Machine Learning to Predict Rice Stock for Food Security: A Brief Study

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Abstracts: The present study aims at shedding light on machine learning in agriculture by thoroughly reviewing the recent scholarly literature based on keywords' combinations of "machine learning" and "rice". Only journal papers were considered eligible that were published within 2020 – 2023. Approximately 49 articles from scopus and google scholar database. It was selected for full content review after the pre-screening process. The results indicated that this topic pertains to different disciplines that favor convergence research at the international level. Prediction criteria related to food security were found to be the most inputs of prediction models. Machine learning models such as Random forest result in high accuracy in predict rice stock on 98%. This study will constitute a beneficial guide to all stakeholders towards enhancing awareness of the potential advantages of using machine learning in predict rice stock and contributing to a more systematic research on this topic.

Keywords: Machine Learning, Predict, rice stock, food security, A Brief Study

1. INTRODUCTION

Agriculture plays a vital role in sustaining all human activities. Significant challenges such as overpopulation competition for resources pose a threat to the planet's food security. To tackle the ever-increasing complex problems in agriculture offers essential tools to overcome food security challenges (Naik & Suresh, 2018). Machine learning holds the key to ensuring rice. Disruptive information and communication technologies such as machine learning can address several issues such as techniques and crop modeling for rice (Sharma et al., 2021).The current study presents the application of machine learning for rice. Rice needs to be sufficient and nutritious while minimizing environmental impact and enabling producers to earn a decent living (Eyhorn et al., 2019). Rice serves as the predominant staple food for over 50% of the global population, with the largest consumption occurring in Asia, Sub-Saharan Africa, and South America. The majority of the world's rice has been identified as Oryza Sativa, a grass-related plant species knew to have started in Asia (Muthayya et al., 2014).

In achieving rice self-sufficiency, many obstacles and challenges are faced, including a slower rate of increase in rice production, conversion of agricultural land to non-agricultural land, or unproductive land, efforts to expand areas are difficult, and the population continues to grow. The increasing demand for rice is in line with the exponential increase in population. One of the staple food sources is rice agricultural products. Agriculture is an important element for the global economy. Rice is a very important requirement for the food needs of the world community. Machine learning as a solution to achieve rice self-sufficiency aimed at food security. Machine learning can be defined as the utilization of data, information, and technologies to enhance the efficiency and effectiveness of intricate agricultural systems. Machine learning focuses on how the information regarding farming can be used in an smart way rather than on how to store data, get to data, or use these farming data (Alfred et al., 2021).

Machine learning in agriculture emerges as a new scientific field. Agriculture technology is a data-driven strategy to increase and improve agricultural output while minimizing environmental impact (Liakos et al., 2018). Machine learning is a solution to overcome the farmer's and industry challenges in generating necessary information. Machine learning devices can support farmers to get the relevant information and make an accurate decision. These capabilities are essentially initiated by a large number of datasets which consist of different variables and a dependent variable, including their relationship (Hashem et al., 2015). In this study, we conducted a systematic literature review (SLR) of the most recent research on intelligent data processing technology used in rice, with an emphasis on techniques and crop modelling for rice. The main datasets or features extracted for data modeling were described. We then elaborate on the role of machine learning algorithms in agriculture.

