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Hybrid Fuzzy Logic, Genetic Algorithms, and Artificial Neural Networks for Cattle Body Weight Prediction

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Abstract. *Cattle serve as the primary means of meat and milk production in numerous regions across the globe. Enhancing efficiency and productivity in cow ranching can provide significant economic consequences. The cattle industry is significant as it enables the estimation of cow weight, directly influencing beef and milk quality. This study aims to enhance the accuracy of cattle weight estimation by minimizing the Mean Squared Error (MSE) values. The integration of artificial neural network (ANN), fuzzy logic (FL), and genetic algorithm (GA) techniques is a promising artificial intelligence tool for predicting and modeling cattle weight in livestock weight prediction systems. The cow weight forecast yielded a Mean Squared Error (MSE) value of 10.9 kg, which is the best result. The results demonstrate the progress made in agriculture using advanced technologies. They offer a detailed examination of how artificial intelligence, fuzzy logic, and evolutionary techniques can be combined to address the many difficulties associated with estimating cattle body weight.*

Keywords: *Artificial Neural Network, Fuzzy Logic, Genetic Algorithm, Hybrid Algorithm, Mean Squared Error*

Abstrak. Sapi berfungsi sebagai alat utama produksi daging dan susu di banyak wilayah di seluruh dunia. Peningkatan efisiensi dan produktivitas dalam peternakan sapi dapat memberikan konsekuensi ekonomi yang signifikan. Industri sapi penting karena memungkinkan estimasi berat sapi, yang secara langsung memengaruhi kualitas daging sapi dan susu. Penelitian ini bertujuan untuk meningkatkan akurasi estimasi berat sapi dengan meminimalkan nilai Mean Squared Error (MSE). Integrasi teknik jaringan saraf tiruan (ANN), logika fuzzy (FL), dan algoritma genetika (GA) merupakan alat kecerdasan buatan yang menjanjikan untuk memprediksi dan memodelkan berat sapi dalam sistem prediksi berat ternak. Prakiraan berat sapi menghasilkan nilai Mean Squared Error (MSE) sebesar 10,9 kg, yang merupakan hasil terbaik. Hasil tersebut menunjukkan kemajuan yang dibuat dalam pertanian dengan menggunakan teknologi canggih. Hasil tersebut menawarkan pemeriksaan terperinci tentang bagaimana kecerdasan buatan, logika fuzzy, dan teknik evolusi dapat dikombinasikan untuk mengatasi banyak kesulitan yang terkait dengan estimasi berat badan sapi.

Kata kunci: Jaringan Syaraf Tiruan, Logika Fuzzy, Algoritma Genetika, Algoritma Hibrida, *Mean Squared Error*

1. INTRODUCTION

In many parts of the world, cattle are the main source of milk and meat. Improving cattle farming's productivity and efficiency can have a significant economic impact (Van Der Heide et al., 2019). The quality of the meat and milk produced by cows is directly impacted by their efficiency and general well-being (Giannuzzi et al., 2023). Because it may be used to predict cow weight, which has a direct impact on the quality of milk and steak, the cattle farming industry is important (Lee et al., 2020). Cattle must be weighed by producers (Bretschneider et al., 2014). Feeding, management, genetics, health, and the environment can all benefit from controlling cow weight. Cows are very valuable economically. Enhancing precision and effectiveness in weighing cattle can significantly enhance productivity and animal well-being.

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According to Gomes et al. (2016), cow body weight is an important indicator and a reliable and efficient way to calculate cattle weight. Because animals that are ready for slaughter might be expensive for feedlots, higher cattle weights can help determine when it is best to sell animals. With a Mean Absolute Error (MAE) of 23.19 kg, a convolutional neural network (CNN) approach predicts cow weight with accuracy. For segmentation model training, the CNN technique's MAE value with the current dataset can be improved (Gjergji et al., 2020).

Due to the weight-dependent nature of milk and meat production, cows' economic value may be affected. This application can be used by farmers to predict cow weight in order to plan their marketing and sales strategies. This can help with the development of more effective administration and sales strategies. The goal of cattle weight prediction is to provide farmers and the livestock industry with an accurate and useful tool for tracking the productivity and health of cattle. Understanding cow body weight can help farmers make better decisions about feeding, health care, sales, and breeding (Dang et al., 2022). Breeders need to predict animal weight in order to monitor animal growth. Knowing the weight of the animal makes it easier for traders to calculate the price of the animal flesh they buy. Various studies have utilized machine learning (ML) and deep learning (DL) to forecast animal weights to innovate technologically.

