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The application of artificial neural network models to forecast wheat production through time series analysis in key countries

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***Abstract*---**This study aims to analyze wheat production data from five major countries (Australia, India, United States, Canada, Canada, and Russia) for the period 1992 to 2022, using machine learning techniques to predict wheat production based on historical patterns. Three neural network models were developed: Multilayer Perceptron (MLP) with two hidden layers, Recurrent Neural Network (RNN) with SimpleRNN layer, and Long Short Term Memory (LSTM). Dropout of 0.3 was used in all models to minimize overfitting. The prediction results showed that the RNN model achieved the lowest values for the mean absolute error and the square root of the mean error, demonstrating its high ability to accurately predict. While the LSTM model provided excellent results in countries such as Australia and India, the MLP model showed poor performance overall, indicating its challenges in accurate prediction. The study highlights the importance of using machine learning techniques to improve the accuracy of predicting the production of strategic crops, and reflects the need to adopt innovative agricultural strategies to address environmental challenges.

***Keywords*---**Artificial Neural Network Models, Time Series Analysis, Wheat Production.

Introduction

Yield forecasting is a critical yet challenging issue for sustainable intensification and optimal use of natural resources (Phalan, 2014). Advance and accurate yield

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forecasting has been and continues to be a pressing issue for any state since the efficacy of a lengthy agri-food chain is dependent on forecast accuracy. Farmers, agronomists, and politicians all engage in this chain and rely on crop projections provided by specialists in their respective fields. The yield of different crops relies on environmental circumstances, management measures, and many more particular characteristics (Fischer, 2015) .Yields are predicted using a variety of techniques, the primary ones being statistical models, models based on processes, and expert estimates (such as field studies and interviews). Towards the conclusion of the season, crop projections from farmer interviews are typically very subjective (Nandram, 2013). Crop trimming in field research allows for an impartial evaluation of yields before harvest. Regression dependences between different statistical data collected via distant and meteorological observations are constructed by statistical models employing a variety of techniques (regression, Bayesian approaches, machine learning methods). (Lobell, 2011) . A statistical model derived from agro meteorological data is one of the most often used techniques for yield forecasting. It is comparatively simple to create and apply this approach. Nonetheless, a primary drawback of this approach is the fact that many environmental parameters are nonlinear, meaning they can deviate significantly from average values. These variables, which have the most effects on the creation of wheat yields, include air temperature and precipitation totals. For this reason, it's imperative to switch from conventional techniques to more precise forecasting techniques. Artificial neural network-based models are the best substitute. substitute. (Puma, 2015) .In addition to producing end-of-season yields, crop simulation models also generate yield dispersion according to crop genotypes, soil conditions, standard management practices, and seasonal weather. These data are acquired by assimilating information from remote sensing or by using past climate or weather forecasts (Kadaja, 2009)).Neural network-based models have the benefit of high forecast accuracy and potential yield increase. Neural network construction and training algorithms rely on functions, in this instance yield, that ascertain how features and predictors depend on output data data (Reynolds, 2000).

Based on the aforementioned discussion, this research paper aims to answer the following question: What is the effectiveness of applying artificial neural network models to forecast wheat production through time series analysis in the following countries: India, the USA, Russia, Australia, and Canada?

Literature Review

(Kaur, 2023) This study deals with the use of artificial neural network (ANN) technology to model and predict energy consumption in wheat production in India. Data from 256 farmers were collected and analyzed using an ANN model, and compared with a multiple linear regression (MLR) model. The results showed that the average energy consumption per hectare was relatively low compared to previous studies, but was higher on small farms. Electric motors, which meet 95% of the irrigation needs, were a key element in modeling energy consumption. Sensitivity analysis showed that electricity and urea are the most influential in this consumption. The ANN model outperformed MLR in terms of prediction accuracy, with a coefficient of determination (R^2) of 0.99 during training and 0.973 during validation. These results can be generalized to similar regions such

as Haryana and Punjab, contributing to improving energy consumption in the agricultural sector and promoting environmental sustainability and food security.
(Sadenova, Beisekenov, Varbanov, & Pan, 2023) This paper addresses the application of machine learning techniques, particularly neural networks, in predicting crop productivity in East Kazakhstan. The study relied on remote sensing data from Sentinel-2 and Landsat-8 satellites during the period from 2017 to 2022, where 1600 agricultural indicators were collected, including vegetation index (NDVI) and weather parameters such as temperature, topsoil moisture, and wind speed. Using Python libraries, a model for predicting agricultural productivity was developed based on this data. The results showed that the Multilayer Perceptron neural network-based model achieved prediction accuracy ranging from 66% to 99%, while polynomial regression achieved accuracy ranging from 63% to 98%. These results were also compared with other algorithms such as Ridge and Support Vector Regression, which also achieved acceptable accuracy. The study showed that using data from the entire growing season increases the accuracy of the predictions compared to using only planting and harvesting data. The results also showed that integrating machine learning and neural network techniques can significantly enhance the accuracy of crop yield predictions, contributing to enhancing agricultural sustainability in similar regions.

