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Assessing the effectiveness of Artificial Neural Networks and PSLR models in predicting per capita food grain production in India

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Abstract

Every living thing needs food. In addition to fostering social progress and economic expansion, agriculture is essential to our everyday existence. India has made great strides toward guaranteeing a sufficient supply of food since gaining its freedom. While India's population has tripled, food grain production has more than quadrupled. Consequently, there are now substantially more food grains available per individual. To meet the country's food needs, rice and wheat production is essential. Decision-makers need access to accurate forecasts to identify this need, put appropriate plans into place and allocate the required administrative resources. Based on artificial neural networks and PSLR, the per capita availability of food grain production in India was estimated. Indiastat and the FAO provided the historical data for the country from 1951 to 2022. To examine the food grain per capita availability (Kgs. Per Year), we used two effective analytical methodologies, artificial neural networks (ANNs) and Partial least squares (PLS) regression. The models' performances were compared using four relevant performance criteria to determine which model is best for future forecasting. The results show that, when it comes to accurately predicting the per capita number of dietary grains, ANN outperforms the PLSR model. For the ANN method, the values of MAE, MSE, RMSE and R^2 were 3272.11, 1.748, 4194.28 and 0.956, in that order. The study discovered that PLS also functioned well, with very little difference between the two models' performance indicators.

Keywords

ANN; food grain; India; per capita; PLSR

Introduction

The world's population is projected to exceed 8 billion by 2023, marking a threefold increase since the mid-20th century (1). According to StatisticsTimes.com (2), there will be 8.12 billion people on the planet by July 2024. In 1992, the UN published five estimates of long-term population growth. According to their medium prediction, there will be 10 billion people on Earth by 2050 and 11.2 billion by 2100. Asia is predicted to have the fastest rate of population expansion, accounting for over 60 % of the global population by the year 2050, especially China, India and the southeast region of the continent (3). The increase in global per capita food consumption is a result of both population growth and higher levels of individual food consumption. In 2020, the United Nations reported that 2.4 billion people, or over 29 % of the world's population, frequently lacked access to enough food for survival, a condition referred to as moderate to serious food insecurity (4). According to the Global Hunger Index published by the International Food Policy Research Institute (IFPRI), 33 countries are currently facing “alarming” or “extremely alarming” levels of hunger. The figure rose to 320 million people in a single year. India is ranked 111th out of 125 countries on the 2023 Global Hunger Index, with a score of 28.7 out of 100. This indicates a significant challenge in addressing hunger and malnutrition within the country (5). In India, agriculture is the most important sector since it provides food and a means of subsistence for 1.4 billion people. The two most significant staple food crops are rice and wheat, with wheat ranking as the second most popular cereal grain globally. Because of its dominance in international trade and business, it's not only a staple meal as well as an excellent cash crop. Furthermore, in contrast to other grain crops, rice and wheat have short growing seasons, very even output rates and are incredibly simple to cultivate (6). The strategy to feed the nation's expanding population has gained significance in recent years. Crop models and other decision-making tools are being used more and more in the agriculture sector to boost crop production efficiency. To boost crop productivity, there has been a recent surge in interest in the use of cutting-edge technologies to agriculture (7). The rapid development of advanced technology is expected to make precision agriculture largely dependent on crop models and forecasting techniques. To monitor food availability and prepare commodities sectors, the government, cultivators, consumers and policymakers depend on precise and accurate crop output forecasts. In their publication titled "Food Production & Availability: Essential Prerequisites for Sustainable Food Security," M.S. Swami Nathan discuss the critical importance of ensuring a reliable and sustainable food supply. The key factors determining sustainable food security are optimal food production and fundamental circumstances (8). Food security is based on food production, which is an essential aspect of food supply. A food-based approach is primarily linked to diet security and nutrition and it has the potential to address hunger in a way that is both socially and economically viable. Food security is usually assessed about needs, which are determined following minimum recommended dietary guidelines, using the actual average daily calorie consumption per person. The primary goal of this research is to forecast the per capita food grain production in India, with a specific emphasis on wheat and rice, through the utilization of Artificial Neural Networks (ANN) and Partial Least Squares Regression (PLSR) models. In a study conducted, PLSR was utilized to develop an algorithm using spectral data to forecast the per capita availability of wheat (9). They also introduced a novel method known as the worldwide search strategy to select PLSR components. Another relevant study examined the NIR yield estimation approach (10). In this research, we have selected and compared the popular ANN and PLSR techniques to create a suitable model for predicting food grain production in India. Furthermore, it was believed that the ANN was a trustworthy technique for predicting grain yield in response to different nitrogen and water treatments. The ANN technology can be used for evaluating different agricultural operational procedures in addition to time series data. One of the most widely recognized machine learning techniques for developing linear empirical algorithms in food grain prediction is artificial neural networks. One of the main reasons for the growing popularity of artificial neural networks (ANNs) is their exceptional capacity to learn from examples autonomously, eliminating the necessity for human intervention. Analyzing patterns within the collected data, this system can accurately forecast the results of comparable data sets. ANNs have been employed in numerous studies in a diverse range of industries, including agriculture (11) and (12). This is due to their ability to self-learn and solve complex issues. In previous research, an experiment to examine the link between the mechanical rice transplanting characteristics and rice yield using ANNs (13). The results demonstrated that the ANN method correctly predicted yield from transplanting variables, with an R^2score of 0.994. In this study, the effectiveness of Artificial Neural Networks and PSLR models in predicting per capita food grain production in India was assessed. The models' performances are compared using four relevant performance criteria to determine which model is best for future forecasting. The results show that ANN performs the best among all the models utilized in terms of accurately predicting the amount of food grains per capita (14). This study aims to examine the per capita availability of the major dietary grains in India, particularly a focus on wheat and rice. To examine the food grain availability pattern in this study, we relied on two proposed models (15).