Cattle weight, specifically live weight (LW), can be predicted with the use of 3D scanning technologies and machine learning analytics. According to the experimental findings, a prediction model with an R2 accuracy of 0.7 and an RMSE of 42 was produced using the artificial neural networks (ANN) approach. According to Miller et al. (2019), the ANN algorithm and 3D images of live animals can still be used to improve the R2 and RMSE values. The use of cow forecasts to evaluate the calving interval (CI) and economic index (EI) has been investigated in earlier research. A model developed with NN MLA produced the most accurate EI forecast, with an MAE of 20.72 and an RMSE of 29.35. With a Mean Absolute Error of 0.79 and a Root Mean Squared Error of 1.27, a model developed with the Gradient Boosting Machine Learning Algorithm produced the best accurate confidence interval prediction. The number of cows is not included in the data set that was used. By using a larger and more diverse training dataset, accuracy can be improved.

A non-invasive method that could improve the efficacy of weight control on farms is the research's attempt to predict sheep's weight using photos (Sant'Ana et al., 2021). Techniques like Tukey's Test and Analysis of Variance (ANOVA) are used to examine images. With a Mean Absolute Error (MAE) of 3.099 kg, the results indicate that the random forest regressor (RFR) technique has a lot of potential. However, to improve the performance of other neural network models and a machine learning technique intended to predict the body weight of Balochi sheep, more training images can be added. With an R2 of 0.988 for the training dataset and 0.916 for the testing dataset, the study found that the random forests approach was the most successful in predicting the body weight of Balochi sheep. According to the study's results, the random forests approach produced the test dataset's lowest Mean Absolute Error (MAE) score of 3.275. However, examining the random forests method's accuracy in predicting livestock body weight at various growth stages should still be improved (Huma & Iqbal, 2019).

With a Mean Absolute Error (MAE) of 4,331 and a Mean Absolute Percentage Error (MAPE) of 4,296 on the test dataset, the StackingRegressor method produced the best results in this investigation. This shows that when it comes to predicting the live weight of pigs, machine learning methods perform better than traditional linear regression models. By using more data preparation techniques, such as outlier detection and normalisation, future research can improve prediction quality and increase prediction accuracy (Ruchay et al., 2022).

The study used a deep learning algorithm to analyse overhead images of the pig's back in order to forecast the pig's weight. The approach is improved by employing a regression neural network and is based on the faster R-CNN object detecting system. Pig weight estimates have a Mean Absolute inaccuracy (MAE) of 0.644 kg and a relative inaccuracy of 0.374%. When the image overlap is less than 30%, the algorithm is able to recognise and locate the pig and accurately estimate its weight. Different pig placements will affect how well the weight is measured. Enhancing accuracy and focussing on creating a non-contact pig weighing system are the objectives of adding more training data (Cang, He, & Qiao, 2019). The goal of this study is to predict cow weight by enhancing the outcomes of lower Mean Squared Error (MSE) values, which are based on prior research and background data. It can improve computer vision research.

2. METHOD OF RESEARCH

Figure 1 depicts a research flow diagram that outlines the procedure for predicting cow weight to obtain the lowest Root Mean Square Error (RMSE) value from combining algorithm models, namely Artificial Neural Network (ANN), Fuzzy Logic, and Genetic Algorithm. The augmentation stage in the pre-processing framework includes data reduction, cleaning, and labeling.

