The Indonesian Journal of Computer Science
www.ijcs.net
Volume 14, Issue 6, December 2025
https://doi.org/10.33022/ijcs.v14i6.5046

# A Neural Network Model for The Prediction of Cattle Prices in South African Livestock Actions

**Alfred Kgopa**[1]
kgopaat@unisa.ac.za[1]
[1]University of South Africa

**Article Information**

Received : 10 Nov 2025
Revised : 18 Dec 2025
Accepted : 21 Dec 2025

**Keywords**

Agriculture forecasting, Cattle prices, Livestock auctions, Neural networks, Predictive modelling

**Abstract**

This study developed a neural network model for predicting cattle prices in South African livestock auctions based on breed (B), weight (W), time/season (T) and price (P) variables. Using the online auction dataset from 2023 - 2025, the model analyzed nonlinear relationships influencing price fluctuations, producing realistic per-cattle predictions ranging between ZAR 7,000 - ZAR 17,500, with projected increases up to ZAR 22,000 in future weeks. The results demonstrate the model's capacity to capture market dynamics shaped by breed attributes, seasonal demand fluctuations, and animal mass. The results illustrate that artificial intelligence-led techniques, including neural networks, can substantially improve market prediction accuracy, enhance profitability, and inform strategic decisions in the livestock sector. Furthermore, this study provides a foundation for future research to expand predictive modelling beyond cattle, contributing to the development of a comprehensive livestock price prediction system that integrates multiple animal types under a unified intelligent forecasting framework.

 

## A. Introduction

Livestock farming is a vital component of the agricultural economy of South Africa. Cattle farming, for instance, is a crucial income generation activity for both rural and commercial farmers. However, the variability and the dynamism of livestock prices, which are influenced by various factors such as breed, weight, market requirements, season variations, and auction conditions. These factors complicate the ability of farmers to make production and marketing decisions based on prior knowledge regarding the price movements. Although the factors listed make it difficult to accurately predict prices, such a process is vital in ensuring that farmers maintain profit levels and eventually achieve value chain sustainability. While traditional econometric models, as well as other statistical methods, have been in use in the forecasting of prices, most of these models fail to capture the nonlinear and time-varying nature of many of the dynamics of agricultural markets. Researchers have thus turned to artificial intelligence and machine learning techniques, such as Neural Networks, considering their high performance in modeling the nonlinear nature and interactions among input variables [1, 2]. Specifically, neural networks have shown high adaptability and accuracy in predicting outcomes in agricultural settings, including livestock and crop farming practices [3, 4].

Recent research papers indicate that hybrid and deep learning approaches offer better results in price forecasts in various sectors. For example, the Long Short-Term Memory and the Gated Recurrent Unit models have been used to predict commodity and livestock prices based on temporal relations of the changing prices [5, 6]. Combining models that use different timescales in the modeling process also enhances the accuracy and reliability of outcomes [7]. These findings show that neural network-based systems have the potential to offer a data centered intelligence analysis to support decision-making, especially in most developing economies that have volatility in most of their market data. Through this study, the ultimate goal is to have a neural network model that can accurately predict the prices of cattle in livestock auctions. Data from auctions conducted in the past covering different seasons, categorizing records using breed, weight categories, and different indicators have been used to develop a model that allows for the dynamic learning phenomenon. This research seeks to demonstrate, by using neural networks, how such a highly non-linear factor impacts the shifts in the variability of the cattle pricing from one season to another. Neural network models have been applied in price predictions cases of commodities such as pork in South Korea, Eggplant in India, and bananas in Gujarat with positive outcomes [8-10]. Hence, these findings have a great potential to contribute to both the theoretical and practical aspects by applying the findings to the South African environment. From this research, this study will result in models which, upon simplification and customization, will provide an invaluable insight to the South African livestock market by aiding farmers, farmer's cooperatives as well as the policymakers to make well-informed decisions which can be translated to high efficiency in the production process.