Materials and Methods

Study area

The seventh-largest nation in the world, India, was chosen as the study area. Its total area, 3287263 km^2, is composed of 9.92 % water and 90.08 % land. Located north of the equator, the country is situated between 68°7′ and 97°25′ E longitude and between 8°4′ and 37°6′ N latitude. The country faces four distinct seasons annually: summer, monsoon, post-monsoon and winter.

Data collection

In many regions of India, particularly in the south and east, rice serves as a staple food, while wheat is a major crop in the northern regions. In the 2022-2023 period, the total production of wheat and rice was estimated at 121.82 LMT and 1308.37 LMT, respectively. It is higher than it was the previous year (GoI press release, 2023). The goal of gathering data is to gather all relevant information from the available sources. The Indian Statistical Department (Indiastat) supplied the population size, per capita (kg/year), production and total consumption data on rice and wheat utilized in this study. The data was collected for the period from 1951 to 2022.

Data splitting

It was carried out to develop and evaluate a prediction model. There are situations where the input data needs to be properly cleaned before being split into training and test datasets. The splitting ratio is out of proportion. The dataset used in this study was divided into two sections: the training dataset, which comprised 80 % of the data, and the test dataset, which made up the remaining 20 %.

Model selection

Two effective analytical strategies that have been used effectively to determine which elements have any meaningful impact on the process to show the model dependent variables are Artificial neural networks and partial least squares regression. Prediction research has been using statistical tools in recent years.

Artificial Neural Network (ANN)

ANN models several artificial neural networks to simulate the architecture of the human brain with dynamic and adaptive connections between them. Most features of ANNs are akin to those of human brains; these include high comparison, autonomous functioning, mistake tolerance, personalization and the ability to manage erroneous input (16). Fig. 1 illustrates how multilayered ANN structures are typically. After receiving the input signals, the first layer multiplies each input (x) by a neural weight (W) that may be adjusted, adds bias (b) and then generates the overall input (n). Soft modeling applies an activation function to the entire input. Performing intricate calculations and translating the input into the output of a brain neuron is the task of this activation function. The model may generate precise predictions thanks to the most often used transfer functions, namely log sigmoid and linear.

The output of a neuron is represented as, Y=f(W*x*+c)

The capability of an ANN to do recurrent dynamic modeling and omnipresent estimation makes it a desirable option for complex problems. Although the model typically necessitates a substantial amount of training data and the learning process can be computationally intensive, it is essential for achieving accurate results (17).

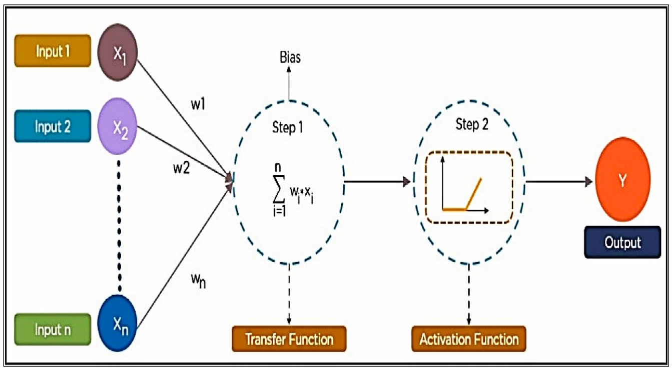

Fig. 1. The general structure of an Artificial neural network. *(Image source: Superdatascience.com)*

Partial Least Square Regression (PLSR)

PLSR is still widely employed in various scientific statistical procedures, having been developed in 1960 (18) for application in the field of social science research (19). A common bilinear component method in the fields of economics (20), agriculture (21) and pharmaceutical sciences (22) is partial least squares regression. Principal component