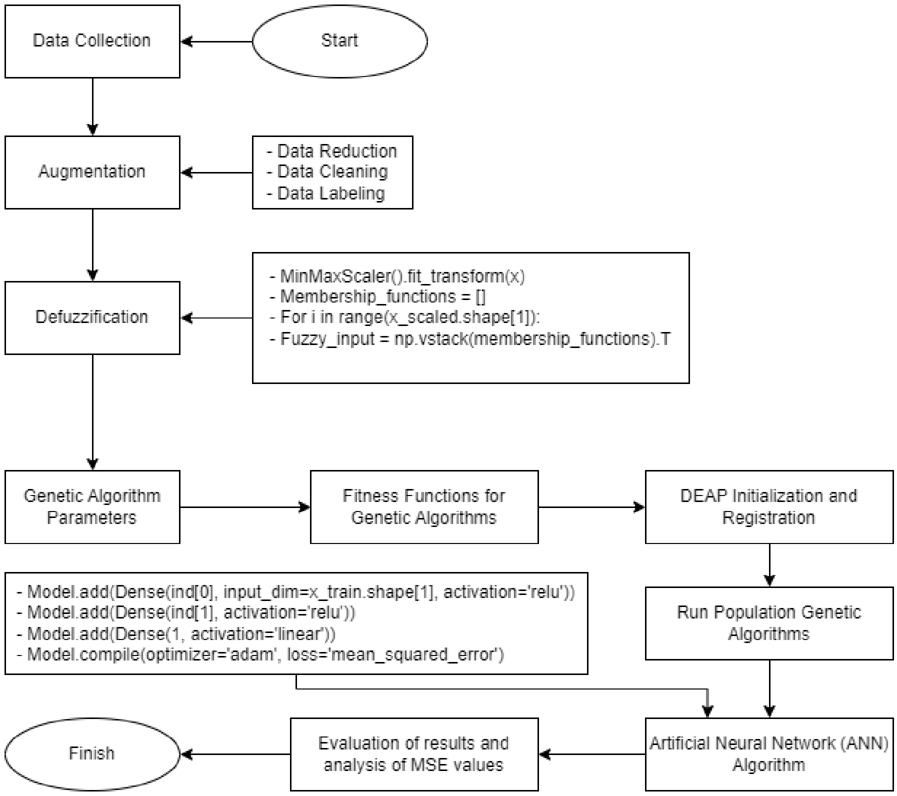

Fig. 1. Research flow diagram

These processes are executed carefully to ensure the production of high-quality data. Next, algorithm scenario modeling is carried out. This study is a comprehensive investigation into their impact on the scientific field, aiming to understand and differentiate each model in predicting cattle weights effectively and efficiently.

Dataset Collection

The dataset consists of manual measurements of saplings taken with measuring sticks and documented in cm. Its 150 data points cover 10 features, including live weight, withers height, sacrum height, chest depth, chest width, maglock width, hip joint width, oblique body length, oblique rear length, and chest girth. The Full Cow Promer (FCP) dataset, which is accessible on GitHub and depicts commercial dairy production in the Nizhny Novgorod region of Russia, will be used in the study (Ruchay et al., 2022).

Preprocessing

Data reduction is a procedure that seeks to simplify and minimize the volume of collected data. The goal of the reduction is to remove unnecessary information regarding cows. Researchers can improve their focus on important and relevant data by decreasing animal data supplied for study. Data cleansing is performed to guarantee data quality. The goal is to remove more accurate, completed, or pertinent data needs. Moreover, it provides accurate and reliable results in research (Setiawan, Utami, & Ariatmanto, 2024). Data labeling is the process of categorizing data related to each cow. The objective is to recognise and distinguish data according to predetermined attributes. In this work, data labelling is crucial for providing more accurate statistical analysis, modelling, and classification.

Fuzzy Model

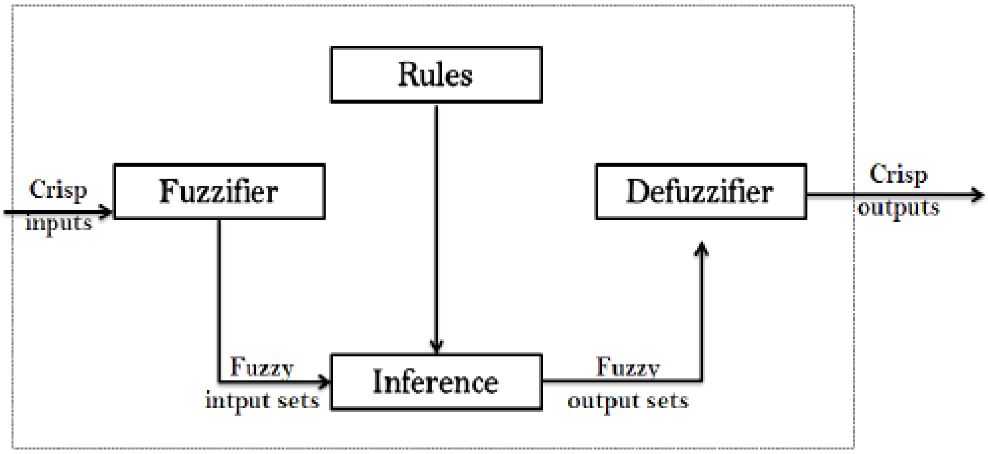

Fig. 2. Fuzzy model general diagram

Figure 2 (Al-Majidi, Abbod, & Al-Raweshidy, 2018) shows the fuzzy model's overall diagram. Instead than concentrating on analysing individual data points, FL studies the ranges of multiple parameters. All data points within a certain range of many parameters can have their results correctly predicted by FL. The method is called ANFIS, which combines FIS and neural networks. This makes it possible to create adaptive fuzzy models by learning from input data. The level of human comprehension determines how accurate a foreign language speaker is. The Mamdani module and the Sugeno module are two distinct modules that make up the rules utilised in the FL system. The input and output parameters are separated into different ranges by the Mamdani fuzzy logic module. The Sugeno module has output parameters that are determined by certain data points and input parameters that span several ranges. The paper is divided into two sections: the performance parameters are shown in the second section, while the impacting parameters are described in the first. The whole range of each input/output parameter is covered by smaller ranges. The fuzzy modular system's rule viewer component is in charge of carrying out rules. There are two basic parts to the rule viewer. The first component includes all input parameters and their corresponding membership functions. The output parameters and the membership functions that correspond to them are included in the second component. Preset rules are applied to the input values in the training dataset in order to predict the output values. The proximity between the actual output value and the expected output value for each input value is evaluated in order to select appropriate controls for the fuzzy model that was generated in the training dataset. The rules are modified in the rule editor to improve the findings' correctness. The output values of a validation dataset are predicted using a fuzzy model with optimal controls that utilises the matching input values. The high level of accuracy in the fuzzy model's predictions for the validation dataset suggests the possibility of generalisability across a broad range of values for each input parameter. A defuzzification technique estimates the exact value by varying the output parameters. This approach considers the imported input value in addition to the relevant rule.