(Morales & Villalobos, 2023) This paper reviews the impact of machine learning algorithms in predicting crop production, namely sunflower and wheat, in five different regions of Spain. The study was based on simulated data from biophysical crop models for the period 2001 to 2020, analyzing the impact of data partitioning, algorithm type, and data quantity on predictive performance. Algorithms such as random forest, artificial neural networks, and linear regularized models were used. The study was conducted in areas between 37.5° and 40°N, characterized by a Mediterranean climate and diverse soil types. The results showed that random forest was the most accurate, with a root mean square error (RMSE) between 35% and 38%, compared to neural networks whose accuracy ranged from 37% to 141%, and linear models whose accuracy was between 64% and 65%. The study also found that random partitioning of data may lead to inaccurate estimates of model errors, compared to temporal partitioning. The results emphasize the need to compare the predictions of machine learning models with baseline estimates to ensure their effectiveness.

(Ying Wang & Wen, 2023) This study investigated the use of machine learning (ML) algorithms to improve winter wheat yield and dry matter prediction in the North China Plain. The study tested five ML models, namely: Linear regression, decision tree, support vector machine, ensemble learning, and Gaussian process regression. The results were based on data from 48 papers covering the period from 1999 to 2019, with the Gaussian Process Regression (GPR) model showing significant superiority in predicting wheat and dry matter yields, achieving 87% and 86% accuracy, respectively. The results showed that the errors in predicting winter wheat and dry matter production were minimal, reflecting the ability of the GPR model to predict the optimal amounts of water and nitrogen required. The GPR model-based data also showed good agreement with the results of field trials. The study concluded that the use of machine learning algorithms can enhance the ability to make more effective agricultural decisions, contributing to better management of water and nitrogen resources and increasing agricultural productivity in the region.

(Hara & Magdalena, 2023) This study demonstrated the importance of accurate pea (Pisum sativum L.) production forecasting and its impact on food security and crop management in light of climate change and population increase. The study relied on several machine learning models, including multiple linear regression (MLR) and artificial neural networks (ANN), to analyze data spanning from 2016 to 2020, which included information on weather, agriculture, and physical characteristics. The experiments were conducted at Polish agricultural stations, where the most favorable locations for pea cultivation were selected. The results showed that the ANN (N2) model was the most accurate in predicting pea production, achieving a correlation coefficient of 0.936, with RMS and MAPE values of 0.443 and 7.976, respectively. On the other hand, the multiple linear regression model (RS2) failed to provide accurate estimates, with a MAPE value of 148.585, indicating its uselessness in practical applications. The analyses also showed that the most influential factors on pea production included maturity date, harvest date, total rainfall, and average temperature. The results reflect the effectiveness of the ANN model in providing accurate predictions 20 days before pea harvest, providing vital information to farmers, agricultural professionals, and decision makers. The study encourages further research to compare the ANN model with other machine learning techniques such as RBF to enhance the accuracy of predictions.

(S. RAY & A. M. G. AL KHATIB, 2023) This study presented the impact of cash crop development on the Indian economy by comparing three statistical models: ARIMA, ETS, and NNAR, to predict the production areas and productivity of crops such as wheat, rice, maize, jowar, and cotton. The study used data from 1980 to 2020 and assessed the quality of the models based on criteria such as RMSE, MSE, and MAPE. The results showed that wheat, rice, and cotton production is expected to increase, while guar and corn production is expected to decrease. The results indicate that time series analysis using these traditional statistical models can contribute to guiding agricultural policies and enhancing food security in India, making this information valuable for planning agricultural reforms and improving the country's economic situation.

(Demirel, Z., Baran, & Gokdogan, 2024) This study examined the effect of agricultural inputs, such as pesticides and fertilizers, on wheat productivity in Diyarbakir province, Turkey, between 2016 and 2020. Data were collected from 177 farmers via questionnaires and analyzed using artificial neural network (ANN) models. The results showed that the average wheat yield was 5482.03 kg per hectare, with a significant effect of pesticide and fertilizer use, with pesticide and fertilizer sensitivity indices of 0.23 and 0.14, respectively. The study emphasized the importance of appropriate use of these inputs to increase efficiency and reduce health and environmental risks associated with overuse. It also emphasized the need to conduct soil analyses and educate farmers on integrated control methods, as well as minimizing the use of pesticides by developing resistant varieties.

(Obaid Zaffar, 2024) This paper presented a time-series forecasting analysis of wheat production, yield and area planted in India from 1961 to 2021 where artificial neural networks (ANN) were used as the main forecasting tool, and compared it with classical methods such as linear regression, exponential regression, logarithmic regression, polynomial function, and power function. Collected from the Food and Agriculture Organization of the United Nations, the results showed that the ANN model was the most accurate, achieving R-values exceeding 0.9 with the lowest error rates, making it the optimal choice for predicting wheat production. In contrast, the accuracy of the classical methods was significantly lower. The study also demonstrated the ability of neural networks to handle short time series using various activation functions.