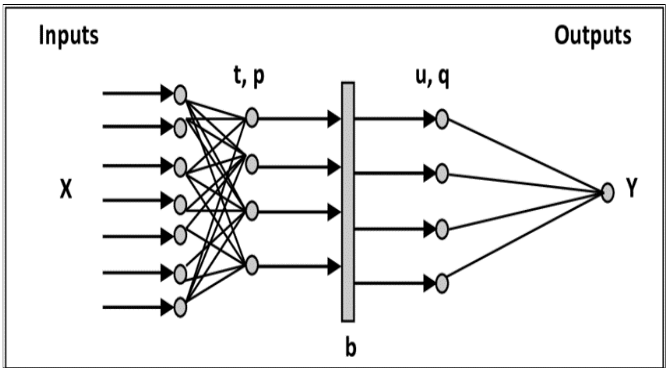

Fig. 2. Partial least squares regression framework. Egarievwe (14) is the source. There is a linear relationship (b) connecting the score vectors t and u, as well as the latent variables p (representing the inputs) and q (representing the outputs). This mapping establishes a connection between the input and output variables, allowing for a clear understanding of the relationship between them.

analysis (PCA) and multiple regression analysis (MLS) techniques that are integrated and utilized in PLSR (Fig. 2). By finding components (factors) from the descriptive (X) variables that are also relevant for the response of the (Y) variables, the approach reduces the degree of dimensionality of the "X" values. PLSR not only solves the problems of overfitting, multicollinearity, and outliers, but it also pinpoints the elements that contribute significantly to the data content that all "X" and "Y" variables share. The concepts of PCA are expanded upon in the process of identifying PLS factors, following which a regression analysis phase is performed to employ "X" variables to predict "Y" (23). In this study, we used population (matrix X) and food grain production and consumption data to predict the per capita availability of food grains, specifically wheat and rice, in grams per year through Partial Least Squares Regression (PLSR). Eqn. 1 - 3 produced the PLSR's optimal factor number.

$$F_{PRESS,h} = \sum_{i=1}^{n}(x_i - x_{\bar{h}(-i)})^2 \qquad \text{Eqn. 1}$$

$$F_{SS,h} = \sum_{i=1}^{n}(x_i - x_{\bar{hi}})^2 \qquad \text{Eqn. 2}$$

$$Q_h^2 \overset{x_{\bar{hi}}}{=} 1 - \frac{F_{PRESS,h}}{F_{SS,h}} \qquad \text{Eqn. 3}$$

where $x_{\bar{h}(-i)}$ is the fitted value of the -ith sample point after all sample points have been used and the "h" component has been extracted using regression modeling and x_i is the original data. The notation indicates that sample point i was eliminated during the modeling phase. Next, by applying the h component from regression modeling to the model, the fitted value of y is found. A new component adds significantly to the created model's predictive capacity when Q_h^2 is less than 0.0975; otherwise, the inclusion of a new element has no discernible effect (24).

Tools used

Python served as the main programming language for this study, covering all stages from data extraction to model evaluation. The performance of the suggested layout is assessed through the development of an application using the Python 3.6 programming environment.

Assessment indicators

Several statistical metrics are used as value indicators while assessing the model. The widely recognized technique for internal evaluation during model training is the cross-validation approach. The effectiveness of the ANN and PLSR models in predicting the food grain was assessed using four statistical metrics: R^2, MSE, MAE and RMSE. The most popular performance indicators for evaluating a predictive model's efficacy are these statistical measurements, which are

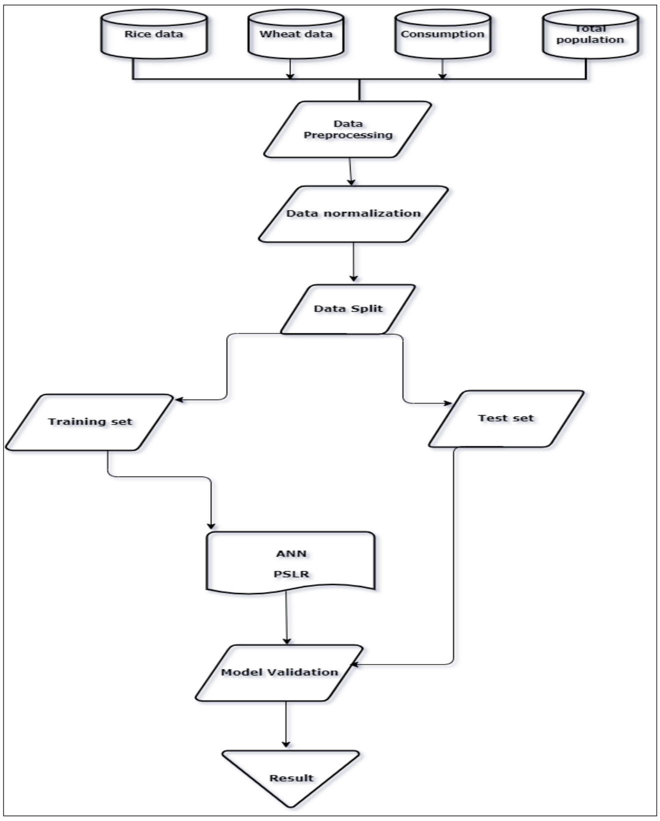

Fig. 3. Proposed Framework for per capita availability of food grain forecasting.