Genetic Algorithms Model

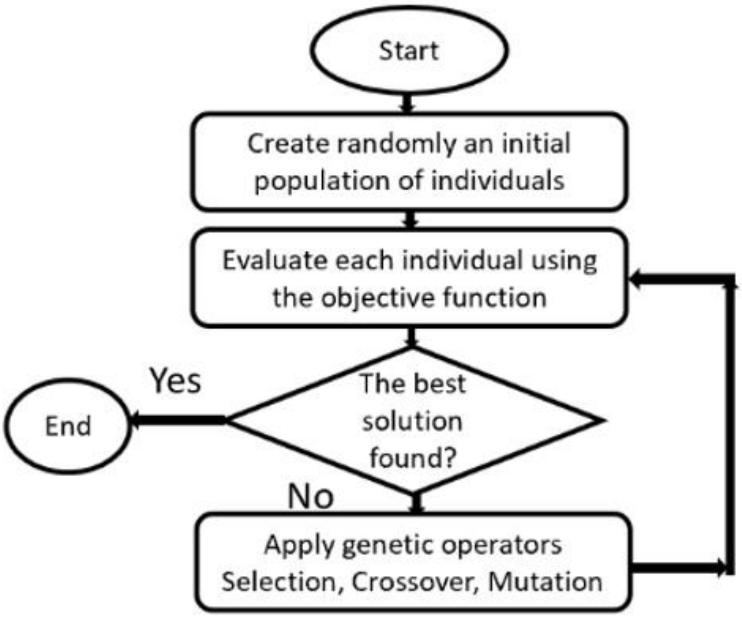

Fig. 3. Flowchart of GA

The primary steps of the codes and the algorithmic structures are made clearer in Figure 3. John Holland is credited with developing Genetic Algorithms (GA). Consequently, the plethora of possible advantages of GA has aided in its widespread application in various fields. The underlying idea of genetic algorithms (GA) is inspired by the idea of genetic evolution found in living things. The four main genetic algorithm (GA) operators are crossover, elitism, mutation, and selection. Darwin's theory of survival based on fitness is applied to evaluate each individual's fitness using an objective function and to choose individuals for further evolution or reproduction. Genetic code crossover between chromosomal pairs enables targeted investigation within a promising location, while genetic code mutation within each chromosome encourages global exploration within a designated search area. An optimisation method called the Genetic Algorithm (GA) effectively produces the optimal solution within the solution domain by using constraints and a fitness (objective) function. Specifically, genetic algorithms (GA) can be classified into two distinct categories: single objective function optimisation and multi-objective function optimisation. Only one objective function is optimised throughout the optimisation process, yielding a single solution with a potential maximum or lowest value. It is possible to optimise a multi-objective process with a large number of objective functions that produce a non-dominated solution space. By selecting a sub-domain from the overall feasible solution domain that is superior to the remaining solution space, this solution space is created. The three fundamental genetic processes of crossover, mutation, and selection are all part of the Genetic Algorithm (GA). Determining the population size is the first stage in using Genetic Algorithms (GA) to create a feasible solution. There are two methods for doing this: selecting a population size based on knowledge or understanding of a potential solution, or selecting one at random (Navot, Shpigelman, Tishby, & Vaadia, 2005). The objective function is assessed for each population size value. Parents are the precise locations within the population size that provide the exact fitness value.

The parents in question are used to produce progeny, sometimes known as children. There are two methods for accomplishing this: crossover and mutation. Combining genetic material from many parents is referred to as crossover, whereas imparting changes to the current genetic makeup of parents based on their fitness value is known as modification. Under some circumstances, it is feasible to use the same parents as parents of offspring, or "elite children," primarily when the initial population of choice produces exact fitness values. Until a workable solution is found, the genetic algorithm (GA) repeatedly creates new populations, producing precise fitness values. The algorithm terminates when reaching a certain fitness value, subject to specific stopping criteria. Genetic algorithms (GAs) frequently employ several stopping criteria, such as a time limit, a fitness limit, a maximum number of generations, a function tolerance, and a constraint tolerance.

Artificial Neural Network Model

Figure 4 depicts the basic construction of the ANN model. Artificial neural networks (ANN) contain neurones in their input, hidden, and output layers. The number of input parameters determines the number of neurones in the input layer, whereas the number of output parameters determines the number of neurones in the output layer. To find the number of hidden neurones, a trial-and-error approach is commonly employed (Mellit & Kalogirou, 2014). Artificial neural networks (ANN) mimic biological neural networks, which effectively connect more ambiguous data points to various parameters.