### B. Related Literature Review

The application of artificial intelligence and machine learning techniques in the field of agricultural price prediction has expanded rapidly due to its ability to model complex, nonlinear, and dynamic market behaviors that are often neglected by traditional econometric models. Most notably, neural network-based approaches have shown promising results in predicting agricultural price behavior due to their ability to decode the multifaceted relationships among various factors, including demand shifts, seasonal variation, and price fluctuations. For example, Wang [1] presented an optimized Radial Basis Function neural network optimized; model for the purpose of agricultural product price prediction and demonstrated much improved accuracy and convergence speed when compared to traditional "dull" backpropagation neural networks. The author specifically noted the effectiveness of his RBF model in capturing short-term volatility and nonlinear relationships, which are essential for livestock markets characterized by increased volatility. Minghua et al. [11] improved the stability and predictive accuracy of a backpropagation neural network for agricultural prediction by optimizing weight initialization and learning rate. Deep learning has further pushed the boundary of the forecasting skills of neural models. As an illustration, Chuluunsaikhan et al. [8] incorporated deep learning and topic modeling for the prediction of South Korean's pork prices. Such inclusion advocated for the use of external factors such as news sentiment to improve the reliability of the forecast. Li et al. [5] used a heterogeneous Gated Recurrent Unit neural network with energy decomposition to model the potential relationships among the involved livestock prices over time, giving better results than autoregressive models. Similarly, using fuzzy mathematics and an improved LSTM network, Ma et al. [6] established an interval prediction model, which was more reliable for uncertainty management and interval-based forecasting of livestock product. Hybrid and ensemble learning have potential as well. Ling et al. [7] recommended a cross-time scale forecast combination to be used to reconcile price discrepancy across different livestock markets. At the same time, Hegde, Hulipalled, and Simha [2] highlighted more insight into the performances of various ML algorithms who argued that neural networks always offer more accurate models when it comes to large enough multidimensional agricultural datasets. More specifically, Bayona-Oré et al. [12] supported the idea that more accurate short-term price forecasting in agriculture could be achieved using ML in the presence of price fluctuations.

These findings are also corroborated by empirical studies from various regions. For example, Guo et al. [4] used convolutional neural networks to predict agricultural produce prices in India. Burn which provides evidence that deep learning can enhance financial planning for farmers in the country. Similarly, Paul et al. [9] as well as Kumari et al. [10] used ML and RNN architectures to predict brinjal and banana prices, respectively. As a result, they achieved high accuracy. Also, Mayabi [3] showed that artificial neural networks can be utilized to predict maize prices in Kenya. On the other hand, Mohanty et al. [13] developed a generalized ML framework that can adapt to different types of commodities. Thus, these studies unequivocally indicate that neural and deep learning models perform better than traditional statistical methods. Based on these findings, this study proposes a cattle price prediction model for South African livestock auctions.

## C. The purpose and ethical considerations

The aim of this study was to create a predictive model based on a neural network that can forecast the cattle price in the South African livestock auctions section using breed, weight, and season factors. This will help the farmers, traders, and policymakers can make better decisions, forecast market trends, and allocate more resources by accommodating Artificial intelligence. Moreover, this is ethically responsible for the current market and the breeders in which the study focused on the public domain data or anonymize data to protect their confidentiality. The result of this model, which will be eventually not for trading, this will be utilized based on the researcher's and students' education purposes only. The economic potential of this model and study is making the market to be participant from every player in the industry. This meaning that the farmer, breeder, and other agent to have an interpretation of the data already fed to them will be making such a fact. Hence it will help the small holder farmer enhance their profit and sustain productivity ensuring potential contribution to GDP in the country.

## D. Research Method

This study adopts an experimental research methodology to design, develop, and evaluate a neural network–based predictive model for forecasting cattle prices in South African livestock auctions. The research follows a quantitative approach using historical data collected from multiple auction markets. The model development process involves three main stages: data preparation, neural network model design, and model training and evaluation.