obtained by contrasting the expected and actual results for data that were not used to fit the model (Eqn. 4-7). The proposed Framework for per capita availability of food grain forecasting was also depicted in Fig. 3.

$$MAE = \frac{1}{N}\sum_{i=1}^{n}(P_i - \hat{P}) \qquad \text{Eqn. 4}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{n}(P_i - \hat{P}_i)^2 \qquad \text{Eqn. 5}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i-\hat{P}_i)^2}{N}} \qquad \text{Eqn. 6}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(P_1-\hat{P}_i)^2}{\sum_{i=1}^{n}(P_i-\underline{P_i})^2} \qquad \text{Eqn. 7}$$

where,

'n' is the total number of samples,

P_i is actual value,

$\hat{P}_i$ is the predicted value

$\underline{P_i}$ an average of the actual values.

Results and Discussion

This section uses the data from the preceding section to demonstrate how the model is implemented. Using the model, we carefully inspect the data to obtain understanding of the data set. Therefore, in this part, the statistical data will be presented to evaluate the effectiveness of the proposed model.

The time series dataset indicates that production increased significantly between 1951 and 2022. Following a steady increase, the production peaked in 2022. The data shows phases of increase and fall with significant production

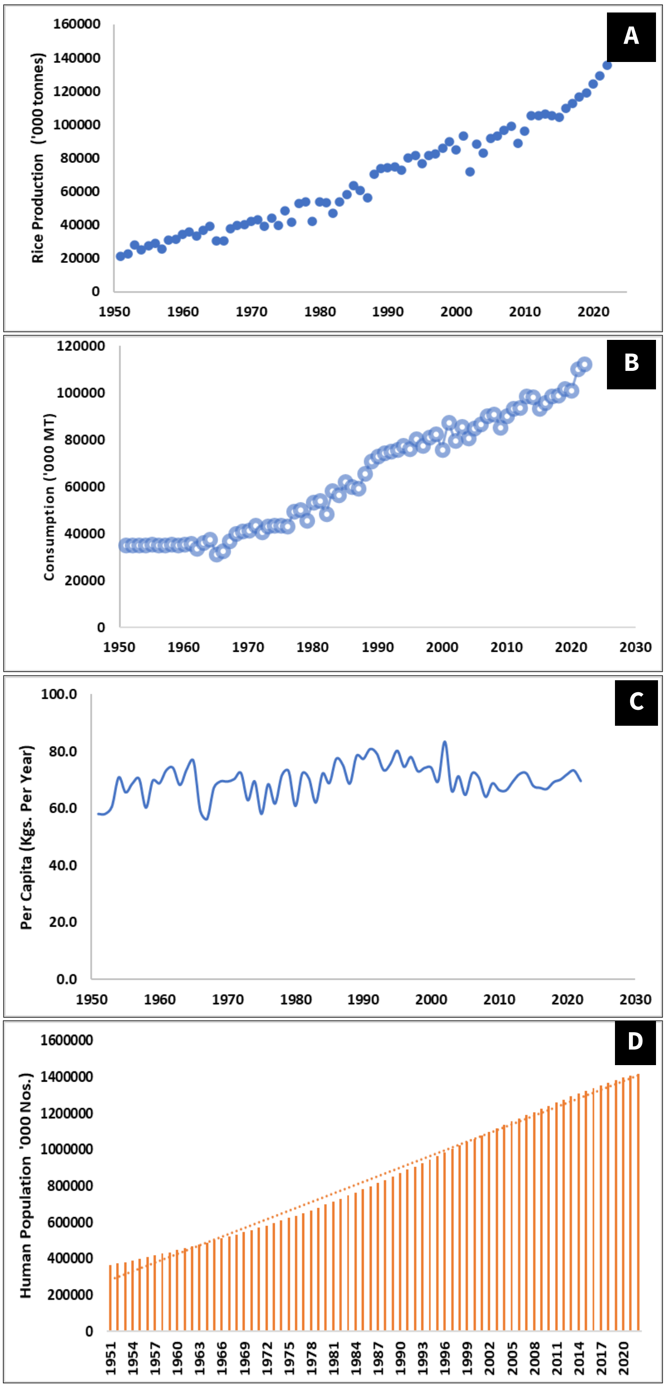

Fig. 4. Intricate visual representation of the detailed variables of food grain-Rice. (A)- Rice Production ('000 tonnes), (B) Consumption of rice grain ('000 MT), (C) Per Capita availability of rice (Kgs. Per Year), (D) Human Population of Indian nation ('000 Nos.).

surges every few years. Fig. 4 and 5 depict an overall trend of increase interspersed with sporadic variations in the rice and wheat, respectively. When predicting the per-capita availability of food grain production-wheat and rice-it is important to compare the ANN and PSLR models.