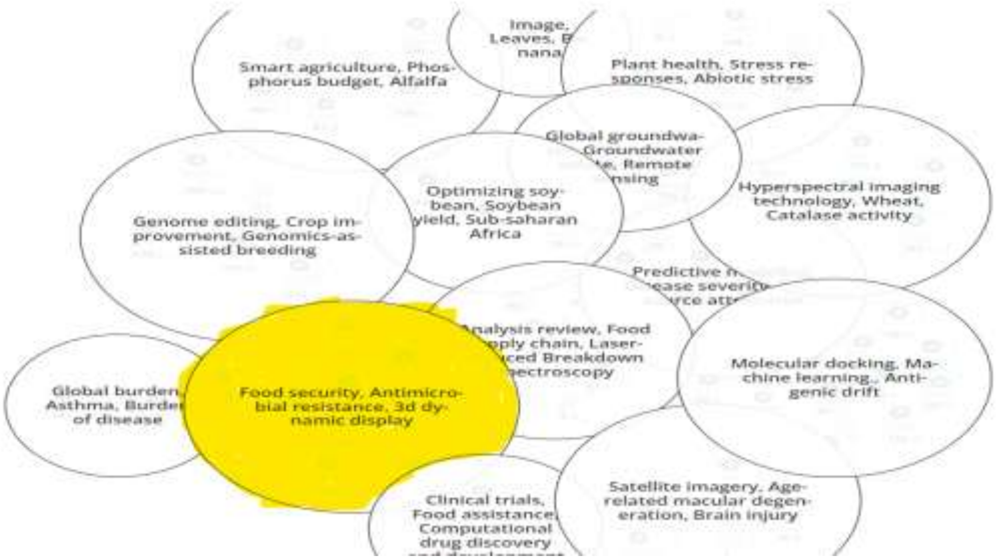

Fig. 1: . Open Knowledge Maps For Gap Research

With Open Knowledge Maps, Gap Research information was obtained for the search of machine learning rice for food security that can still be further researched related to food security, antimicrobial resistance, 3d dynamic display. It was found that the food security dataset integrates several open data sources, so the Cross-Industry Standard Process for Data Mining methodology was used to guide the dataset construction (S. et al., 2022). Furthermore, by utilizing the unique global dataset, the proposed model can explain up to 81% of the variation in insufficient food consumption and up to 73% of the variation in crisis or above food-based response levels (Martini et al., 2022). To measure the actual state of food insecurity, expert and consensus-based approaches and surveys are currently used (Westerveld et al., 2021). By studying articles in Open Knowledge Maps the authors are looking for machine learning models that can produce high prediction accuracy for rice, especially for food security.

2. MATERIAL AND METHOD

This research applied a Systematic Literature Review (SLR) approach based on high-standing journal papers relying on reliable sources of information. As a result, academic articles in the last five years (2020-2023) were collected and archived 49 from Scopus and Google Scholar databases, which are known as reliable sources for academic literature. Our search was limited to scholarly articles published in reputable journals, excluding other bibliographic materials, such as book chapters, dissertations, conference papers, and other articles, to ensure high document quality. The subject area of the article is limited to Machine Learning rice for food security as it is within the scope of the analysis. The keywords used are "machine AND learning; AND rice; AND food AND security". This research is supported by several previous studies that recommend organizations in various countries to monitor the success of machine learning to predict rice for food security. According to several studies, machine learning for rice commodity is essential to improve food security. The figure below illustrates the linking structure between previous studies and the ongoing study.

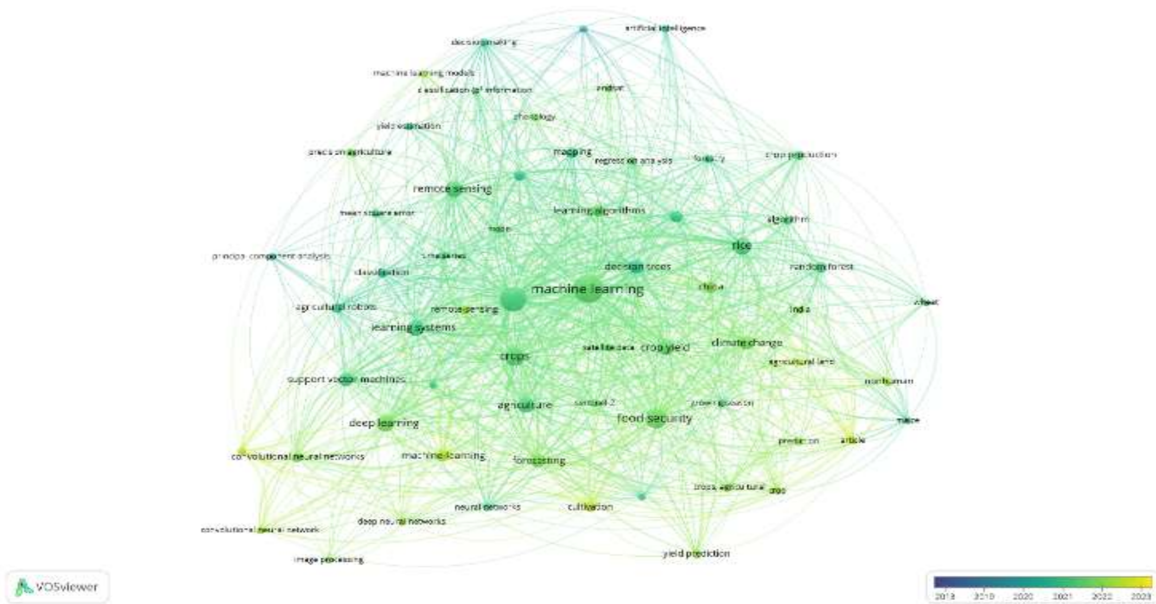

Fig. 2: Vos viewer results for previous research, 2023.

