Analysis of Machine Learning Technique to Predict Eggs Production in Poultry Farms

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Machine learning techniques have emerged as a great tool for improving agriculture's economic activities. Machine Learning has specifically been applied in chicken farming to forecast egg output, enhancing both the economies of the farmers and the nation. In this research, we present a study devoted to the analysis of machine learning approaches to forecast egg output. The study looked at four (4) machine learning algorithms, the quantity of features utilized as input, and the strengths and weaknesses of each method. A number of features with a mean value of more than 6 are employed by an Artificial Neural Network, yet this network is unable to extract features from the dataset. Fuzzy logic uses many features with a mean value of more than 4.5 but few datasets. Few datasets and features with a mean value of less than 4 are used by Random Forest and Support Vector Machine. Compared to other techniques, Artificial Neural Network is the most popular and has a high mean value of features, but it is unable to extract core features from the dataset. Additionally, it only employs small datasets. The model's stability is reduced when limited features and datasets are used. Deep learning is built on the Artificial Neural Network, but so far only feedforward and backward architecture have been applied. It is obvious that poultry farmers would benefit from using machine learning to manage both their marketing and production processes. This study recommends the use of deep learning techniques with the best architecture due to the drawbacks of the currently existing techniques. These techniques will be able to employ numerous features and a large number of datasets, improving the stability of the model.

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1. Introduction

Egg production by poultry type refers to the overall production of eggs in the shell by all sorts of hens in both the traditional (small flocks held by individuals) and contemporary sectors (commercial poultry farms that are large and intensive). Total output includes hatching eggs but excludes farm waste (Food, 2020). Egg production, which is sometimes regarded as a commercial enterprise, requires working full-time and is aimed at generating a sufficient number of eggs (Omomule, Ajayi & Orogun, 2020). Worldwide, the activity of producing eggs keeps on growing each year. Global hen egg production reached 83 million tons in 2019, representing a 63 percent increase over 2000 levels, resulting in an additional 32 million tons (Food, 2020). Asia is the biggest producer of eggs, accounting for 62% of global output in 2019. This was followed by the Americas (21%), Europe (13%), Africa (4%) and Oceania (4%) (Food, 2020). The report shows that Africa is still in the infant stage of producing eggs, and therefore, Tanzania, as well, is included in the African state of being an infant in egg production. According to a Tanzanian study, egg consumption has dramatically grown, from 75 eggs in 2014 to 106 eggs per capita in 2015. However, poultry meat consumption has only increased slightly (United Republic of Tanzania, 2015). Furthermore, Tanzania, a member of the Southern African Development Community (SADC), the East African Community (EAC), and the Tripartite Free Trade Area/Common Market for Eastern and Southern Africa (COMESA), has a population of over 600 million people and is thus a prospective market for poultry products (Commodity and Chain, 2019). However, about 70% of the chicken breeds in Tanzania are low-yielding in terms of egg production (Ringo, 2018). As per (ILRI and CGIAR, 2017), the production of eggs is about 4 billion per year, which is low compared to the human population in Tanzania, which is about 57.6 million (URT-NBS, 2021). hat results in food shortages in society and lowers the national income. Using machine learning predictive techniques, this study shows how to take care of layer chickens in the best way to improve their ability to lay eggs.

Machine learning (ML) techniques have arisen as a valuable resource for understanding the intensive processes of data and are used as a tool for proper management of laying chickens in this case. It allows machines to learn without having to be strictly programmed (Liakos *et al.*, 2018). In this study, deep learning techniques are suggested to make sure that layers are managed well and that production goes up.