Comparative analysis with previous studies has been

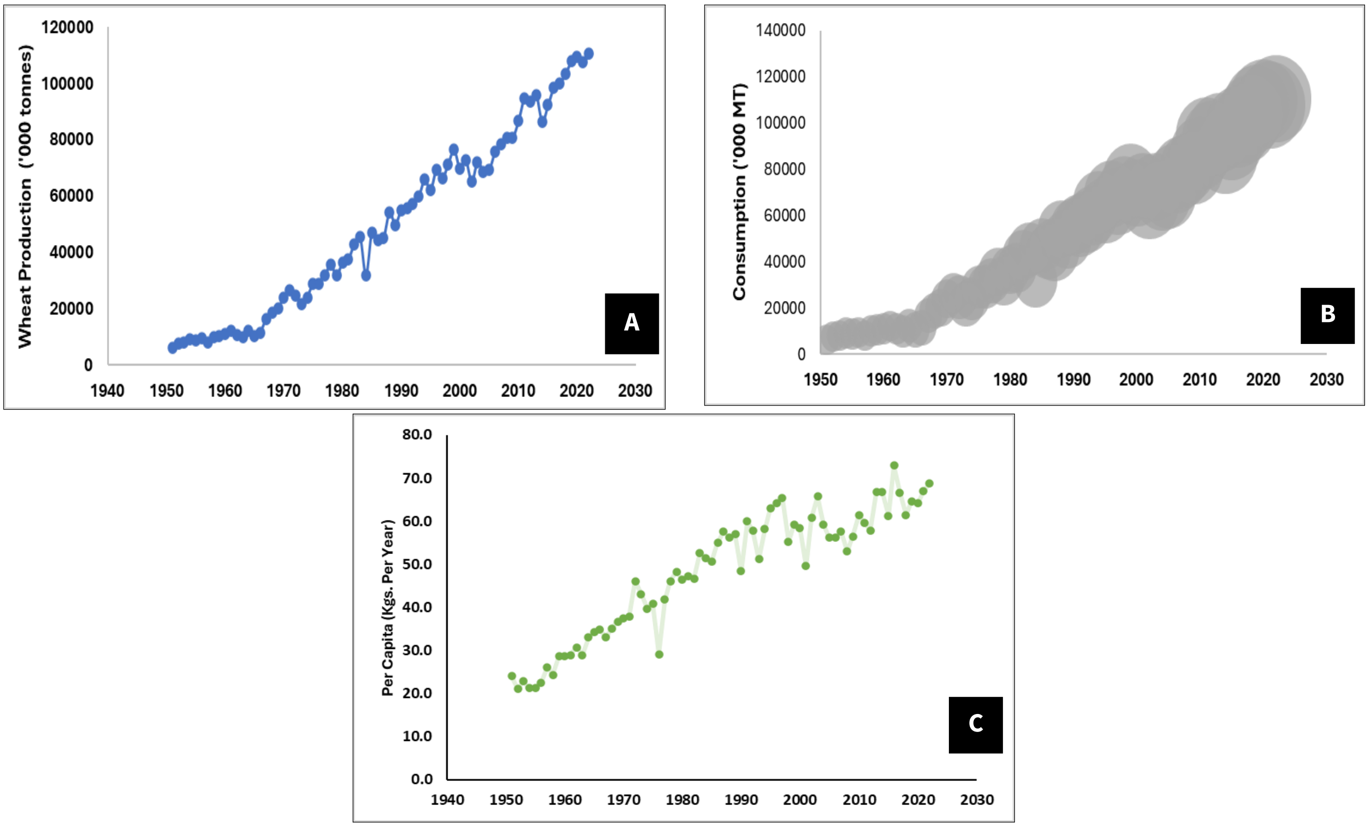

Fig. 5. Intricate visual representation of the detailed variables of food grain (Wheat). (A)- Wheat Production ('000 tonnes), (B) Consumption of wheat grain ('000 MT), (C) Per Capita availability of wheat (Kgs. Per Year).

included to contextualize the present findings within the broader scope of food security and predictive analytics. The section elaborates on how machine learning models, particularly ANN and PLSR, have been utilized to enhance forecasting accuracy and improve decision-making in agriculture. Several studies have demonstrated the efficiency of ANN in capturing non-linear relationships in agricultural data, while PLSR has been recognized for its robustness in handling multicollinearity issues. Integrating these findings, the study establishes a solid foundation for the application of these models in predicting food grain availability. The implications of these methodologies for sustainable agricultural planning and food security policies in India. Critical evaluation of the study's findings in comparison to existing literature highlights key areas where ANN and PLSR models have shown predictive strength, as well as potential limitations. The discussion also emphasizes the significance of incorporating real-time climate and socio-economic data into these models to enhance predictive accuracy.

