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An artificial neural network model for predicting maize prices in Kenya

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ABSTRACT

In the current globalization era, food security management in developing countries like Kenya that consider agriculture as a dominant economic activity require efficient and reliable food price forecasting models more than ever. Due to rare data availability and data time lag in developing agricultural dominated economies, normally needs reliance on time series forecasting models. Artificial Neural Network (ANN) modelling methodology gives a possible potential price forecasting method in developing countries based on available data. This study demonstrated the superiority of ANN over linear model methodology based on Root Mean Squared Error (RMSE) and Mean Absolute Deviation (MAD) performance metrics. Lower comparative RMSE value would imply a better prediction while results with lower MAD were more close to actual values. Empirical study showed that an ANN model is able to capture adequate number of directions of monthly price change as compared to the linear models. It has also been observed that feeding the model with lagged observation of the same variable leads to more accurate forecasts than its performance in its multivariate form. Models reviewed during this study, showed little effort in development of research tools, therefore we purposed to develop a user- friendly ANN prototype based on the proposed model.

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1. Introduction

Previous research in the area of agriculture and food security in Kenya, came up with consumption figures of maize in that provided computational foundation of food balance sheets and formulated estimations in regards to import and export prices of cereals. [1] reported that maize accounts for up to about 29 percent of total farm yield from the small-scale farming part. This is because of its importance in Kenya's economy based on agricultural production trends.

The general perception as reported by [1] is that policy makers and other sectors of the society about food security in Kenya, is similar to maize security. Therefore, maize security is used as the significant parameter in determining the food situation in the country. Previous research by [1] indicated that maize is the most common crop grown by rural poor households for food. Their research also concluded that the importance attached to maize by policy-makers in Kenya can be deduced from the emphasis laid on maize in current and past national food policies. This means that volatility of food prices has been a problem in Kenya and such fluctuations have ramifications for every individual in Kenya. Currently non-policy makers rely on their experience, technical analysis and fundamental analysis when buying and selling maize. These methods are subjective and misleading since they are not backed by actual figures. We did not come across any artificially intelligent predictive tool for future maize prices in Kenya. In the 21st century artificial intelligence (AI) has become an important area of research in virtually all fields: engineering, science, agriculture, education, medicine, business, accounting, finance, marketing, economics, stock market and law, among others [2,3,4,5,6,7]. Studies involving the field of AI have been segregated into many areas, therefore it is important that Kenya adopts the AI approach especially in formulation of agricultural policies.

There are some tools that provide information on maize price trends; however, they do not have predictive mechanisms. These tools provide information that point to the use of fundamental and technical analysis methods as being their basis of prediction of future maize prices. The tools neither show trends in future maize prices nor shows the actual figures of the most probable future maize prices. It is therefore desirable to have a tool that does not just point to the direction of price movement but also provides the most likely price value of maize itself. AI methods that can actually analyze maize prices over time and gain intelligence then use this intelligence in prediction can be used to model such a tool. The predictive model shall provide information that will be a basis for consumers in making important decisions with regards to their expenditure on maize and maize related products. The conceptual model that can accommodate both modes (multivariate and univariate) is as shown on Figure 1.