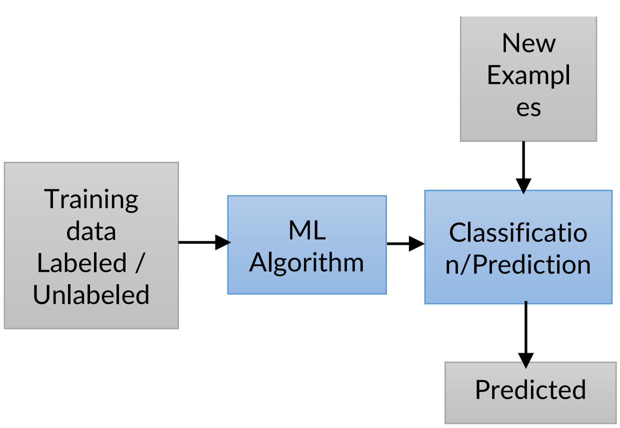
Despite its huge contribution to the country's economy, egg production is threatened by poor management of factors affecting egg production throughout the production process, leading to low production (Omomule, Ajayi and Orogun, 2020). These external and internal factors include food, management issues, breed genetic factors, age, diseases, molting flocks, housing, egg gathering, existence of light, and body weight. (Omomule, Ajayi & Orogun, 2020). Several machine learning techniques have been used to mitigate the underproduction of eggs. The techniques achieved the highest accuracy, showing that they can perform better in the management of egg production. However, they have used a small number of datasets and some have used few features, reducing the quality of the models. This paper looks at four (4) machine learning techniques used to predict egg production. It lists their strengths and weaknesses and then suggests the best technique for Tanzania's poultry environment.

1.1. Machine Learning (ML)

Machine learning is a growing subset of computational algorithms that aim to mimic human intelligence by learning from their surroundings. The algorithm uses input data to complete the task at hand without being programmed to do so (Naqa and Murphy, 2015). It entails a learning process in which one learns to perform a task based on "experience" (training data) (Liakos *et al.*, 2018). In ML, data is made up of examples. An individual example is typically described by a set of attributes, also known as features or variables (fig 1). The features that can be used are nominal (enumeration), binary (i.e., 0 or 1), ordinal (e.g., A+ or B-), or numeric (integer, real number, etc.).

Fig 1

Machine Learning Approach



1.2. Fuzzy Logic Approaches

The fuzzy predictive model is one of the artificial intelligence techniques for predicting the future. Omomule, Ajayi and Orogun (2020) proposed a model of fuzzy prediction for forecasting egg production. The proposed model's architectural view is primarily divided into three modules: data preprocessing; variable mapping (inputs and outputs) into fuzzy space; and a fuzzy inference process. The model's inputs include chick age, body weight, feed quantity, feed quality, and room temperature, with the output being the total number of eggs produced. The model had the highest prediction accuracy of 100%, but with a relative error between actual and prediction of 0.11744. Furthermore, the proposed technique was successful in capturing a limited number of samples and features. Other features such as light intensity was left, which are very important, particularly in the case of Tanzania.

Sefeedpari *et al.*, (2016) proposed a multi-layered adaptive neural fuzzy inference system approach for predicting egg production based on consumption of energy. The selected farms used machinery, diesel fuel, electricity, human labor, pullets, and feed. The products were eggs and manure. With coefficients of determination (R2), root-mean-square error (RMSE), and mean absolute percentage error (MAPE) parameters of 0.92, 448.126, and 0.014, respectively, the proposed technique performed well in prediction. In this approach, few datasets were used to develop the model, and other important features such as age, weight, quantity of food, and light were not considered. However, a large number of sample data sets and potential features need to be used to make the model robust.

This fuzzy technique has not been much used in predicting egg production but in several other applications, such as forecasting of COVID-19 infected cases and deaths (Kumar and Kumar, 2021), Prediction of rainfall (Janarthanan *et al.*, 2020), prediction of prostate cancer (Boadh *et al.*, 2022), Prediction of energy consumption of residential buildings (Al-Shanableh and Evcil, 2022), Air quality prediction (Lin *et al.*, 2020), Heart disease prediction (Shiny Irene, Sethukarasi and Vadivelan, 2020), etc. The model does not work well for a large number of data points and features. The model also doesn't give accurate results, so it needs to be tested a lot while people give input.

1.3. Artificial Neural Network (ANN)

With a feed-forward and back-propagation approach, neural networks have been demonstrated to be an effective method for forecasting time-series events. Many nonlinear time series events have been forecasted using this technique (Ghiassi, Saidane and Zimbra, 2005). Egg production is a non-linear process. The ANN is very good at classification, clustering, pattern recognition, and prediction in many disciplines, but is not capable of extracting features (Abiodun *et al.*, 2018). The use of ANN for egg production prediction was proposed by Felipe *et al.* (2006). The age and bodyweight of the chicks were given as an input feature to the model, and the total number of eggs produced as an output. The technique achieved an accuracy of more than 0.7 for prediction, although few of the features were used. Other features which are very important in the case of Tanzania, such as temperature, light, quantity of food, etc., were not considered.