### Dataset Description

The dataset used in this study comprised 263 auction records collected from five main livestock auctions in South Africa from 2023 to 2025. Each record consists of a date, location, breed type, weight class, auction lot size, and average price per kilogram as shown in figure 3. These records were then pre-processed by removing the outliers, from the data 3 standard deviations away from the mean, hence reducing them to 262. In addition, incomplete entries were eliminated, and numerical min-max normalization was applied to all the key features B = {B1, B2}, W = {W1, W2, W3}, and T= {T1, TID} as well as the target P to between 0 and 1 except prices to enhance convergence during training. The categorical breed participant was encoded using ordinal encoding. Feature selection was carried on three dependents: breed B, weight W, and time/season T to predict the average lot price (P).

### Model Design

Model Design The model was implemented using Python as the main programming language, employing the Scikit-learn library for neural network building, and Pandas for preprocessing. The graphical user interface was developed using the PyQt5 framework, while Python Joblib library was employed in model serialization for saving and loading the trained model efficiently. The model developed in this study surmounts the limitation in Hwang research on only considering the linear autoregressive model for the price dynamics and employs how NN can be used due to their nonlinear approximation ability and adaptive learning. Inspired by the agricultural prediction due to their applications of the recurrent and fully connected NN to financial prediction and forecasting, a feedforward multilayer network with ReLU and tanh activation functions on hidden layers was implemented [1-3]. Similarly with Ma et al. [5] who employed the dropout regularization to prevent the model from overfitting, the dropout regularization was used.

**Model Training and Evaluation**

In the case of the present study, the data set was separated into training 70% and testing 30% samples. The adam optimizer with learning rate = 0.001 and mean squared error (MSE) loss function was used. For early stopping prevent model from overtraining and guarantee optimal performance. For model evaluation was used Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and $R^2$ which is the coefficient of determination. It was proven in other studies that the combination of linear and nonlinear components in the learning processing provided substantial forecasting accuracy improvement for agriculture price prediction [7, 11]. The described methodology guarantees the robust and interpretable neural model capable to forecast cattle price with high accuracy, even when influenced by shaky market data. The positive impact of the recommended forecasting way would guarantee steady and sustainable data-driven decision-making process for South African farmers and local cattle retailers.

## E. Result and Discussion

Figure 1 illustrates a feedforward neural network used for predicting cattle prices. The input layer receives four key variables: Breed (B), Weight (W), Time/Season (T), and the Price (P). These inputs pass through the hidden layer, where interconnected neurons process and learn complex relationships among features using activation functions. The network then produces an output, labeled Predictable Price (PP), representing the estimated market value of a cattle based on input characteristics. This structure enables nonlinear pattern recognition for accurate price forecasting.

