crop types, enabling to forecast with greater precision and specificity. This allows to provide detailed information at both a general level (total yield) and a more granular level (percentage of individual crops). The approach aligns with current yield modelling trends, which place a growing emphasis on model adaptability and attention to specific environmental and crop conditions.

The results obtained emphasize the potential of implementing cutting-edge technologies, including artificial intelligence and machine learning, in the field of agriculture. Neural networks, with the capacity to examine and interpret extensive data sets, can play a significant role in enhancing the precision of crop yield projections and streamlining cultivation operations. The implementation of these technologies facilitates the employment of accurate resource management procedures and interventions that lead to higher quality and quantity of crops, while mitigating the adverse environmental impact.

Additionally, the amalgamation of quality management systems in agriculture with artificial intelligence introduces novel possibilities for ensuring and monitoring the quality of agricultural products. Machine learning algorithms can analyze data from different stages of the supply chain, such as cultivation and distribution. This detects potential quality issues early on and facilitates rapid responses. As a result, agricultural brands can increase consumer satisfaction and build trust in the rapidly changing food product market, which is critical.

4. CONCLUSIONS

The study's exploration into the use of Artificial Neural Networks (ANN) for predicting agricultural yields in Kazakhstan has yielded significant insights with practical implications for the management of the country's economy. The ANN models developed for forecasting both the total gross yield of main crops and the share of individual crops demonstrate high accuracy and reliability, as evidenced by the high R and R^2 values obtained in both training and validation phases.

The ANN model for predicting the total gross yield of main crops showed an overall R-squared value of 0.98, indicating a strong linear relationship between the predictors and the yield. Similarly, the model for individual crop displayed R value of 0.994, suggesting a high level of accuracy.

The ability to accurately predict crop yields can significantly improve resource allocation, crop selection, and overall agricultural planning in Kazakhstan. This is crucial for a country where agriculture plays a key role in the economy. The insights gained from the ANN models can aid in predicting market trends and making informed decisions regarding import-export strategies.

Integrating AI with quality management systems in agriculture can enhance the monitoring and assurance of product quality. This is increasingly important in a consumer-driven market where trust and satisfaction are paramount.

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