Semsarian et al., (2017) proposed an ANN model for predicting the number and weight of eggs. In this model, the information on body weight (BW) at birth, at 8 and 12 weeks of age, weight at sexual maturity, and the polymorphism of the prolactin gene were used for the prediction. The technique's accuracy was respectable, with an R2 of over 0.7. The method does employ a few aspects, though.

The egg volume prediction technique based on the Pappus theorem and an artificial neural network was proposed by Soltani, Omid and Alimardani, (2015). The major and minor diameters of an egg were provided as an input to the model in this technique. Even though it only uses a few features, this method makes a model that is accurate, with an R2 of more than 0.9.

Ahmad, (2011) proposed a model for egg production forecasting. The model employs age and feed intake as features in the neural network. Even though the model only uses a few characteristics and data sets, it was still able to get an accuracy of 0.7. Precision-fed broiler breeder hens were used in the development of the artificial neural network model to estimate the likelihood of oviposition events (You *et al.*, 2021). Although only a small number of data sets were used to construct the model, it has 26 features and an accuracy of more than 0.9, suggesting exceptional performance.

Cost-sensitive ANN was suggested by Ramírez-Morales *et al.* (2017) to automatically detect irregularities in egg production. Cost-sensitive learning refers to a specific set of algorithms that are sensitive to various costs associated with certain characteristics of considered problems (Sheng and Ling, 2011). Experts are interested in cost-sensitive learning ANNs because they can model the occurrence of rare events. In Ramírez-Morales et al. (2017) model, the number of eggs produced, dead hens, existing hens, and cracked eggs were used as features of the model. This effort aimed to aid decision-making in chicken farms by using automatic early detection of egg production irregularities. As a result of the model's accuracy of greater than 0.9, the results demonstrate that anomalies can be identified early. The method did not, however, indicate how egg production might be boosted.

The artificial neural network technique has been used in many other predictions, such as stock closing price prediction (Liu and Ma, 2022), airport capacity prediction (Choi and Kim, 2021), Indoor environmental quality prediction in a school building (Cho and Moon, 2022), Prediction of fracture parameters of concrete (Xu *et al.*, 2021), Prediction of greenhouse tomato yield (Belouz *et al.*, 2022), prediction of food effects on bioavailability(Bennett-Lenane, Griffin and O'Shea, 2022), etc.

1.4. Support Vector Machines (SVM)

SVM has gained popularity as a classification technique because of its excellent adaptability in a variety of data science applications, including the study of brain disorders. An SVM uses a hyperplane to separate (i.e., "classify") observations that belong to one class from those that don't, based on a pattern of information about those observations called "features," and then it makes a decision (Pisner and Schnyer, 2019).

It should be noted that the SVM algorithm predicts using a small number of samples (Huang and Zhao, 2018). The early warning model for detecting problems in egg production curves from commercial hens was proposed by Morales *et al.* (2016). Age, the total number of produced eggs, deceased birds, and other features were used as the model's input features. The goal is to identify issues that could cause a reduction in egg production. The model's accuracy of 0.9874 demonstrates its strong ability to identify issues that could result in reduced production. The method does not, however, have all the components needed to boost output.

Deng *et al.* (2010) propose an eggshell crack detection model based on the support vector machine technique (SVM). The technique uses resonance scale (FS), the s-coordinate (SC), and t-coordinate (TC) of the centroid, and weighted standard deviation (WD). The technique had the highest detection rate of 98.9%. However, it does not show how egg production can be increased. This technique has not been much used in forecasting egg production, but in several other applications.

SVM has been used to predict and classify diseases like cirrhosis (Prakash and Saradha, 2021), iron dust minimum ignition temperature (MIT) (Arshad *et al.*, 2021), wind power (Li *et al.*, 2022), petroleum reservoir properties (Otchere *et al.*, 2021), age prediction and gender classification using face images (Chandra Sekhar Reddy *et al.*, 2020).

1.5. Random Forest

Random forest is a widely used tool for implementing classification and regression. Gonzalez-Mora *et al.* (2022) proposed a model for evaluating environmental control approaches in housing systems to analyse egg production. The model is based on the random forest technique. The model uses temperature, age, and humidity as variables. The results show that temperature has a great impact on the production of eggs. The model has an accuracy of 0.78, despite the fact that only a small portion of the data set was used. Other important features such as light, weight, etc. are not considered.