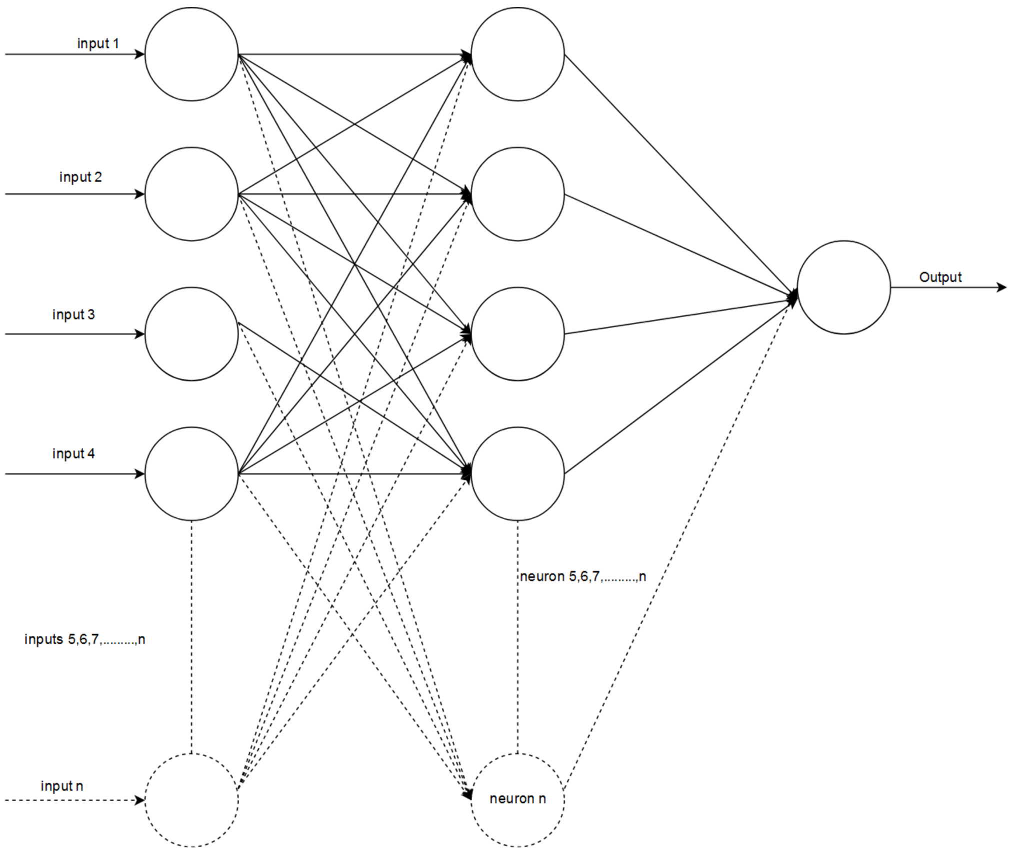

Figure 1. Conceptual model. (Source: author)

2. Materials and Methods

We used both exploratory and applied research to create a specific artificial intelligence tool based on a model and tested its performance on a practical problem. The exploratory part of the research was attempting to identify new insights into the possibility of incorporating more diverse predictors for maize price forecasting. For purposes of designing and evaluating the model, the research needed historical monthly maize price data (data from Nairobi, Kisumu and Eldoret counties), country wide yearly price data for agricultural products identified as staple foods in this study and yearly maize production data. Data collection method was not experimental and included collection of secondary data from relevant publications and the internet. The Food and Agriculture Organization (FAO), a specialized agency of the United Nations that leads international efforts to defeat hunger provided monthly maize price data from Nairobi, kisumu and Eldoret counties through their website. Country wide yearly price and production was obtained from the knoema website, a free to use public and open data platform for users with interests in statistics and data analysis. Data was later imported into mysql database for ease of retrieval during model development and testing. The design approach for developing the model was the CRISP-DM methodology. As shown on Figure 2, It incorporates six design phases that comprehensively cover the model development process. As used by [8], the methodology works well with Artificial Neural Network for predictive purposes.

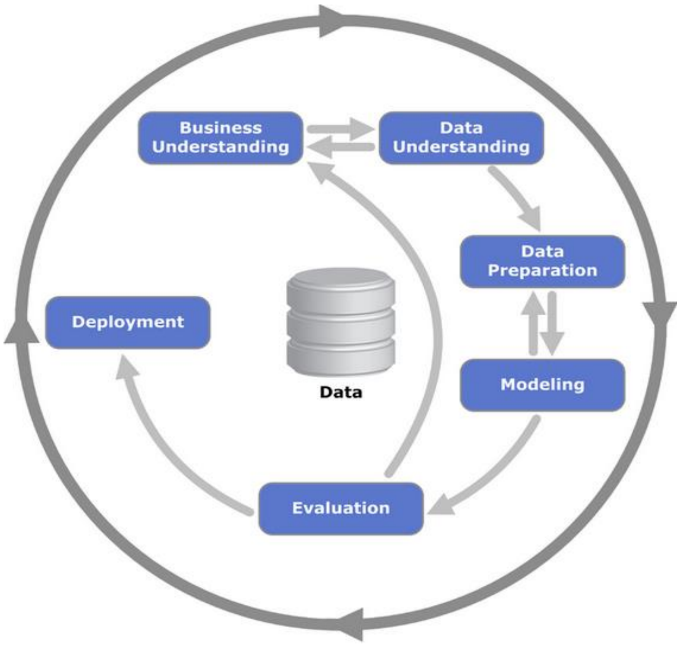

Figure 2. CRISP methodology [9]