Simple or complex mathematical formulas are not necessary for ANN models to connect many aspects. ANNs are therefore less computationally intensive than standard methods for associating many parameters to uncertain data points.

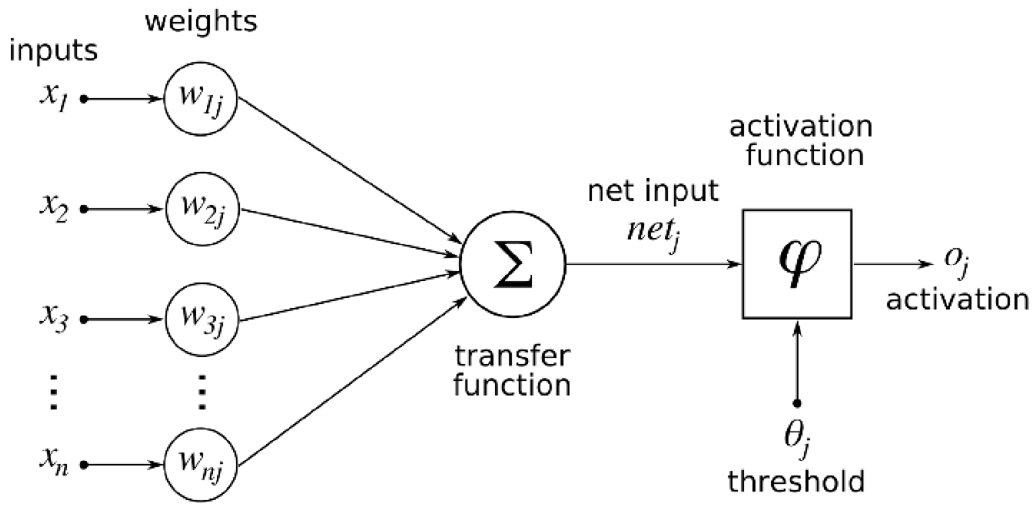

Fig. 4. An artificial neural network model's basic structure

Training, supervised learning, or imported data can all be used to train ANNs. An ANN is composed of several neurones, similar to the neurones seen in the human brain. A Multilayer Perceptron (MLP), also referred to as a feed forward neural network since neurones are coupled to one another in the form of layers only in the forward direction, is the structure that NN employs. This enables exact outcome forecasting by allowing the weights to be adjusted.

3. RESULT AND DISCUSSION

Artificial Neural Network Model

The combined use of three prediction models is becoming increasingly popular as a realistic strategy to address complex real-world circumstances to achieve greater levels of forecast accuracy. A hybrid model usually describes a combination of three prediction models. Each prediction model has certain limitations. Therefore, hybrid models are preferred to overcome or reduce the limitations of single models by combining them with other models, thereby producing better results. Recently, there has been a significant increase in the number of hybrid models used in cattle weight prediction research. Existing literature clearly shows that the combination of Artificial Neural Networks (ANN) with Fuzzy Logic (FL), the The most popular hybrid models for predicting cow weight are those that combine ANN and Genetic Algorithms (GA) and FL and GA.

ANN + GA and FL + GA

Frequent observations indicate that autonomous artificial neural networks (ANN) and fuzzy models may lack the precision to predict output values for all possible input parameter values reliably. The developed model needs to show the expected level of precision. This statement needs to be more specific and accurate. The model provides correct predictions exclusively for input values similar to those used for training. The person concerned has received formal instruction or education in a particular skill or profession. In situations like this, it is very important to minimize errors. Comparing the observed and projected values is important for the model's generalization. Therefore, progress in prediction accuracy is achieved by utilizing self-contained artificial neural networks (ANN), fuzzy models, and genetic algorithms (GA).

Adaptive Neuro-Fuzzy Interface System (ANFIS)

Adaptive Neuro-Fuzzy Inference System (ANFIS) is proposed as a unique strategy to improve prediction accuracy by overcoming the limitations of Artificial Neural Networks (ANN) and Fuzzy Logic (FL) (Setiawan & Ariatmanto, 2024). The neuro-fuzzy paradigm uses a training procedure to optimize predefined rules to predict events correctly. Figure 2 illustrates the basic neuro-fuzzy modular framework. In neuro-fuzzy modeling, the input-output data is divided into different subsets for training and validation purposes. Neuro-fuzzy modular systems use neurons to integrate input-output values from training data sets. The selection of the type, quantity, and range of membership functions depends on the imported training data. This is done in the grid division section of the module. Rules in the rule editor are defined by defining membership functions derived from the provided training data. The constraints implemented are designed to use appropriate training algorithms, such as backpropagation or hybrid approaches.