Fig. 6 illustrates the comparison between actual and predicted per capita food grain availability, employing ANN and PLSR models. The x-axis represents the years, while the y -axis denotes the per capita availability of food grains. The blue curve corresponds to actual values, whereas the orange curve represents the predicted values generated by the respective models. Subfigures (A) and (B) depict rice predictions using ANN and PLSR, while subfigures (C) and (D) present wheat forecasts under the same modeling approaches. A close examination of the graphs reveals that the ANN model consistently tracks actual values with greater accuracy, effectively capturing both short-term fluctuations and long-term trends. The PLSR model demonstrates a relatively lower predictive capability, with noticeable deviations in periods of sharp variation. The results indicate that ANN models exhibit superior performance due to their ability to process complex, nonlinear relationships between variables.

The results derived from Fig. 6 align with existing literature that highlights the effectiveness of ANN in agricultural forecasting. The predictive superiority of ANN observed in this study further validates its applicability in modeling food grain availability. While PLSR provides reasonable approximations, its reliance on linear relationships limits its adaptability to dynamic agricultural conditions. This limitation is particularly evident in periods characterized by sudden fluctuations in food grain availability. The capability of ANN to efficiently capture such variations makes it a valuable tool for decision-makers in the agricultural sector.

Comparative analysis of proposed models

Based on Fig. 7 and 8 and Table 1 and 2, the comparative analysis of the models' performance on the training and test datasets highlights the effectiveness of ANN and PLSR in predicting food grain per capita availability. The evaluation metrics used for comparison include R^2 (coefficient of determination), Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The training dataset results in Table 1, ANN outperformed PLSR with a slightly higher R^2 value (0.956 vs. 0.955), indicating better predictive accuracy. The MAE for ANN (3272.11) was marginally lower than PLSR (3285.99), suggesting ANN had a better capability to minimize absolute errors. Similarly, ANN exhibited a slightly lower MSE (1.748) and RMSE (4194.28) compared to PLSR (1.759 and 4205.62, respectively), demonstrating its superior performance in handling training data. The test dataset in Table 2, ANN also achieved a higher