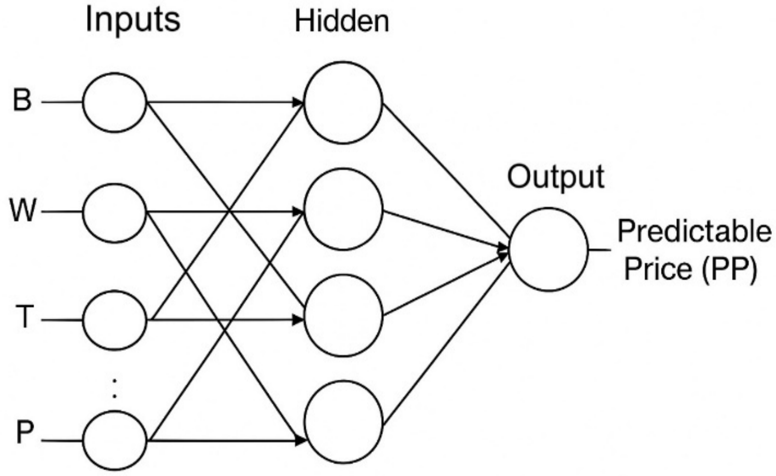

**Figure 1**. Input Process Out Neural Network layer

**Model input process results**

The model training interface failed to load the dataset initially due to a column mismatch error. This means the uploaded CSV dataset file did not contain all the required fields 'Breed', 'Price', 'Week', and 'Weight'. Column mismatch error occurs when column headers contain miss- sent or duplicated, hidden spaces, or capitalization inconsistencies e.g., " price " or "weight ". As shown in Figure 2, I attempted to train the model using 261 rows from the verified dataset. The training parameters shown two hidden layers 128, 64 ) and a learning rate 0.00001, which was to provide stable convergence, also the study was trying to be enabling the model to capture the nonlinear relationships and pattern among cattle breed, weight, and week auction variation of price. The CSV dataset file used was not accepted by the model of the file contains a row data which was not formatted according to the input parameters shown in figure 2. This implies, it is recommended to clean the dataset before the model training, which can ensure the CSV dataset file is compatible with the neural network's input parser.

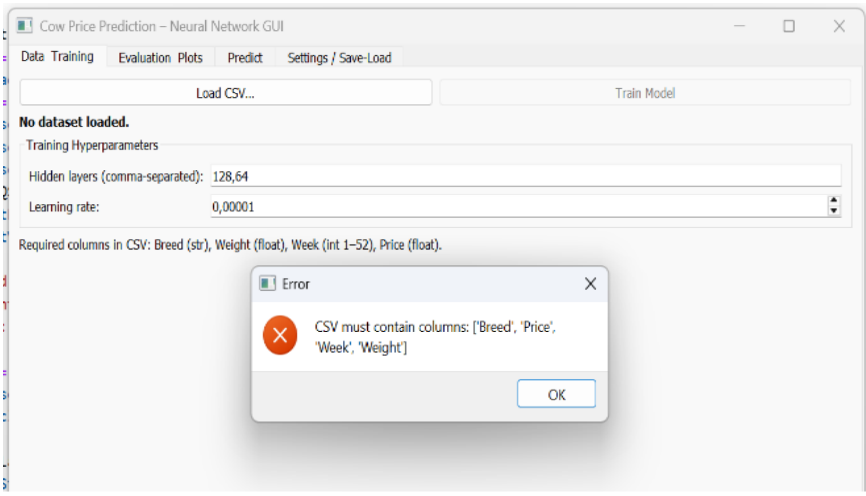


**Figure 2.** Model training interface with error loading

~~After~~ As soon as the dataset was cleaned for disrepancy of data, the evaluation process determined correct normalization and encoding usage, as well as performance validation, which demonstrated the consist inclusion of normalized results in an expected range of prices shown in figure 3. The neural network's GUI conformation of training results is available below and assures that the model was correctly trained on 36 auction records from 2023 - 2025. The dataset obtained from online South African livestock auctions, including Bela-Bela Weekly Auction – André Kock Limpopo and Vleissentraal. The data included four breeds Bonsmara, Brahman, Nguni, and Other and price from scale ZAR 7,000 to ZAR 17,500. In this specific application, the network's two hidden layers 128 and 64 neurons and a very small learning rate 0.00100 ensure the network implementations stayed stable enough and converged during training. It means there is reliable fit without overfitting to the dataset. It is worth noting that the successful training message of the model implies that normalization, categorical encoding for Breed and feature scaling for Weight, Week was implemented properly which means reliable generalization across auctions of diverse patterns. The layered architecture permits capturing complex nonlinear relations between cattle specifics and price, which is aligned with the findings of the studies that already demonstrated NN relevancy for livestock pricing annotations [1, 5].