Theoretical framework

The ANN was pioneered more than 40 years ago and nowadays, there has been a great interest in neural network since an artificial network shares some of the physical and behavioral aspects of a biological one. The ANN structure which is parallel system is based on human brain's biological neural process used to solve complex problems where it tries to imitate into mathematical models. (Siti Khairunniza-Bejo, 2014)

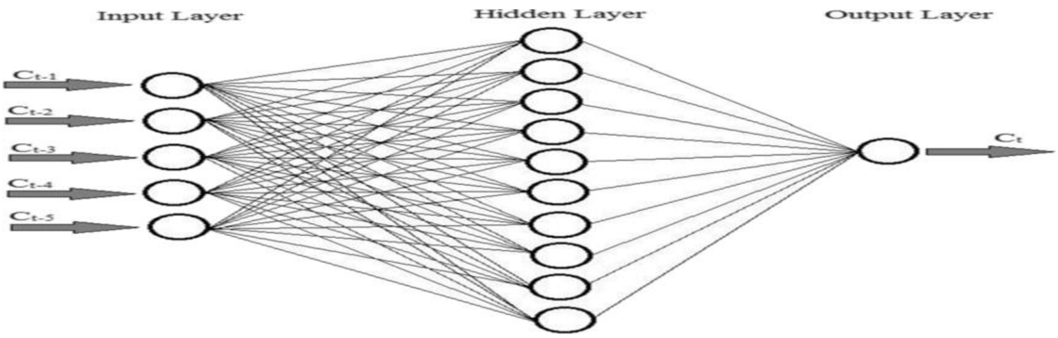


Fig.1: A schematic view of the fifth ANN-based model (J.A. Marchant, 2002)

1- Multi Layers Perceptron (MLP)

The Multi-Layer Perceptron (MLP) model is a type of feedforward artificial neural network (ANN) that serves as a foundation architecture for deep learning or deep neural networks (DNNs) (Mustapha, 2023). It operates as a supervised learning approach. The MLP consists of three layers: the input layer, the output layer, and one or more hidden layers. It is a fully connected network, meaning each neuron in one layer is connected to all neurons in the subsequent layer. In an MLP, the input layer receives the input data and performs feature normalization. The hidden layers, which can vary in number, process the input signals. The output layer makes decisions or predictions based on the processed information (K.-C. Ke and M.-S. Huang, 2020). Figure 3 depicts a single-neuron perceptron model, where the activation function φ (Equation 1) is a non- linear function used to map the summation function ($xw + b$) to the output value y. $y = ø\ (xw + b)$ (1)

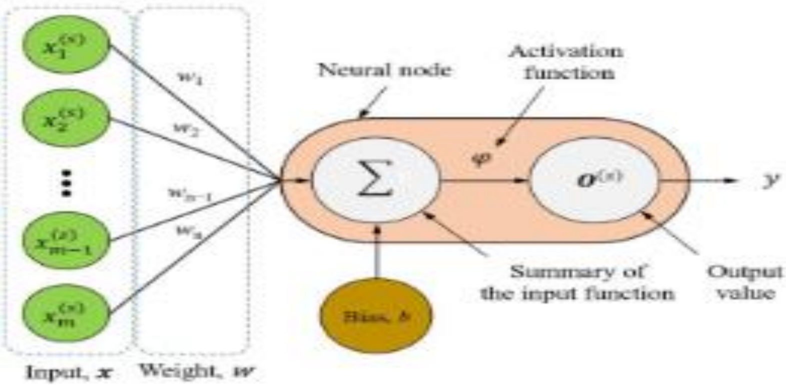
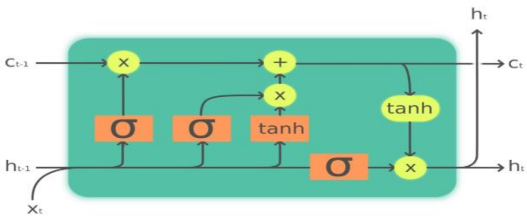


Fig.2: Single-neuron perceptron model. (Huang, 2020)

2-Recurrent Neural Networks (RNN)

Recurrent Neural Networks (RNNs) are a class of deep learning models that possess internal memory, enabling them to capture sequential dependencies. Unlike traditional neural networks that treat inputs as independent entities, RNNs consider the temporal order of inputs, making them suitable for tasks involving sequential information (T.R. Green, 2007, pp. 23-37). By employing a loop, RNNs apply the same operation to each element in a series, with the current computation depending on both the current input and the previous computations . (Y. Chtioui, 1999, pp. 47-58)

The ability of RNNs to utilize contextual information is particularly valuable in tasks such as natural language processing, video classification, and speech recognition. For example, in language modeling, understanding the preceding words in a sentence is crucial for predicting the next word. RNNs excel at capturing such dependencies due to their recurrent nature (M.M. Rahman, 2010, pp. 350-356.) . However, a limitation of simple RNNs is their short-term memory, which restricts their ability to retain information over long sequences .