2. Materials and Methods

The review was carried out based on the real-world circumstances surrounding egg production and machine learning methods used to forecast egg production. As a criterion for the model to increase egg production, the number of features, size of the dataset, and type of techniques were taken into consideration. Both the technique suggested and the author's name were noted. Also, the parts of each model that were used as input were listed, and each model's flaws were talked about.

2.1. Search Strategies

The IEEE Xplore and ScienceDirect databases were utilised to search for papers. A wide range of pertinent keywords were used to extract relevant articles. We divided the terms into five groups: language, publication year, egg production, prediction, and machine learning. The AND operator was used to combine the keywords.

2.2. Study Selection

The following criteria for inclusion were met by studies to be considered:

- focusing on predicting egg production.
- Only original research, no reviews.
- Instead of just an abstract or notes, the full paper is available.
- An article from a reputable journal only

2.3. Data Analysis Method

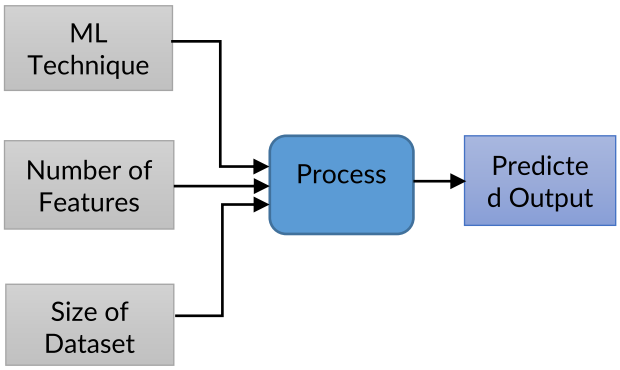
In this investigation, the content analysis method was used. Using this strategy, we can determine how frequently the features for enhancing egg production and machine learning techniques occur when they are used as inputs to different models. STATA software was used as a tool for analysing the data.

3. Results and Discussion

We found 70 studies from ScienceDirect and 6 from the IEEE Xplore databases. After removing duplicates and screening the abstract and title, 46 studies were deemed potentially relevant. Following thorough article screening, 11 articles were considered relevant to the studies. Out of 11 studies, 5 were published as peer reviewed in the journal of Computer and Electronics in Agriculture; 4 in the journal of Poultry Science; 1 in the journal of Food Science and Technology; and the last one in the journal of Advanced Biological and Biomedical Research. As shown in the graphic below (fig 2.), this study considered three crucial components of increasing egg production: the machine learning technique, the number of features, and the size of the dataset. As can be seen from Fig. 2, a machine learning technique must consider both the size of the dataset and the number of features in order to produce a prediction that is as accurate as possible. Results from a machine learning technique that makes use of the biggest training sets are accurate and reliable (Ajiboye et al., 2015). Additionally, a method with multiple features aids in capturing all the crucial qualities needed to increase egg production. The size of the dataset and the number of features per technique utilised were examined in this study.

Fig 2

Three Aspects Considered for Strong ML Technique in Improving Eggs Production

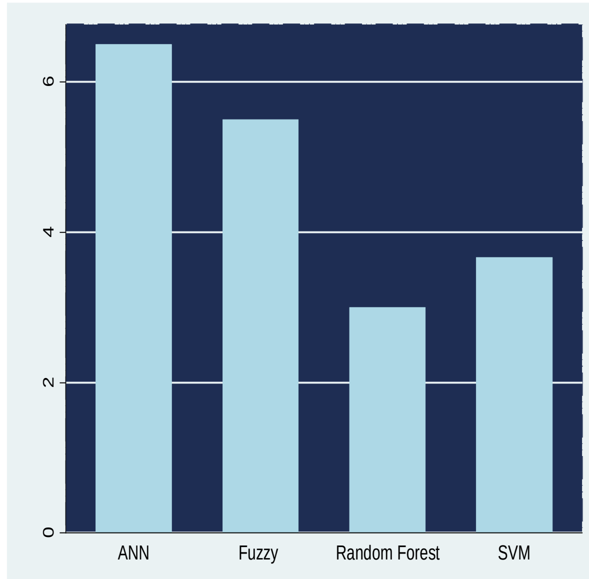


According to the analysis in Table 1, the Artificial Neural Network (ANN), which has a frequency of 6, is more frequent than the fuzzy approach, which has a frequency of 2, the random forest method, which has a frequency of 1, and the support vector machine (SVM), which has a frequency of 2. The frequency of ANN shows how widely used this method is among authors for predicting egg yield.