First cluster contains articles published in 2020-2023 that cover the topics of agriculture land, climate change, crop production, food security, machine learning, and yield prediction. The second cluster consists of articles published in 2021 that cover the topics of algorithms, learning algorithms, time series and artificial intelligence. The third cluster consists of articles published in 2022 on the topics of agriculture robots, learning systems, machine learning, support vector machines. The fourth cluster contains articles published in 2023, and the topics covered are machine learning mode, forecasting, precision agriculture, yield estimation and regression analysis. Previous studies on machine learning rice food security have mostly focused on agriculture land. Studies on machine learning rice food security are still limited. If we search the ScienceDirect database with the keywords "machine AND learning; AND rice; AND food AND security" for a span of 3 years (2020-2023), there are 49 results that are considered the most relevant to the topic.

3. RESULTS AND DISCUSSION

3.1. Food Security

The World Food Organization's 1996 definition of food security is the most frequently cited. The FAO defines food health as "the state in which all people, for whatever reason, have access to adequate, safe, and healthy food in accordance with their needs in an active and healthy lifestyle." Summarizing the indicators of food security from (Burki 2022) as follows: 1) Prevalence of undernourishment, and 2). Prevalence of moderate or severe food insecurity in the population, based on the Food Insecurity Experience Scale. The issue of food insecurity is very important in food security to be predicted early. In Indonesia, in Law No. 18/2012 on Food, food security is defined as "the condition of food fulfillment for the state to individuals, which is reflected in the availability of food that is sufficient, both in quantity and quality, safe, diverse, nutritious, equitable, and affordable and does not conflict with religion, beliefs and culture of the community, to be able to live healthy, active and productive lives in a sustainable manner." From the FAO document, food security has four dimensions, namely adequate availability, access to food, proper food utilization, and stability of food stocks and prices. With these four dimensions, measures are made to look at food security.

3.2. Machine Learning

All industrial machine learning (ML) initiatives' ultimate objective is to create ML products and quickly put them into production (Kreuzberger et al., 2023). Machine learning algorithms attempt to find pattern in data. In their basic forms, that frequently means identifying a predictive relationship between factors (Bengio, 2012). These are several machine learning approaches to build predictive models. Machine learning is a field in data analytic that focuses on mathematical algorithms development to forecast future events (Menagie, 2018).

Computer/systems in machine learning can learn from the past data, and practice. Finding patterns in big data is the purpose of machine learning algorithms, without being specifically programmed. Computers are capable to analyse big data in order to discover patterns and rules in a manner that are too difficult for humans to do. The fundamental concept behind machine learning is that computers or machines can automatically learn from experience. The computer analyses big data in order to uncover patterns and rules hidden in the data. Machine learning is a subfield of artificial intelligence that aims to create systems that are capable of learning from their previous experience. Machine learning methods are often data-driven, inductive and general in nature. A systematic review of real-world implementation studies of sepsis prediction algorithms was used to validate an end-to-end staged implementation framework that can account for key factors that need to be focused on to ensure successful deployment and builds on previous AI implementation frameworks (van der Vegt et al. 2023).

Three major categories in machine learning problem exist: classification, clustering, and regression. The classification involves assignment a set of potential classes to an observation, for example an email message: spam or not. As a result, Classification produces discrete n-array output. Clustering separates a set of observations into groups in order to maximise the similarity of observation within each group and as different as possible from one group to the next, for example: pattern recognition (Giridhar et al., 2019). Specifically, this is the main issue under consideration in this research. Regression defines as the estimation of the relationship of a response from one or more predictors. Both the response and one or more predictors have continuous value ranges in general.