. **Fig. 3:** depicts a simple recurrent neural network (W. Fang, 2021) **.**

3-Long Short-Term Memory (LSTM) Networks

LSTM networks are a type of recurrent neural network (RNN) designed to capture long-term dependencies in sequential data. Unlike traditional feed forward networks, LSTM networks have memory cells and gates that allow them to retain or forget information over time selectively. This makes LSTMs effective in speech recognition, natural language processing, time series analysis, and translation (T.

Morimoto, 2007, pp. 1-10) . The challenge with LSTM networks lies in selecting the appropriate architecture and parameters and dealing with vanishing or exploding gradients during training.in Applications of LSTM using the following steps : (R. Linker, 2004, pp. 19-29)

- **Natural language processing**: LSTMs excel at modeling sequential data, making them highly effective in tasks like language translation, sentiment analysis, and text generation.
- **Speech recognition**: LSTMs are used to process audio data, enabling accurate speech recognition systems.
- **Time series analysis**: LSTMs can capture long-term dependencies in time series data, making them suitable for tasks like stock market prediction and weather forecasting.

Methodology

A comprehensive data analysis methodology was adopted to forecast wheat production in major producing countries, using data obtained from the Food and Agriculture Organization (FAO) website for the period from 1992 to 2022. These countries include the United States of America, India, Russia, Canada, and Australia. Neural network techniques were used to build models aimed at improving forecasting accuracy based on historical patterns. Three neural network models have been developed: MLP (multilayer perceptron), RNN (recurrent neural network), and LSTM (long and short-term memory).

1. MLP (Multilayer Perceptron): The model was built using two hidden layers, where the ReLU activation function was used in each layer. To reduce overfitting and improve the performance of the model, a dropout of 0.3 was applied.
2. RNN (Recurrent Neural Network): This model is based on a SimpleRNN layer consisting of 100 units with the activation function Tanh, and a dropout of 0.3 was used to reduce overfitting and improve the performance of the model.
3. LSTM (Long Short Term Memory): The LSTM model is based on a 100-unit layer with the activation function Tanh, as well as a 0.3 projection, to enhance the model's ability to predict long-term changes in the data.

Table 01: Structural Overview of the Neural Network Models Used (MLP, RNN, and LSTM)

Network Type	Layers Used	Number of Units	Activation Function	Dropout	Input Shape	O+utput	Epochs	Training Set	Testing Set
MLP	Dense	128	ReLU	-	input_dim = 12	1	100	70%	30%
	Dropout	-	-	0.3	-	-			
	Dense	64	ReLU	-	-	-			
	Dense	1	-	-	-	1			
RNN	SimpleRNN	100	Tanh	-	input_shape = (12, 1)	1	100	70%	30%
	Dropout	-	-	0.3	-	-			
	Dense	1	-	-	-	1			
LSTM	LSTM	100	Tanh	-	input_shape = (12, 1)	1	100	70%	30%
	Dropout	-	-	0.3	-	-			
	Dense	1	-	-	-	1			

Source: Prepared by researchers using the Python program

Results

1- Results of training and testing neural networks in the selected countries:
Table () presents the performance indices of three different neural network models (MLP, RNN, and LSTM) applied to wheat production data from five countries: Australia, India, the United States, Canada, and Russia. The indicators used to evaluate the models include root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2) for both training and test sets.

1. MLP (multilayer perceptron) model analysis:

- ✓ **Training indicators:**

Training RMSE values range between 2.0 and 3.69, indicating that the MLP model has higher relative error rates in predicting wheat production in Australia compared to other countries.

The MAE values also show the same trend, with the highest value of mean absolute error (3.185) recorded in Australia.

R^2 values range from 0.821 to 0.959, showing that the model is able to explain a good proportion of the variance in the training data, especially in Canada (0.959).

- ✓ **Test indices:**

The RMSE values for the test show significantly higher values, 9.539 for India and 8.39 for Australia, indicating poor model performance on the test data.

The MAE values for the test also represent a significant increase, with India recording 9.42, indicating that the model has difficulty in predicting accuracy.

The R^2 values for the test range from 0.823 for Australia to -2.653 for India, indicating that the model has failed to make accurate predictions for some countries.

2. Analyze the RNN (recurrent neural network) model:

✓ **Training Indicators:**

The RNN model is characterized by very low RMSE values, with the lowest value of 0.38 for the United States, indicating good training performance.

MAE values were also relatively low, with the highest value of 0.822 in Australia.

R^2 values indicate the model's ability to explain variance very well, ranging from 0.994 to 0.997.

✓ **Test indicators:**

The RMSE values of the test show a marked improvement, with the lowest value of 0.734 in the US.

The MAE values of the test also reflect good performance, being less than 2 in all countries.

The R^2 values of the test indicate strong performance, reaching 0.986 in Australia, indicating the model's high predictive power.

3. Analysis of the LSTM (long and short-term memory) model:

✓ **Training Indicators:**

The training RMSE values show a slight increase compared to the RNN model, scoring 1.222 for Australia and 0.945 for Russia.

MAE values were close, with 0.958 for Australia.

R^2 values indicate good performance, ranging from 0.990 to 0.974.

✓ **Test indicators:**

Test RMSE values show an increase, with 5.623 for Canada and 4.559 for Russia, indicating that the model's performance on the test data is not perfect.