The bar graph in Fig 3 shows that ANN outperforms other machine learning algorithms in terms of the mean of features. The goal is to build a model that can forecast egg production by adding more features

Fig 3

Mean Value of Features with Different Machine Learning Techniques



In table 2, the performance accuracy and metric error of several ML approaches are compared. Fuzzy logic has the highest error but good precision. To prevent underfitting of the model and enhance model performance, error must be decreased (Bilal Mahmood, 2016)

Although ANN and SVM had good accuracy, their error was not disclosed. To boost the model's performance, Random forest's accuracy needs to be increased.

Table 1
Frequency Distribution Table of the Technique for Predicting Eggs Production

ModelName	**Freq.**	**Percent**	**Com.**
ANN	6	54.55	**54.55**
Fuzzy	2	18.18	**72.73**
Random Forest	1	9.09	**81.82**
SVM	2	18.18	**100.00**
Total	**11**	**100**	

According to this trend in model techniques, artificial neural networks have received more attention than other techniques and are therefore regarded as the best technique when compared to others. A feed-forward ANN with only one hidden layer was suggested by all authors based on the review. The model's ability to extract more features is reduced when there is only one hidden layer (Zhang, 2019). In light of this, ANN needs to be improved with more technology in order to enable it to extract internal features from datasets. The concept of deep learning, which comprises the designs of convolutional neural networks, recursive neural networks, and neural networks, comes to life by adding more layers and neurons to ANNs. Additionally, large data analysis makes good use of deep learning (Abiodun *et al.*, 2018).

Table 2

Comparison Analysis between Different ML Techniques

Different model	Accuracy %	Error metric	Feature Selection algorithm	Quote
Fuzz logic	100	0.11744	correlation coefficient analysis	(Omomule, Ajayi and Orogun, 2020)
ANN	70	-	SWCFS	(Felipe et al., 2006)
SVM	98	-	-	(Morales et al., 2016).
Random	78	0.00368	-	(Gonzalez-Mora et al.,

4. Conclusion

This study analysed 11 studies on the use of machine learning to forecast egg output. The study investigated numerous methods for enhancing egg production and their efficacy by utilising paired key words and the AND operator. It was discovered that the Random Forest technique uses a few environmental factors while SVM and Fuzzy logic techniques use only a few internal factors. In the case of ANN, some studies use external elements while others use internal factors. It is obvious that taking into account both types of factors that affect egg production is necessary. It is clear from the analysis that there is a significant trend toward using huge data sets and many attributes to strengthen the model and forecast egg output. Since Artificial Neural Network uses more features than other techniques, it has emerged from this review as the best.

However, this method employs small datasets and is unable to extract features. Additionally, the approach only employs one hidden layer. Table 2 reveals that the performance accuracy of ANN is low in comparison to the other approaches, which indicates the model is inadequate and other strategies must be used to enhance the model's functionality. Numerous features are used in the fuzzy approach. The method, however, cannot be used to model huge datasets. Furthermore, the technique has a larger error compared to others, as seen in table 2. Both Support Vector Machines and Random Forest make use of small data sets and few variables. Even though they appear to have good accuracy, this makes the model less stable. The idea of combining a lot of variables with a big dataset can make the model stronger, but feature engineering must be taken into account. As some studies in this field have shown, the model can be strengthened by choosing the crucial traits. Two of the techniques in this study included feature selection algorithms, whereas the other two did not. The results in Table 2 show that in order to improve the model's performance, the optimal feature selection strategy must be identified. The seen methods can be used to predict egg production, but a strong and reliable model is needed.

5. Recommendations

In this work, we recommend using deep learning methods to enhance the model for predicting egg production. The deep learning technique ought to be able to handle a sizable number of features, a sizable number of datasets, incorporate a feature selection mechanism, and be able to extract more features from the model. Farmers in Tanzania are not currently employing any of these methods. Therefore, creating a deep learning model and integrating it with the decision-making process will aid farmers in increasing their output, income, and the economy of their nation. Also, an extension officer will use the model for training poultry farmers.

6. Conflict of Interest

The authors declared no conflicts of interest.

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