3.3. Machine Learning For Food Security

The food security early warning system uses various indicators to assess the food security situation. Some of the indicators commonly used in this system include: total production, planting area, irrigated area of land, export proportion (Sun et al. 2022). These indicators are analyzed using statistical methods, data mining techniques, and predictive models. Historical data is collected and analyzed to identify trends, patterns and potential food security risks. The data is processed and evaluated to generate early warning signals and assess the severity of the food security situation. Predictive models, such as machine learning algorithms, can be used to forecast future food security conditions based on analyzed indicators and historical data (Bux et al. 2022).

3.4. Food Security : Accessibility And Availibility

Food security is one of the things that needs to be prepared for the global economic recession. Controlled food security will maintain the availability of food consumption needs, especially rice. There are three pillars of food security that must be considered, availability, accessibility, and food consumption and utilization. We observe that in general, food security, especially rice availability prediction, can be grouped into two methods, namely conventional statistical methods, and machine learning methods. Each method has advantages and disadvantages. Along with the development of technology, machine learning and deep learning methods provide faster and more accurate data information.

Table 1. Example of Conventional Statistical Methods for Rice Availability Prediction

Ref. & Publication Year	Algorithm	Crop	Result
Arumugam	Gradient Boosted Regression	rice	The model performance improved further when

et al. (2021)	(GBR)		estimating separate models for different rice cropping densities (up to r = 0.93). An additional out-of-sample validation for the years 2016 and 2017, proved successful with r = 0.84 and r = 0.77, respectively.
Bowden, Foster, and Parkes (2023)	Random forest modelling	rice	In comparison to conventional parametric models, machine learning modeling can disclose more information on crop-climate variability in monsoonal agriculture.
Fernández-Urrutia, Arbelo, and Gil (2023)	Methods based on remote sensing to map paddy croplands.	rice	The constant development of cloud detection algorithms will benefit multispectral technologies.
Liu et al. (2022)	In this study, by combining time-series satellite data, environmental factors, and rice yield records from 2001 to 2016, we developed a transformer-based model, Informer, to forecast rice production across the Indian Indo-Gangetic Plains.	rice	The outcomes demonstrated that Informer outperformed four other deep learning and machine learning models for end-of-season prediction (R 2 = 0.81, RMSE = 0.41 t/ha).

Conventional statistical methods have a number of advantages and disadvantages in the context of food security. Advantages of Conventional Statistical Methods: ability to analyze history, easy interpretation, use of limited data, identify simple causal relationships, stable models. While the weaknesses of conventional statistical methods: limitations in handling complex data, limitations in forecasting the future, lack of rigor in complex cases, limitations in processing big data, unable to handle complicated nonlinearities, difficulty in detecting unknown patterns.

Table 2. Example of Machine Learning Methods for Rice Availability Prediction

Ref. & Publicat ion Year	Algorithm	Crop	Result
Ahmed et al. (2019)	KNN(K-Nearest Neighbour), J48(Decision Tree), Naive Bayes and Logistic Regression.	rice	The decision tree method displayed a high level of accuracy, reaching 97%, when tested using a 10-fold cross validation technique and applied to the test dataset.
Zha et al. (2020)	Single VI (SVI); stepwise multiple linear regression (SMLR); random forest (RF); support vector machine (SVM); and artificial neural networks (ANN) regression.	rice	The results showed that for NNI estimation, machine learning techniques performed better than VI-SLR and SMLR techniques. The RF approach fared the best at estimating NNI, with R2 values of 0.94 (SE) and 0.96 (HD) for calibration and 0.61 (SE) and 0.79 (HD) for validation. The root mean square errors (RMSEs) were 0.09, and the relative errors were all under 10%. It is concluded that RF machine learning regression may considerably improve the assessment of rice N status utilizing UAV remote sensing.
Shrivastava	Support Vector Machine	rice	Support vector machine (SVM) classifier