MAE values range from 1.565 for Australia to 4.905 for Canada, indicating that the model has some prediction challenges.

R^2 values ranging from 0.990 for Australia to 0.574 for Russia, indicating that the model is able to explain the variance to an acceptable degree.

Table17: Comparison of the Training and Testing Results of the Applied Neural Network Models for Each Country

Train Model		Australia	India	U.S.A.	Canada	RUSSIA
MLP	Train RMSE	3.698	3.116	2.686	2.027	2.009
	Train MAE	3.185	2.293	2.364	1.761	1.658
	Train R2	0.939	0.929	0.821	0.959	0.955
	Test RMSE	8.399	9.539	6.681	5.518	7.453
	Test MAE	7.956	9.429	6.630	5.323	7.376
	Test R2	0.823	-0.425	-2.653	0.5302	-0.137
RNN	Train RMSE	1.125	0.559	0.381	0.613	0.702
	Train MAE	0.822	0.494	0.306	0.506	0.572
	Train R2	0.994	0.997	0.996	0.996	0.994
	Test RMSE	2.302	0.816	0.734	1.848	1.354
	Test MAE	1.858	0.762	0.630	1.6109	1.253
	Test R2	0.986	0.989	0.955	0.947	0.962

Train Model		Australia	India	U.S.A.	Canada	RUSSIA
LSTM	Train RMSE	1.222	0.981	1.014	1.069	0.945
	Train MAE	0.958	0.737	0.698	0.821	0.717
	Train R2	0.993	0.993	0.974	0.988	0.990
	Test RMSE	1.960	1.053	2.041	5.623	4.559
	Test MAE	1.565	0.983	1.646	4.905	3.998
	Test R2	0.990	0.982	0.659	0.512	0.574

Source: Prepared by researchers using the Python program

2- Analysis and Comparison of the Models Used in the Study

In this figure, a comparison between predicted and actual values of wheat production in the five major countries (Australia, Canada, India, India, Russia, and the United States) using MLP, RNN, and LSTM models is shown. The following analysis can be extracted from these plots:

- Australia and Canada:

The predictions show a fairly good agreement with the actual values in both countries.
The LSTM model seems to offer higher prediction accuracy with a similar trajectory to the actual values compared to the other models.
The MLP model shows some noticeable differences between the predictions and actual values, especially when there are fluctuations in the data.

- India:

The MLP model shows a larger deviation from the actual values, and the performance in this country seems to be weaker compared to other countries.
RNN and LSTM show better performance, but RNN offers better agreement with actual values than LSTM.

- Russia:

RNN and LSTM models show good agreement with the actual values, while MLP shows a clear deviation, especially in periods with high volatility.
The LSTM model seems to be the most accurate in predicting general trends in wheat production.

- United States:

Both RNN and LSTM show acceptable agreement with actual values, but RNN shows better performance, with some variation in the LSTM model.
MLP again shows a significant deviation from the actual values, indicating less efficient performance compared to the other models.