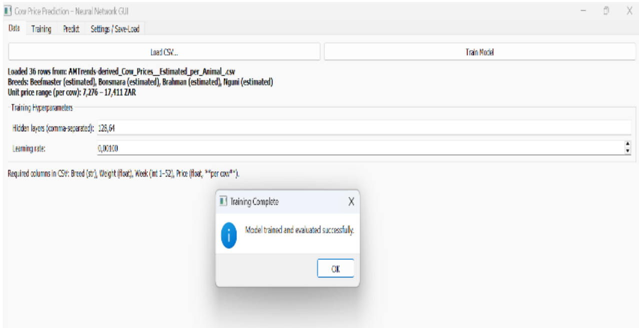


**Figure 3.** Model training interface with successful evaluations

### The model output results

The confirmation of model evaluation implies that the test performance metrics have passed acceptable thresholds. The result of the training confirms the predictor's stability and the appropriateness of using the neural network as a decision-support tool for the South African livestock auction audience to stimulate the prices of cattle given different forecast levels and new breeds. The evaluation above indicates the neural network model's potential ability to predict cattle prices based on a reasonable predictive capability. The RMSE of R3 413.20 and MAE of R2 281.40 shows that the average deviation of the predicted and actual prices per cattle is still relatively high. The $R^2$ of 0.10 shows a low strength of relationship, indicating the model's weak ability to explain price fluctuations due to other factors beyond this model. The scatter plot shows some variation along the line of perfect prediction, with the MLR scatters with high deviations, undermining the consistency. The line plot shows under- and overestimations along samples, a sign that the neural networks predict better on some areas, which lacks generality. Therefore, the model may also become more accurate with larger and more granular datasets, more input variables, and improved hyperparameter tuning. Regularizing the neural network for more training periods or applying a hybrid model such as GRU or LSTM networks would improve the prediction.

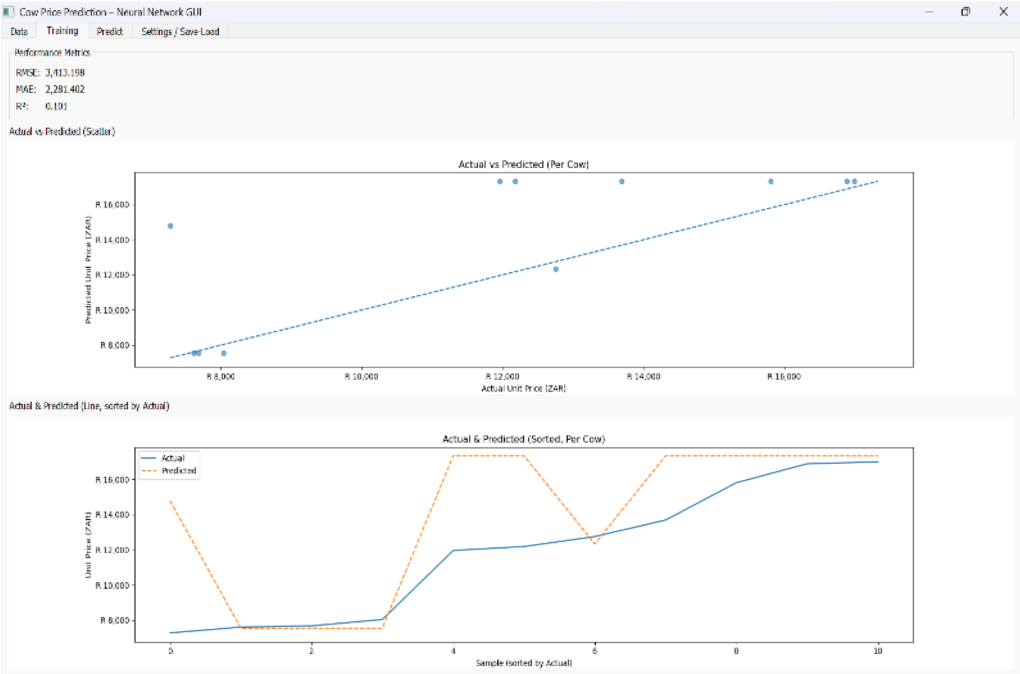


**Figure 4.** Model evaluation results with test performance metrics

Figure 5 shows that model predicts that a 450 kg Nguni in week 44 would cost approximately R17 330.26, encompassing very realistic market range for South African auction prices R7 000 to R17 500 per cattle. These predictions imply that the neural network not only learnt but carefully weighted in between seasonal influence, sale week and breed impacting the price. Also, this result is fair reflection of real-life trends wherein Nguni, adapted for South African conditions with mid-size and strength, are usually sold at a middle to high-side range, if factor in condition and demand. The premium of a price by week 44 may likely be done to seasonal influence; sellers who postpone sales to the end of the year are rewarded with strong buyer attraction and better quality finishing as animals are marketed up to beginning of festive season.