Additionally, a predefined upper limit on the number of epochs is applied for training purposes. The training process involves using appropriate methods until the maximum number of epochs is reached or the difference between the predicted and actual output values of the training data set is reduced to a satisfactory threshold. After reaching the allowable error threshold, the training procedure is stopped, and the rule in effect is considered optimal. Additional training is implemented to reduce the problem of incorrect results until the correct results are achieved.

The process of data collecting pertaining to a specific group of cows was conducted within a controlled enclosure in order to perform manual body measurements. The compilation comprises information pertaining to bovine livestock maintained by privately owned agricultural establishments situated in the Nizhny Novgorod area of Russia. Figure 5 depicts nine manually taken anthropometric measurements by a proficient practitioner using a tape measure, who documented them in centimeters.

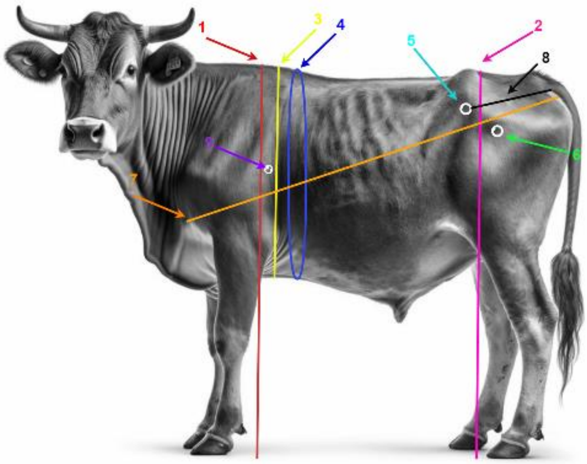

Fig. 5. Nine dimensions of the cow's body

White paint is applied to the cow's body to create hand-sized markers. Anatomical indicators based on the physical characteristics of the cow are then used in the automated process. Prior study has successfully assessed anatomical markers on the surface of cattle's bodies, including bony prominences and depressions (Setiawan & Utami, 2024). Figure 4 shows a cow's many measurements, such as withers height, hip height, chest depth, heart circumference, ilium width, hip joint width, oblique body length, hip length, and chest width. Identifying the model with the lowest mean square error (MSE) value and determining which model was best for predicting livestock weight were the primary objectives of the study.

Fig. 6. A series of RGB-D shots of cows

The diagram depicting the picture capturing system is presented in Figure 6. The animal route is equipped with two RGB-D cameras, which are positioned around 2.0 meters apart from the animal. In addition, a third Kinect camera is positioned around 3.0 meters above the corridor. The experimental setup utilizes three Microsoft Kinect v2 cameras capable of capturing RGB and depth images from specific perspectives, including the top, left, and right.

Hybrid model performance of fuzzy logic (FL), genetic algorithm (GA), artificial neural network (ANN)

The first step of the nine independent variables and one target variable that have been cleaned and label is to present them in the world of Fuzzy Logic. The input feature is geared toward a more universal scale with Min-Max Scaling, providing more measurable dimensions in the 0 to 1 range.

The following process involves Fuzzification, where each feature is transformed by a fuzzy membership function (trim). This innovation aims to produce a fuzzy input matrix, creating a foundation for handling data uncertainty more adaptively and responsively. Next, the data is split intelligently, dividing it into an 80:20 ratio for training and test sets. It is also a critical step in presenting Genetic Algorithms in the battle to optimize neural network architecture.

The initial population is formed and built with the POPULATION_SIZE policy. Then, the robust eaMuPlusLambda Genetic Algorithm was tasked with unearthing the most effective neural network architecture. Each individual's performance evaluation is translated through Mean Squared Error (MSE), measuring the accuracy of the model's predictions after training.

The final process involves creating and training a neural network model. The best individual emerges victorious on the genetic stage and becomes the network architect. Once trained, the model is exposed to a test data set for final evaluation. Model performance is measured by MSE, determining the extent to which the model can accurately predict targets. The process is a challenging and dynamic journey from initial data processing to developing the best model, illustrating an efficient synthesis between Fuzzy Logic and Genetic Algorithms for precise predictions.