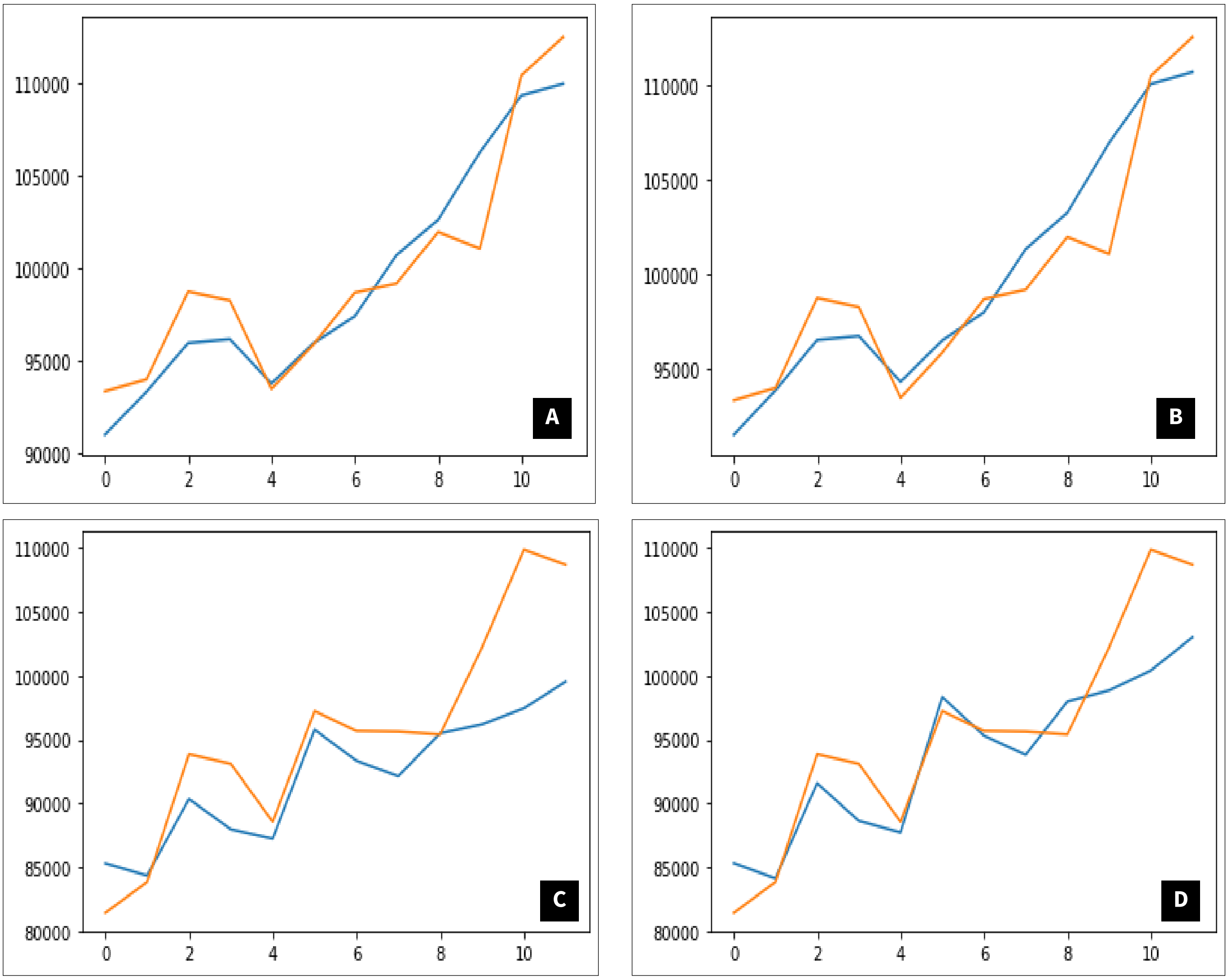

Fig. 6. Representation of the train dataset's actual and predicted values for food grain per capita availability. The blue curve shows actual numbers, and the orange curve shows the expected values produced by the suggested approaches. The years are displayed on the x axis, and the per capita availability of food grains is shown on the y axis. (A). Rice-ANN model, (B). Rice-PSLR, (C). Wheat-ANN model, (D). Wheat-PSLR.

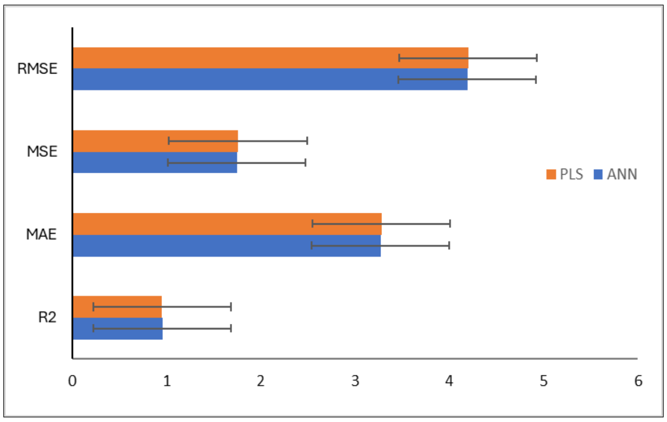

Fig. 7. Comparative analysis of the models' performances using train dataset.

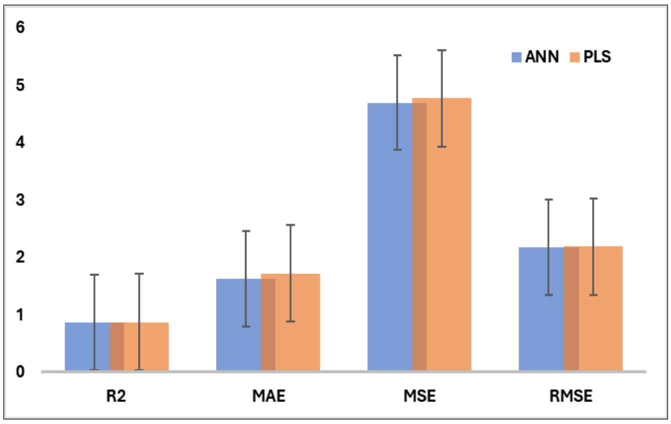

Fig. 8. Comparative analysis of the models' performances using test dataset.

Table 1. Comparative analysis of the models' performances using training dataset

TRAIN	R^2	MAE	MSE	RMSE
ANN	0.956	3272.11	1.748	4194.28
PLS	0.955	3285.99	1.759	4205.62

Table 2. Comparative analysis of the models' performances using test dataset

TEST	R^2	MAE	MSE	RMSE
ANN	0.865	1619.56	4.69	2167.06
PLS	0.862	1715.13	4.77	2186.04

R^2 (0.865) compared to PLSR (0.862), reaffirming its robustness in generalization. The MAE for ANN (1619.56) was lower than that of PLSR (1715.13), signifying that ANN produced more accurate predictions with reduced deviations from actual values. The MSE and RMSE for ANN were 4.69 and 2167.06, respectively, which were also lower than PLSR (4.77 and 2186.04), indicating its greater efficiency in minimizing errors in the test dataset. The comparative analysis suggests that ANN outperformed PLSR in both training and test datasets, making it a more reliable predictive model for food grain per capita availability. The graphical representation in Fig. 7 and 8 illustrates these differences, showing that ANN generally yielded lower error metrics and better predictive capabilities than PLSR. The findings support the suitability of ANN in complex nonlinear datasets where capturing intricate patterns is crucial for accurate forecasting. However, the minimal difference between the two models suggests that PLSR also holds considerable predictive strength and may be a viable alternative in certain cases.