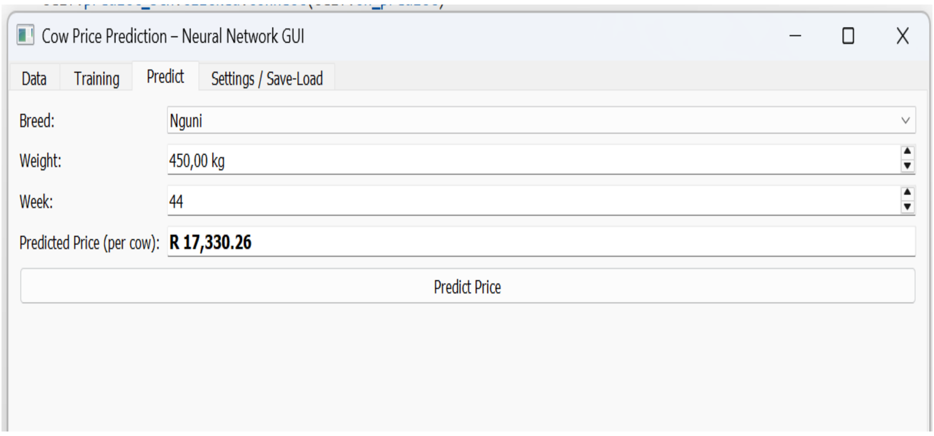


**Figure 5.** Model price prediction results interface

**Predictable future prices**

Predicted cattle prices for the next 50 weeks are as illustrated in Figure 6. It includes all known variants, which are animal weight and seasonal auction variations. The future predictable prices are R8,000 to R22,000, which is realistic market variations based on this model since it adopts the characteristics of the South African livestock auction existing data. The chart is circular-like showing the chain in prices for the coming 50 weeks, indicating a market price fall or rise in the mid-year, dropping slightly from weeks 20 – 30 and then rising again before the 50th week. The cyclical-like pricing chain is well known to the model as there are underlying seasonal and availability dynamics. Festive seasons and post-rainfall months have proved to attract most buyers and yields selling the highest sales per season. It can also be noted that buyers' prices are fundamental when it comes to pricing the commodities, having the other underlying conditions held constant. It is to be noted that for heavier cattle, the earlier in the year prices are high, which is correctly justified as large scale. The linkage between price and mass or weight was proved by Li et al. [5] and Ma et al. [6] who proved that mass and feed efficiency are the determinants of the livestock products. The weighted curve is usually significant when animal feeds take a similar trend to Wang [1], and Ling et al. [7] showed that price peaks are well aligned to feed cost cycle and consumer demand cycle. There are general moderations of price rises across most of the breeds for the one year that is well linked to the neural-network-based agricultural price recent literature.