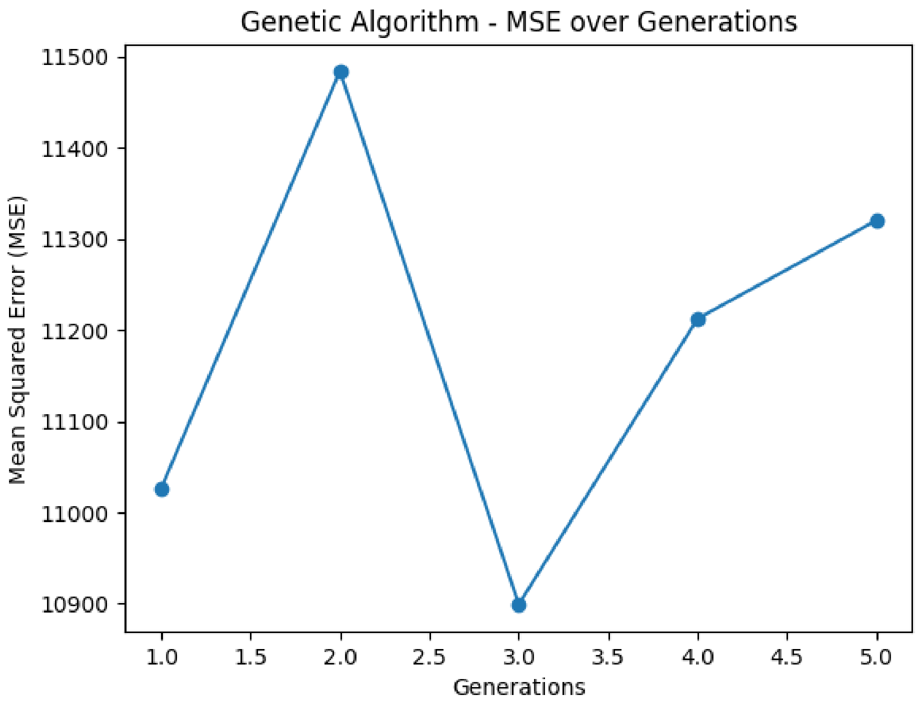

Fig. 7. A series of RGB-D shots of cows

The results from Figure 7 show an MSE value of 10.9 kg from 100 epochs and three algorithm models carried out from generations 1 to 5. This research uses a hybrid ANN, Fuzzy Logic, and GA model to calculate each variable from a cleaned dataset. The Fuzzification process helps convert input features into a scale of 0 to 1 using advanced fuzzy membership functions. Next, the data is divided into training and test sets to prepare a solid foundation.

A Genetic Algorithm is then applied to find the best neural network architecture. With a defined initial population, we navigate through several generations with careful crossover and mutation probabilities. Focusing on the estimation quality, the fitness function is optimized by measuring the Mean Squared Error (MSE). The MSE graph across generations provides a clear picture of the performance improvement of the genetic algorithm. It then combines all these elements in the best neural network model.

Table 1. Matrix Evaluation

No	Matrix Evaluation		
	Generations	Epoch	Mean Square Error (MSE)
1.	1.0	100	11.050
2.	2.0	100	11.500
3.	3.0	100	10.900
4.	4.0	100	11.200
5.	5.0	100	11.300

Table 1 shows that by using a hybrid model the performance of fuzzy logic (FL), genetic algorithm (GA), artificial neural network (ANN) results in the smallest MSE error in the third generation with an error value of 10.9 kg. Estimation on test data produces MSE that reflects the model's reliability in facing new challenges and embracing complexity with an intelligent and structured approach. Application of Hybrid Fuzzy Logic methods, Genetic Algorithms, and other Artificial Neural Networks in the real world, such as autonomous vehicles, industrial control, pattern recognition, medical image processing, security systems, and robot control, which can be used in various industries globally.

4. CONCLUSION

With the prediction results of cow weight, it produces the best Mean Squared Error (MSE) value of 10.9 kg after undergoing a training series for 100 epochs. This success results from a harmonious combination of three mainstay models: Artificial Neural Network (ANN), Fuzzy Logic, and Genetic Algorithm. By combining the three, we achieve significant accuracy and dig into the complexity of the data with a comprehensive approach. This process includes Fuzzification to handle uncertainty, Genetic Algorithm to find the best neural network architecture, and ANN as final modeling. Generations 1 to 5 of Genetic Algorithms provide an exciting journey, creating an evolution of models that produce increasingly accurate predictions. By combining the strengths of these three approaches, we create a solution that is robust in predictions and reliable in the face of data variations. Our approach of combined ANN,FL and GA protocols could also useful in other hot research areas such as quantitative medical imaging such as optical coherence tomography (OCT) 29. (Chung et al., 2022). These results reflect technological advances in agriculture and provide an in-depth look into how we can combine artificial intelligence, fuzzy logic, and evolutionary approaches to address the complex challenge of predicting cow body weight. However, the algorithm model and other training data can still be improved for further research.

REFERENCES

Al-Majidi, S. D., Abbod, M. F., & Al-Raweshidy, H. S. (2018). A novel maximum power point tracking technique based on fuzzy logic for photovoltaic systems. *International Journal of Hydrogen Energy, 43*(31), 14158–14171. https://doi.org/10.1016/j.ijhydene.2018.06.002

Anjar Setiawan, Utami, E., & Ariatmanto, D. (2024). Cattle body weight prediction using regression machine learning. *Jurnal Teknik Informatika (JUTIF), 5*(2), 509–518. https://doi.org/10.52436/1.jutif.2024.5.2.1521

Bretschneider, G., Cuatrín, A., Arias, D., & Vottero, D. (2014). Estimation of body weight by an indirect measurement method in developing replacement Holstein heifers raised on pasture. *Archivos de Medicina Veterinaria, 46*(3), 439–443. https://doi.org/10.4067/s0301-732x2014000300014