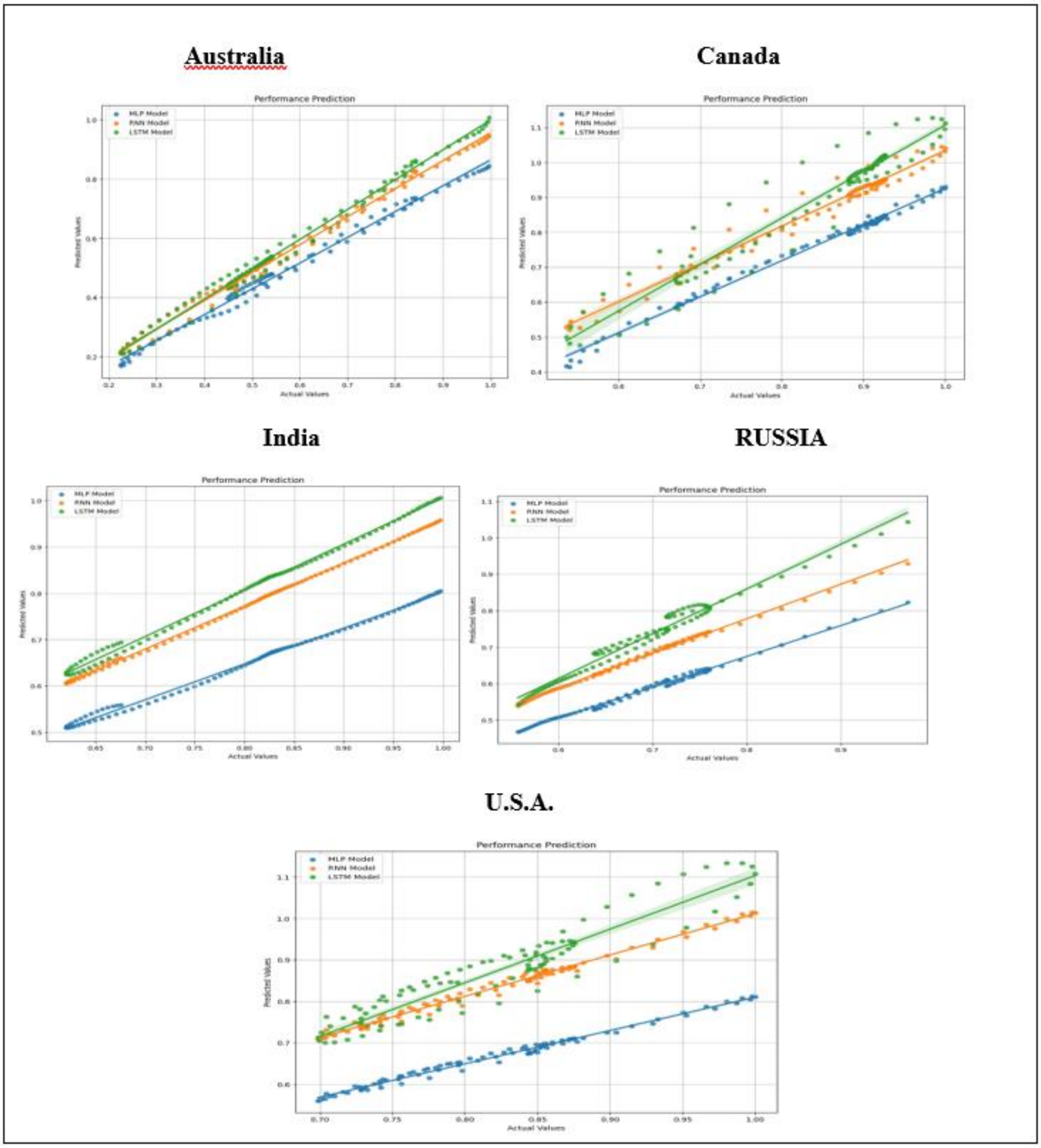


Figure 5: Comparison of Predictions vs. Actual Values for Different Models (India, Russia, Canada, U.S.A., Australia)"
Source: Prepared by researchers using the Python program

The table presents the performance of three neural network models (MLP, RNN, LSTM) in predicting wheat production in five countries: Australia, India, the United States, Canada, and Russia. The performance of the models is evaluated using four metrics: MSE (mean square error), RMSE (root mean square error), MAE (mean absolute error), and R^2 Score (coefficient of determination)

For the MLP model, the model appears to perform acceptably in Australia and Canada, with acceptable R^2 values (0.83 and 0.58, respectively), meaning that the model explains a large proportion of the variance in the data for these countries. However, the model performs very poorly in the US, India, and Russia, where the R^2 values are negative (-2.9, -0.71, and -0.6839), indicating that the model fails to predict correctly in these cases.

The RNN model appears to be the most stable and accurate across all five countries. The MSE and RMSE values are very low, indicating the model's high prediction accuracy. In addition, R^2 values are very high in all countries, especially in the US (0.967) and Australia (0.9826), which means that the model explains almost all of the variance in the data.

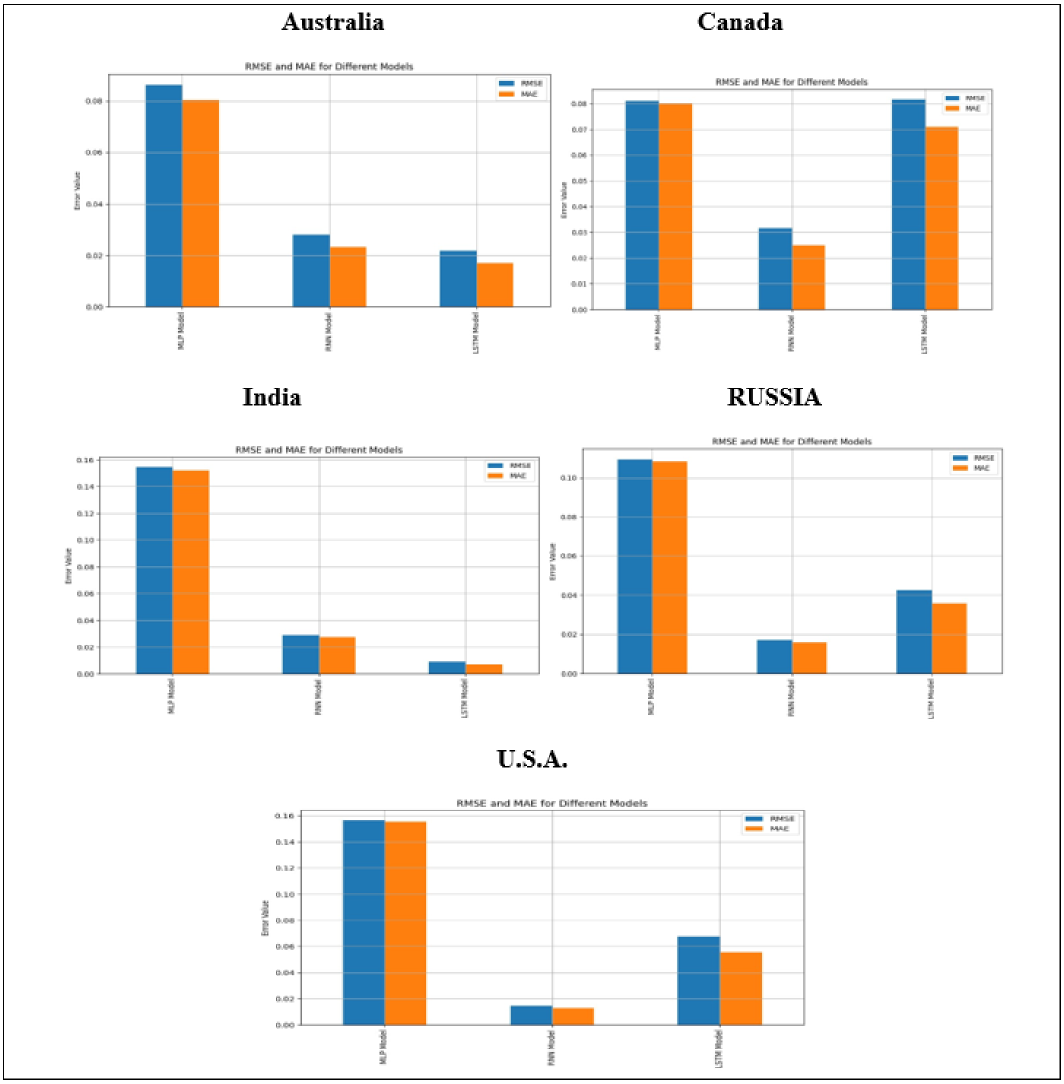
On the other hand, the LSTM model performs well in India and Australia with R^2 values of 0.996 and 0.98, making it the most accurate model in these countries. However, the model shows lower performance in the US and Canada compared to RNN, with R^2 values (0.276 and 0.58) being lower than expected. For Russia, LSTM achieves relatively good results with an R^2 of 0.7451.