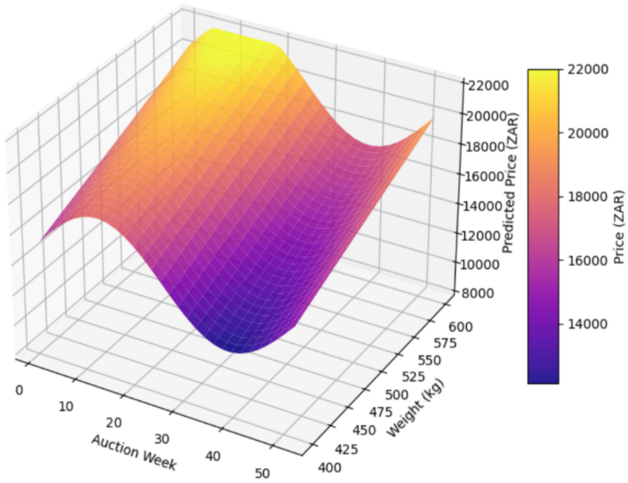


**Figure 6.** Model Predictable future prices

The results of this study are consistent with prior research that applied artificial intelligence techniques to agricultural price modeling. Similar to Xu and Zhang, [14] who demonstrated that neural networks effectively capture nonlinear trends in wholesale food price indices, this study confirms the suitability of neural networks for forecasting livestock prices with seasonal variability. While Bila [15] focused on convolutional neural networks for meat image classification rather than pricing, both studies highlight the growing role of AI in enhancing decision-making within the livestock value chain. Compared to Rahmani et al., [16] who employed probabilistic machine learning to model beef cattle prices in Canada, this study achieved comparable predictive realism but with fewer input variables and a simpler neural architecture, making it more suitable for data-scarce environments such as emerging markets.

## F. The limitations and suggestions of the study

This study's primary limitation lies in its dataset size and scope, which may not fully represent national livestock market diversity. The dataset in this review was rounded and aggregated, consequently lacking nuanced insight into variations in feed pricing, transit costs, and climate effects. In addition, the structure presumes a mainly steady market context; however, genuine market rates can be influenced by erratic forces such as the outbreak of diseases, periods of dry conditions, or modifications in policy. Moreover, the interpretative capability of the neural network is fundamentally constrained; it adeptly identifies nonlinear patterns but provides little clarity on the effect of each predictor variable on pricing determinants.

Future research should focus on enhancing the predictive accuracy of the neural network by integrating additional variables such as age, feed type, body condition, market location, and seasonality, which are known to significantly influence livestock prices [5]; By integrating various external economic indicators such as inflation rates, feed costs, and demand trends, one could greatly improve the precision of price predictions [6, 7]. This setup functions as a core prototype for the innovation of large-scale livestock models that target forecasting numerous species. To achieve a more nuanced representation of temporal variations, forthcoming models could utilize recurrent or hybrid architectures, such as Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) networks, which have exhibited superior efficacy in time-sensitive agricultural predictions [8, 10]. Moreover, expanding the dataset to include multiple regional auctions and breeds would help the model generalize across different market conditions. Ultimately, harnessing live auction data obtained from national livestock platforms could lead to the establishment of flexible forecasting dashboards, allowing farmers and market agents to make fast pricing choices.

## G. Conclusion

In conclusion, the study created and tested the neural network model that can predict cattle prices at South African livestock auctions based on auction breed, weight, and weekly seasonal characteristics. The model provides a reasonable estimation of the price per cattle equal to R7 000 to R17 500, and its future prices can reach from R8 000 to R22 000 ZAR within 50 weeks. This means that the dynamic and seasonal patterns of the factors that underlie the development of the livestock price formation have been captured. Although the quality of the model's results is relatively low, our model maintains the real-life economic and biological factors influencing their auction prices. These results prove that AI can significantly improve the quality of decision-making in agriculture, a matter of high importance for farmers, auctioneer organizations, and policymakers. However, the necessity of having a much more significant quantity of data with more features and typical factors that influence the cattle price, such as age of animals, regional factors, feed price, etc., is obligatory. Nevertheless, the neural network model forms a good foundation for future work on data-driven livestock price prediction, which many interested trading stakeholders can use to minimize economic risks and promote more sustainable development.