& Pradhan (2021)			ditemukan memiliki akurasi klasifikasi terbesar pada 94,65% setelah kinerja tujuh classifier yang berbeda dibandingkan.
Cao et al. (2021)	Least Absolute Shrinkage and Selection Operator (LASSO) regression, one machine learning (Random Forest, RF), and one deep learning (Long Short-Term Memory Networks, LSTM)	rice	LSTM (with R2 ranging from 0.77 to 0.87, RMSE from 298.11 to 724.3 kg/ha) and RF (with R2 ranging from 0.76 to 0.82, RMSE from 366 to 723.3 kg/ha) models outperformed LASSO (with R2 ranging from 0.33 to 0.42, RMSE from 633.46 kg/ha to 1231.39 kg/ha) in yield prediction; LSTM was superior to RF.
Onojeghuo et al. (2018)	Support Vector Machine (SVM) and Random Forest (RF)	rice	The RF algorithm generated the highest overall classification accuracy (95.2%) and for paddy rice (96.7%) when it was applied to combined multitemporal VH polarization and NDVI data.
Guo et al. (2021)	Back propagation neural network (BP), support vector machine (SVM) and random forest (RF).	rice	The RMSE (R2) between predicted and observed rice yields was 800 (0.24), 737 (0.33), and 744 (0.31) kg/ha for BP, SVM, and RF, respectively. Phenological variables considerably improved yield prediction accuracy, and they were even more important to climatic variables than the SVM, which had the best yield prediction precisions.
Grinberg et al. (2020)	Compared the elastic net, ridge regression, lasso regression, random forest, gradient boosting machines (GBM), and support vector machines (SVM) as well as other common machine learning techniques.	rice	GBM classifier demonstrated superior performance.
Ramesh and Vydeki (2018)	Artificial Neural Networks.	rice	The simulation findings demonstrate an accuracy of 99% for the blast-infected photographs and 100% for the healthy images during the training phase. For infected images, testing phase accuracy is determined to be 90%, whereas for healthy images, it is found to be 86%
Das et al. (2020)	Partial least square regression (PLSR), PLSR- and principal component analysis (PCA)	rice	The results revealed that PLSR-combined models performed the best, followed by PCA-based models, and indices-based models performed the worst
Zhang et al. (2020)	Four convolutional neural network (CNN) algorithms (one-dimensional (Conv-1D), two-dimensional (Conv-2D) and three-dimensional (Conv-3D_1 and Conv-3D_2) convolutional neural networks) were developed and compared with four widely used classifiers (random forest (RF), extreme	rice	The RF and XGBoost models achieved acceptable F1 scores for transfer (RF = 0.6673 and 0.6469, respectively, XGBoost = 0.7171 and 0.6709).

	gradient boosting (XGBoost), support vector machine (SVM) and multilayer perceptron (MLP))		
Son et al. (2020)	random forests (RF) and support vector machines (SVM)	rice	We processed the data from 2000 to 2018, completing three major steps: (1) data pre-processing to generate smooth time-series Normalised Difference Vegetation Index (NDVI) data, (2) development of yield prediction models based on the heading date (HD) NDVI value and the accumulated NDVI value of the dates from heading to maturity (DHM).
Amin et al. (2021)	artificial neural network, artificial neuro-fuzzy inference system	rice	R2 values of 0.98, 0.89, 0.70, and 0.63 are determined for ANN, ANFIS, RSM, and LR, respectively. Based on the results and statistical parameters, it can be concluded that ANN and ANFIS are the most accurate AI techniques for predicting CS. Thus, these two AI techniques can be utilised for RHAC's preliminary design.
Conrad et al. (2020)	Support vector machine (SVM) and random forest	rice	With an overall testing accuracy of 86.1% (N = 72), the SVM-based model achieved the maximum accuracy in comparing mock-inoculated and inoculated plants. The most accurate SVM model attained an overall testing accuracy of 73.3% (N = 105) in the comparison of control, mock-inoculated, and inoculated plants.
Azmi et al. (2021)	Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Random Forest, and Multi-layer Perceptron (MLP)	rice	Random Forest is a dependable model that can be used to predict the level of moisture in rice because it provides high accuracy even when only one input feature is used.
Cinar and Koklu (2022)	K - nearest neighbor, decision tree, logistic regression, multilayer perceptron, random forest and support vector machines.	rice	A random forest algorithm was employed to achieve a classification accuracy of 98.04% for the morphological and shape features. The colour features were successfully modelled using logistic regression, resulting in an accuracy rate of 99.25%. The multilayer perceptron achieved a final accuracy of 99.91% when utilising morphological, shape, and colour features.
Liu et al. (2021)	The developed multilayer perceptron (MLP), support vector machine (SVM), Elman recurrent neural network (Elman RNN) and probabilistic neural network (PNN)	rice	The PNN performed best in the study, with an F-measure (= 2) of 96.8%.
Tseng et al. (2022)	EfficientDet-D0 and Faster R-CNN, and to compare the results to the legacy approach—histograms of	rice	The results indicate that both CNN-based models outperform HOG-SVM, with a mAP and mIoU that are 10% greater.