The model design describes the organization of the ANN and defined the number of input neurons. The input neurons were used to capture each independent variable. Model design also involved determining the number of ANN hidden layers, the number of neurons in the hidden layer, number of output neurons and the ANN activation function. The first step was to be the formulation of a baseline model as per the proposals by other researchers. The third step would then be the development of the new proposed model based on the baseline model after change of parameters as determined by experimentation. The model needed to be dynamic in a way that it can be trained in both univariate and multivariate modes. Therefore, the model input varied depending on the training mode. The two modes (univariate and multivariate) of the baseline model were developed for experimental purposes so as to evaluate the performance of the model and help in determining the best mode so as to come up with a new model. Table 1 shows the model parameters that were used. Based on other research, the hidden neurons should be one [10]. The first experiment was done on the model in its univariate mode using real prices of monthly maize data from 2006 to 2018. The baseline model, with a configuration of 4:8:1 was subjected to training using 70% data (Jan-2006 to Apr- 2018) and the balance for testing. The number of training repetitions was set at 50,000 maxima, after which the training was stopped.

3. Results and Interpretation

The process of model analysis encompasses evaluation of the model from its baseline as shown on Table 1 to final proposed stage based on the parameters and provided data. This is captured by defining the model requirements analysis. The main objective of conducting this evaluation was to obtain optimal model parameters.

Table 1. Baseline model parameters.

Mode	No of inputs	No of hidden layers	Hidden Layer (No of neurons	No of outputs	Bias per layer	Transfer function	Maximum error	Learning rate	Maximum iterations
Univariate	4	1	8	1	1	Sigmoid	0.01	0.5	50000
Multivariate	5	1	8	1	1	Sigmoid	0.01	0.5	50000

The performance of the ANN baseline models was analyzed based on their accuracy in predicting maize prices for a continuous range of dates beyond the last date of their training. Training effectiveness was determined using the root mean square error (RMSE), over the range of training cycles. RMSE (Eq.1) was also used to compare the performance of model, where a lower comparative RMSE value would imply a better prediction. However, the testing phase was measured on the basis of mean absolute deviation error (Eq.2), to determine exactly how far the actual and predicted values were.

$$RMSE = \sqrt{\frac{\sum_{i=0}^{i}(y'_i - y_i)^2}{n}} \ . (1)$$

Where n = number of observations, i= predicted value, y^i= actual value.

$$MAD = \frac{\sum_{i=0}^{i}(y'_i - y_i)}{n} \ . (2)$$

Where n = number of observations, i= predicted value, y^i= actual value.

Table 2. Final model parameters.

Input Layer (No of inputs)	Hidden Layer (No of neurons)	Output Layer (No of neurons)	MAD (Mean Absolute Deviation)	MAPE (%) (Mean Absolute Percentage Error)	RMSE (Root Mean Squared Error)
UNIVARIATE MODE					
4	11	1	2.182236	7.445803	2.938315
MULTIVARIATE MODE					
8	9	1	2.355522	8.834932	2.9716

The following three observations were made – firstly, the low rates of RMSE was obtained with neurons per hidden layer of 8, 10 and 11 during testing the model in its univariate mode. Secondly, based on MAD, the best configuration was obtained from the models multivariate mode with 8 neurons for 9 neurons per hidden layer i.e. 8:9:1. Based on this determination, the configuration of 8:9:1 was therefore the optimal multivariate ANN configuration and 4:11: 1 for the univariate ANN configuration as shown in Table 2. The final model states were evaluated based on the settings as shown in Figure 3 with varying number of neurons at the hidden layer. The corresponding results are as shown in Table 3.