Table 02: Comparison of different applied neural network models

Model Performance		Country				
		Australia	**India**	**U.S.A.**	**Canada**	**RUSSIA**
MLP	MSE	0.0074	0.0238	0.0245	0.0066	0.0199
	RMSE	0.0861	0.1544	0.1564	0.0810	0.1093
	MAE	0.0802	0.1519	0.1555	0.0801	0.1084
	R^2 Score	0.8348	-0.71	-2.8915	0.5845	-0.6839
RNN	MSE	0.0008	0.0008	**0.0002**	**0.0010**	**0.0003**
	RMSE	0.0280	0.0287	**0.0145**	**0.0316**	**0.0173**
	MAE	0.0232	0.0273	**0.0128**	**0.0249**	**0.0160**
	R^2 Score	0.9826	0.9408	**0.9666**	**0.9367**	**0.9578**
LSTM	MSE	**0.0005**	**0.0001**	0.0046	0.0067	0.0018
	RMSE	**0.0217**	**0.0091**	0.0675	0.0816	0.0425
	MAE	**0.0169**	**0.0072**	0.0554	0.0710	0.0357
	R^2 Score	**0.9895**	**0.9941**	0.2756	0.5783	0.7451

Source: Prepared by researchers using the Python program

Overall, it can be said that RNN provides superior and consistent performance in all countries, while LSTM achieves excellent results in some countries (India and Australia), but shows lower performance in others (US and Canada). MLP shows mixed results, performing well in some cases and suffering from prediction issues in others, especially in the US and Russia.



"Figure 06: Comparison of Neural Network Models for Predicting Wheat Production in India, Canada, USA, Australia, and Russia Based on Key Performance Metrics."
Source: Prepared by researchers using the Python program

3- Forecasting Future Wheat Production Using the Optimal Neural Network Model for Each Country"

The curves shown in the figure reflect future forecasts of wheat production in Australia, Canada, India, the United States, and Russia using the LSTM and RNN model

✓ **In Australia and Canada**, the forecasts show a continued rise in wheat production, indicating the ability of these two countries to increase their yields. This positive trend is due to the adoption of advanced agricultural technologies, such as precision farming, and the development of high-yielding, climate-resilient wheat varieties. Government support for agricultural research and innovation in the sector has also contributed to boosting production. This increase is important because it reflects the ability to meet the growing demand for wheat in global markets, boosting the economic position of these two countries.

- ✓ **In contrast, India** is showing a gradual decline in wheat production, which may be attributed to a range of challenges it faces, such as degraded farmland, water shortages, and reliance on unsustainable traditional farming methods. These conditions point to the need to develop effective strategies to improve production efficiency, such as improving water resource management, adopting modern farming methods, as well as investing in agricultural technology to boost yields.

- ✓ **In Russia**, projections show a downward trend in wheat production, indicating that the country faces challenges in maintaining its production levels. This decline may be attributed to multiple factors, such as climate changes and the effects of agricultural policies

- ✓ **In the United States**, the curves show a downward trend in wheat production, which reflects structural issues in the agricultural sector, such as the loss of farmland due to urbanization and climate change. This trend requires a rapid response by adopting sustainability-focused strategies, such as promoting agricultural practices that minimize environmental impact and promote resource efficiency.