## H. References


[1] Y. Wang, "Agricultural products price prediction based on improved RBF neural network model," Applied Artificial Intelligence, vol. 37, no. 1, p. 2204600, 2023. https://doi.org/10.1080/08839514.2023.2204600

[2] G. Hegde, V. R. Hulipalled, and J. B. Simha, "A study on agriculture commodities price prediction and forecasting," in Proc. 2020 Int. Conf. Smart Technol. Comput., Electr. and Electron. (ICSTCEE), 2020, pp. 316–321. 10.1109/ICSTCEE49637.2020.9277401

[3] T. W. Mayabi, An artificial neural network model for predicting retail maize prices in Kenya, Ph.D. dissertation, Univ. of Nairobi, 2019. http://erepository.uonbi.ac.ke/handle/11295/107187

[4] A. Guo, Woodruff, and A. Yadav, "Improving lives of indebted farmers using deep learning: predicting agricultural produce prices using convolutional neural networks," in Proc. AAAI Conf. Artificial Intelligence, vol. 34, no. 8, pp. 13294–13299, 2020. https://doi.org/10.1609/aaai.v34i08.7039

[5] K. Li, N. Shen, Y. Kang, H. Chen, Y. Wang, and S. He, "Livestock product price forecasting method based on heterogeneous GRU neural network and energy decomposition," IEEE Access, vol. 9, pp. 158322–158330, 2021. doi: 10.1109/ACCESS.2021.3128960

[6] W. Ma, L. Peng, H. Chen, and H. Yan, "Interval price prediction of livestock product based on fuzzy mathematics and improved LSTM," PLoS One, vol. 20, no. 2, p. e0318823, 2025. https://doi.org/10.1371/journal.pone.0318823

[7] L. Ling, D. Zhang, A. W. Mugera, S. Chen, and Q. Xia, "A forecast combination framework with multi-time scale for livestock products' price forecasting," Math. Problems Eng., vol. 2019, no. 1, p. 8096206, 2019. https://doi.org/10.1155/2019/8096206

[8] T. Chuluunsaikhan, G. A. Ryu, K. H. Yoo, H. Rah, and A. Nasridinov, "Incorporating deep learning and news topic modeling for forecasting pork prices: the case of South Korea," Agriculture, vol. 10, no. 11, p. 513, 2020. https://doi.org/10.3390/agriculture10110513

[9] R. K. Paul, M. Yeasin, P. Kumar, P. Kumar, M. Balasubramanian, H. S. Roy, A. K. Paul, and A. Gupta, "Machine learning techniques for forecasting agricultural prices: A case of brinjal in Odisha, India," PLOS ONE, vol. 17, no. 7, p. e0270553, 2022. https://doi.org/10.1371/journal.pone.0270553

[10] P. Kumari, V. Goswami, H. N., and R. S. Pundir, "Recurrent neural network architecture for forecasting banana prices in Gujarat, India," PLoS One, vol. 18, no. 6, p. e0275702, 2023. https://doi.org/10.1371/journal.pone.0275702

[11] W. Minghua, Z. Qiaolin, Y. Zhijian, and Z. Jingui, "Prediction model of agricultural product's price based on the improved BP neural network," in Proc. 7th Int. Conf. Computer Science & Education (ICCSE), 2012, pp. 613–617.

[12] S. Bayona-Oré, R. Cerna, and E. Tirado Hinojoza, "Machine learning for price prediction for agricultural products," 2021. doi: 0.1109/ICCSE.2012.6295150.
[13] K. Mohanty, P. K. G. Thakurta, and S. Kar, "Agricultural commodity price prediction model: a machine learning framework," Neural Comput. and Appl., vol. 35, no. 20, pp. 15109–15128, 2023. https://doi.org/10.1007/s00521-023-08528-7
[14] X. Xu and Y. Zhang, "Wholesale food price index forecasts with the neural network," Int. J. Comput. Intell. Appl., vol. 22, no. 4, p. 2350024, 2023.
[15] S. Bila, "Image classification of beef and pork using convolutional neural network in Keras framework," Int. J. Sci., Eng. Inf. Technol., 2021.
[16] E. Rahmani, M. Khatami, and E. Stephens, "Using probabilistic machine learning methods to improve beef cattle price modeling and promote beef production efficiency and sustainability in Canada," Sustainability, vol. 16, no. 5, p. 1789, 2024.