The models used to forecast the availability of food grains per capita for the years 2023-2033 are specifically examined in this portion of the study. As a result of the models, the projected values are shown in Fig. 9 which presents future projections of per capita food grain availability in India. The key trends observed, highlight fluctuations in food grain availability over the forecasted years. The analysis now compares these projections with historical trends, providing insights into the accuracy and reliability of ANN-based forecasting models. The study examines the implications of these projections for food security and policy planning. The role of ANN and PLSR in capturing the critical factors influencing food grain production and consumption has been emphasized. The expanded section also discusses how these findings can help policymakers strategize long-term food security measures, ensuring stability in agricultural output and availability. A closer look has been given to potential future challenges such as climate variability, shifts in cropping patterns and resource constraints that may affect food grain production. The importance of adaptive agricultural strategies and technology-driven interventions has been underscored. The findings highlight the necessity for continuous monitoring and revision of food security policies to mitigate risks and enhance resilience in the agricultural sector.

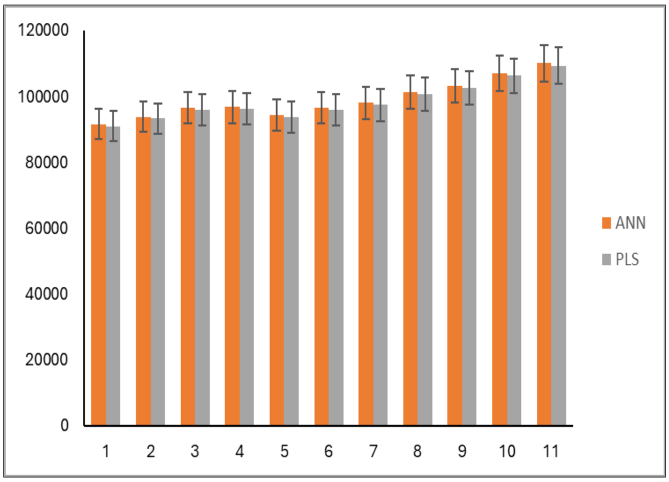

Fig. 9. Model's predictions and their outcomes. The y-axis represents the availability of food grains per capita, while the x-axis represents the years.

Conclusion

Ensuring grain security is crucial for the overall well-being of the population, fostering social cohesion and driving economic growth. The primary indicator used to evaluate food grain security is per capita grain consumption because of its high nutritious content. The agricultural sector is the backbone of our country, yet even though the production capacity of various agricultural products is currently dropping dramatically when compared to other nations like the USA and China, the sector's percentage of GDP has declined over time due to recent economic expansion. This study provides a comprehensive analysis of per capita food grain availability in India, focusing on wheat and rice, using ANN and PLSR. The findings indicate that ANN outperforms PLSR in predictive accuracy, as evidenced by higher R^2 values and lower error metrics in both training and test datasets. The superior performance of ANN highlights its ability to capture complex nonlinear relationships, making it a valuable tool for forecasting food grain availability. The results underscore the significance of advanced machine learning models in agricultural data analysis, particularly in improving food security assessments. With the increasing variability in food production due to climate change and socio-economic factors, accurate predictive models play a crucial role in policy formulation. The study's insights can assist policymakers in making informed decisions regarding food distribution, storage and production planning. Despite of these results, the study acknowledges certain limitations, including the need for incorporating additional variables such as climate change indicators, policy interventions and regional disparities. Future research should focus on refining predictive models by integrating satellite imagery, real-time market data, and socio-economic parameters. Expanding the dataset to include a longer time frame and diverse crop categories could enhance model robustness. The adoption of hybrid modeling techniques, combining statistical and machine learning approaches, may further improve accuracy and reliability.

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Authors' contributions

VPNB contributed to the conceptualisation, framing the methodology, obtaining resources, carrying out the investigation, analysis and writing the original draft. KM helped in the statistical analysis, conducting the investigation, formulating the methodology, employing software and writing the original draft. BN has assisted with the analysis, investigation, methodological framework, software application and writing. SA, BV participated in writing, review and editing the manuscript. BV took part in framing the methodology, utilization of software, writing, review and editing. SM involved in writing, review and editing. RM and DR contributed to writing, review and editing the manuscript. All authors have read and agreed to the published version of the manuscript.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interest to declare

Ethical issues: None

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