	oriented gradients (HOG)-based support vector machine (SVM) classification.		
Aznan et al. (2021)	Artificial neural network (ANN), and the Bayesian Regularization (BR) algorithm	rice	The Bayesian Regularisation (BR) algorithm of the artificial neural network (ANN) with ten hidden neurons yielded the highest classification accuracy at 91.6% (MSE = 0.01) and 88.5% (MSE = 0.01) for the training and testing stages, respectively.
Ruslan et al. (2022)	logistic regression	rice	The RGB image used the logistic regression (LR) model to develop the best optimum model, which achieved 85.3% sensitivity, 99.5% specificity, 97.9% accuracy, and 92.4% average correct classification using all 67 features.
Aznan et al. (2022)	Artificial neural network (ANN) algorithms	rice	Results showed that both sensing devices could find adulterated rice at different mixing ratios with high correlation coefficients through direct (e-nose; R = 0.94–0.98) and non-invasive measurements through the packaging (NIR; R = 0.95–0.98).
Cedric et al. (2022)	Decision tree, multivariate logistic regression, and k-nearest neighbor models to build our system	rice	The decision tree model performs well with a coefficient of determination(R 2) of 95.3% while the K-Nearest Neighbor model and logistic regression perform respectively with R 2 = 93.15% and R 2 = 89.78%.
Chaudhary and Kumar (2022)	convolutional neural networks (CNNs) have been developed over the support vector machine (SVM) techniques to identify rice diseases (Brown spot) and measure their accuracy	rice	ML techniques give 82% accuracy using the SVM classification method, while the CNN method gives 95% accuracy
Kinnunen et al. (2022)	algorithm XGBoost	rice	Over the entire time span, anthropogenic influences explained 40%–60% of the variation in yield loss risk, but their explanatory power during shock years was considerably lower (5%–20%). On a continental level, the factors, particularly in Europe and Africa, accounted for a significant share (up to almost 80%) of the variation in yield loss risk.
Xu et al. (2022)	Method that conducts experimental research and is based on the merging of several machine learning models	rice	The model comparison shows that the risk assessment model performs better than other common machine learning algorithms, and its evaluation accuracy is as high as 99.54 percent, demonstrating that the model suggested in this paper is more stable and accurate and can provide regulatory authorities with an accurate and effective decision-making basis.
Gumma et al. (2022)	Product 1, was meant to assess irrigated versus rainfed croplands in South	rice	The overall accuracy of the irrigated vs rainfed 30 m product was 79.8%, with a producer accuracy of 79% for the irrigated farmland class

	Asia using Landsat 30 m data on the Google Earth Engine (GEE) platform. Product 2, was tailored for major crop types using Moderate Resolution Imaging Spectroradiometer (MODIS) 250 m data. Product 3, was designed for cropping intensity (single, double, and triple cropping) using MODIS 250 m data.		and a producer accuracy of 74% for the rainfed cropland class. The cropping intensity product's overall accuracy was 85.3%, while the producer's accuracy for single, double, and triple cropping was 88%, 85%, and 67%, respectively. Accuracy rates for mapping different crop kinds ranged from 72% to 97%. 63-98% of the variability was explained by comparing crop-type area statistics with national statistics.
Sholikah et al. (2021)	Normalized Difference Vegetation Index (NDVI) on Landsat Imagery using Machine Learning through Google Earth Engine (GEE) to identify land use changes and mathematical calculations in analyzing regional food security.	rice	It causes regional food security to be in a food-insecure condition, even though the availability of rice fields can be used for food selfsufficiency for up to 53 years. Other factors such as climate, rice seeds, soil, and water quality, in this case, are quite influential in rice production, not only productivity and agricultural land area.