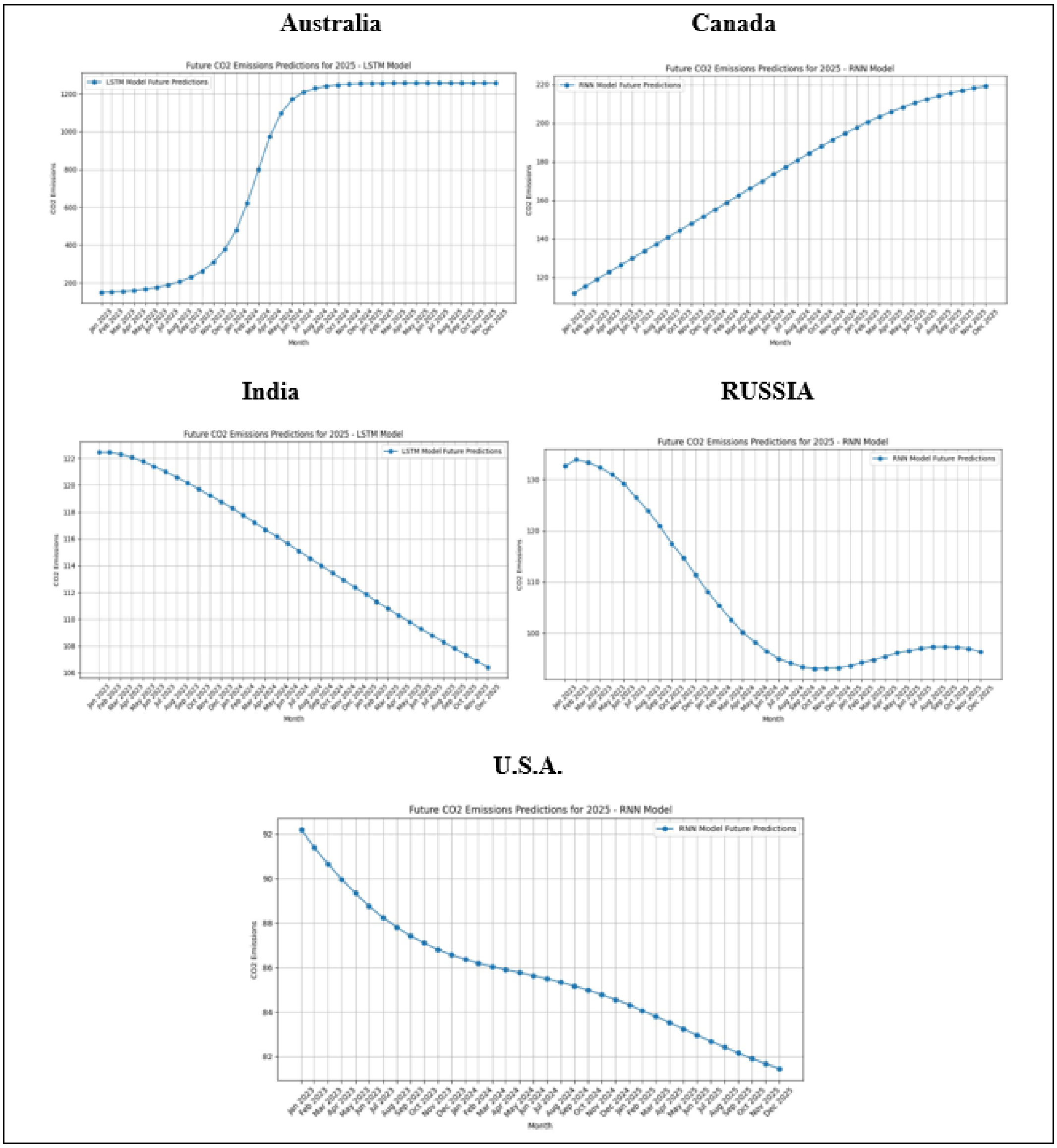


Figure 07: "Forecasting Future Wheat Production Using the Optimal Neural Network Model for Each Country"
Source: Prepared by researchers using the Python program

4- Conclusion

Wheat production is a vital component of global food security, and the results of the analysis and interpretation presented in this study reflect a range of notable trends in wheat production across the countries studied, namely Australia, Canada, India, Canada, India, the United States, and Russia. Future projections, based on advanced neural network models, indicate that some countries are able to boost their wheat production through the adoption of innovative agricultural technologies and effective resource management.

The analysis showed that Australia and Canada have stable or increasing production levels, reflecting their ability to respond to global food security challenges. In contrast, India, Russia and the United States are struggling with declining production, highlighting the need for changes in agricultural policies and the adoption of sustainable agricultural practices.

Environmental challenges, such as climate change and natural resource shortages, call for innovative strategies aimed at improving the efficiency of agricultural production. This study highlights the importance of research and development in sustainable agriculture, supporting farmers through technology and better practices to enhance wheat production and ensure food security.

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