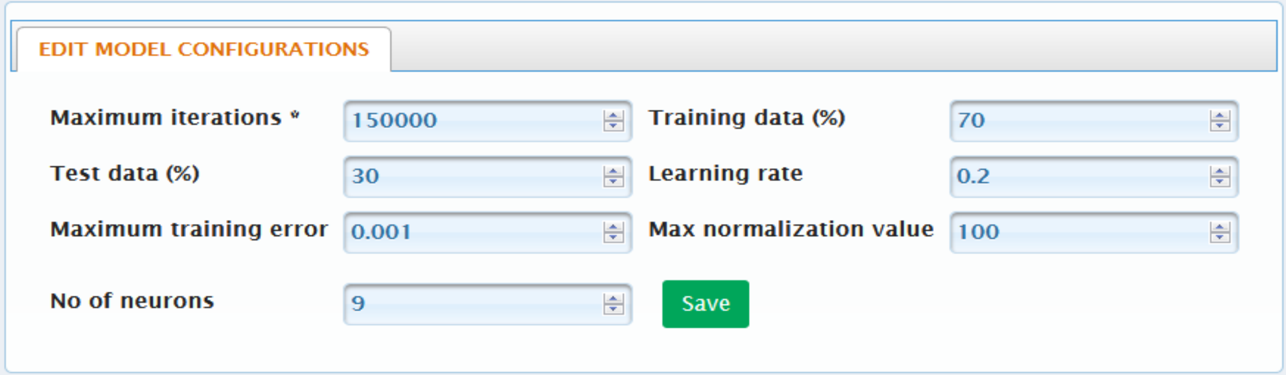

Figure 3. Model configurations

Table 3. Model results. Hidden layer with 9 neurons

Model state	**RMSE(Root Mean Squared Error)**	**MAD (Mean Absolute Standard Deviation)**
Univariate (Time series prediction state)	3.07	2.31
Multivariate (Structural state)	2.97	2.36

4. Discussion

The main advantage of univariate time-series forecasting is that it needs data only of the time series that is being analyzed. This characteristic is useful if we are to forecast a huge amount of price series. Performance of model estimation largely depends on data and if this data has some missing values then restrictions over which the model can be estimated occurs. However agricultural commodity prices are shaped by various factors which need to be considered during forecasting, therefore the study identified average rainfall, alternative staple and cereal prices, maize production, inflation and political intervention as factors that can serve as model inputs for predicting maize prices. This study has made a comparison between ARIMA and ANN models in terms of forecasting using monthly retail maize price data in three Kenyan counties, namely; Eldoret, Nairobi and Kisumu. Comparisons made between ANN and ARIMA models indicate that ANN provided a better forecast accuracy in terms of measures based on RMSE and MAD values. Nonlinearity of data determines the reliability on the forecasting accuracy of ARIMA and ANN models based on RMSE measures. Globalization and interaction among various world markets have brought about the need for proper decision making. Therefore, an effort towards designing intelligent systems is needed for purposes of integrating traditional statistical methods with emerging technologies like neural network, fuzzy logic, etc. to provide reliable forecasting information that can be used by farmers, retailers and policymakers so that they may make production, marketing and policy decisions well in advance. Market regulatory conditions greatly affects the price of maize and maize products, therefore, farmers and producers should take future prices of this input into account. Considering price of maize in the future, agricultural authorities can reduce price variations and consequently reduce the high risk present in maize and maize related products` market and finally can increase producers and consumers` interests. In fact, they can support maize farmers and maize product units in making the right decision by identifying and showing future price condition in this sector at different times.

5. Conclusions

Price forecasting is a key factor, it is therefore important to have updated information by examining market condition in future researches at universities and research centers and also to make use of different prediction models such as artificial neural network in order to reduce maize production risk in Kenya's agricultural sector. This study showed the superiority of ANN in its univariate state compared to the multivariate state based on MAD and RMSE performance metrics. Accurate maize price predictions were achieved when a lagged observation of the same variable (Historical maize prices) was supplied to the model. However, the ANN model can work in either of the states depending on the variables supplied to it. i.e. different variables or lagged observation of the same variable. Future studies needs to explore the possibility of using a hybrid model (combined linear and non- linear model) for predicting maize prices in specific Kenyan counties based on aggregated price data from all counties. Finally, further research is needed to determine how long a trained ANN system remains valid and effective in prediction before it is found to be in need of retraining.

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