Machine learning and deep learning are two fields in artificial intelligence (AI) that have various advantages that can be applied in the context of food security. Here are some of the advantages of these two groups of methods in supporting food security: fast and efficient data processing, quantitative prediction, supply chain optimization, crop disease classification and consumer sentiment analysis. Both machine learning and deep learning have great potential to support food security, but the choice of the appropriate method should be based on the type of data and the analysis objectives to be achieved. In practice, a combination of conventional statistical methods and artificial intelligence techniques such as machine learning or deep learning may be the optimal approach for analyzing food security with varying degrees of complexity. In some cases, these techniques can complement each other and result in a deeper understanding of food security issues.

The functions of machine learning technology in rice are elaborated in this section, By analyzing the applications of machine learning algorithms can address several issues such as techniques and crop modeling for rice. As mentioned earlier, machine learning technologies can be applied in various scenarios in all Rice Leaf Disease Detection, Rice Husk Ash Concrete, Moisture Content Determination in Rice, Rice Yield Prediction, Rice Sheath Blight, salinity stress phenotyping of rice, predicting phenotype studies in rice, and rice yields prediction, paddy rice sample recognition and classification.

The mostly research in machine learning concentrate on rice. To identify several issues such as techniques and crop modeling for rice has received more attention in the area of machine learning. Machine learning methods developed by different researchers are discussed theoretically. Literature review about Machine Learning and rice is discussed in detail. Why there was a need to develop each regression method and what are the uses of each method, from the theoretical background it can be observed. For the objective of machine learning to forecast rice. Machine learning algorithms such as We compared standard machine learning methods; elastic net, ridge regression, lasso regression, random forest, gradient boosting machines (GBM), and support vector machines (SVM), Artificial Neural Networks, KNN(K-Nearest Neighbour), J48(Decision Tree), Naive Bayes and Logistic Regression. Single VI (SVI); stepwise multiple linear regression (SMLR); random forest (RF); support vector machine (SVM); and artificial neural networks (ANN) regression, Partial least square regression (PLSR), PLSR- and principal component analysis (PCA), Four convolutional neural network (CNN) algorithms (one-dimensional (Conv-1D), two-dimensional (Conv-2D) and three-dimensional (Conv-3D_1 and Conv-3D_2) convolutional neural networks) were developed and compared with four widely used classifiers (random forest (RF), extreme gradient boosting (XGBoost), support vector machine (SVM) and multilayer perceptron (MLP), probabilistic neural network (PNN), E Faster R-CNN,artificial neural network (ANN), and the Bayesian Regularization (BR) algorithm logistic regression.

While machine learning and deep learning have many advantages in the context of food security, there are also some disadvantages to note: limitations in data, limitations in rare cases, unable to handle drastic changes, limited interpretability, dependence on computing resources. In the context of food security, it is important to consider these drawbacks when choosing machine learning or deep learning methods. Sometimes, simpler approaches or more interpretable models may be more appropriate depending on the problem to be solved and the resources available. Applying Machine Learning in food security is a complex endeavor and is faced with a number of constraints and challenges. Here are some of them: data limitations, rare cases and external variables, unbalanced data problems, model interpretability, technology infrastructure and access, technology awareness and acceptance, costs and resources, policy and law, data security, reliance on external resources. Overcoming these obstacles and challenges requires cross-sectoral collaboration, good planning, investment in technology infrastructure, education and training, and adequate regulation. With the right efforts, Machine Learning can be a powerful tool in improving food security.

CONCLUSIONS

In this paper, predicting rice stock for food security using macine learning is analysed. Two entities, including machine learning and rice in smart farming tasks, drawing on reviews of several previous works. The types of machine learning algorithms used in this review heavily depend on the data's accessibility. These machine learning algorithms are used to predict in order to help farmers with the aforementioned tasks. Predicting rice production for food security is an important task that can utilize various machine learning methods. The choice of a particular method depends on the data available, the complexity of the problem, and the computational resources available. Recommendation: Depending on the context and stakeholders involved, it may be necessary to make a trade-off between model interpretability and prediction accuracy. Linear regression and decision trees tend to be easier to interpret, while deep learning models offer high accuracy but are less interpretable. For a more comprehensive follow-up study, the number of articles should be increased and other food security parameters analyzed for more accurate recommendations.

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