Cang, Y., He, H., & Qiao, Y. (2019). An intelligent pig weights estimate method based on deep learning in sow stall environments. *IEEE Access, 7*, 164867–164875. https://doi.org/10.1109/access.2019.2953099

Chung, S. I., et al. (2022). CRISPR-based VEGF suppression using paired guide RNAs for treatment of choroidal neovascularization. *Molecular Therapy. Nucleic Acids, 28*, 613–622. https://doi.org/10.1016/j.omtn.2022.04.015

Dang, C. G., et al. (2022). Machine learning-based live weight estimation for Hanwoo cow. *Sustainability, 14*(19), 12661. https://doi.org/10.3390/su141912661

Danandeh, M. A. (2018). A new architecture of INC-fuzzy hybrid method for tracking maximum power point in PV cells. *Solar Energy, 171*, 692–703. https://doi.org/10.1016/j.solener.2018.06.098

Dettori, S., Iannino, V., Colla, V., & Signorini, A. (2018). An adaptive fuzzy logic-based approach to PID control of steam turbines in solar applications. *Applied Energy, 227*, 655–664. https://doi.org/10.1016/j.apenergy.2017.08.145

Férnández, E. F., Almonacid, F., Sarmah, N., Rodrigo, P. M., Mallick, T. K., & Pérez-Higueras, P. (2014). A model based on artificial neuronal network for the prediction of the maximum power of a low concentration photovoltaic module for building integration. *Solar Energy, 100*, 148–158. https://doi.org/10.1016/j.solener.2013.11.036

Gianuzzi, D., et al. (2023). Prediction of detailed blood metabolic profile using milk infrared spectra and machine learning methods in dairy cattle. *Journal of Dairy Science, 106*(5), 3321–3344. https://doi.org/10.3168/jds.2022-22454

Gjergji, M., et al. (2020). Deep learning techniques for beef cattle body weight prediction. In *2020 International Joint Conference on Neural Networks (IJCNN)*. https://doi.org/10.1109/ijcnn48605.2020.9207624

Gomes, R. A., Monteiro, G. R., De Freitas Assis, G. J., Busato, K. C., Ladeira, M. M., & Chizzotti, A. (2016). Technical note: Estimating body weight and body composition of beef cattle through digital image analysis. *Journal of Animal Science, 94*(12), 5414–5422. https://doi.org/10.2527/jas.2016-0797

Huma, Z. E., & Iqbal, F. (2019). Predicting the body weight of Balochi sheep using a machine learning approach. *Turkish Journal of Veterinary & Animal Sciences, 43*(4), 500–506. https://doi.org/10.3906/vet-1812-23

Jena, D., & Ramana, V. V. (2015). Modeling of photovoltaic system for uniform and non-uniform irradiance: A critical review. *Renewable & Sustainable Energy Reviews, 52*, 400–417. https://doi.org/10.1016/j.rser.2015.07.079

Ke, G., et al. (2017). LightGBM: A highly efficient gradient boosting decision tree. *Advances in Neural Information Processing Systems, 30*, 3149–3157.

Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization. *arXiv*. https://doi.org/10.48550/arxiv.1412.6980

Kumar, M., Murukeshan, V. M., Seah, L. H., & Shearwood, C. (2015). Quantification of biofilm thickness using a swept source based optical coherence tomography system. *Proceedings of SPIE*. https://doi.org/10.1117/12.2190106

Lee, D.-H., et al. (2020). Estimation of carcass weight of Hanwoo (Korean native cattle) as a function of body measurements using statistical models and a neural network. *Asian-Australasian Journal of Animal Sciences, 33*(10), 1633–1641. https://doi.org/10.5713/ajas.19.0748

Meleppat, R. K., Prabhathan, P., Keey, S. L., & Murukeshan, V. M. (2016). Plasmon resonant silica-coated silver nanoplates as contrast agents for optical coherence tomography. *Journal of Biomedical Nanotechnology, 12*(10), 1929–1937. https://doi.org/10.1166/jbn.2016.2297

Mellit, A., & Kalogirou, S. A. (2014). MPPT-based artificial intelligence techniques for photovoltaic systems and its implementation into field programmable gate array chips: Review of current status and future perspectives. *Energy, 70*, 1–21. https://doi.org/10.1016/j.energy.2014.03.102

Miller, G. A., Hyslop, J. J., Barclay, D., Edwards, A. J., Thomson, W., & Duthie, C.-A. (2019). Using 3D imaging and machine learning to predict liveweight and carcass characteristics of live finishing beef cattle. *Frontiers in Sustainable Food Systems, 3*, 30. https://doi.org/10.3389/fsufs.2019.00030

Navot, A., Shpigelman, L., Tishby, N., & Vaadia, E. (2005). Nearest neighbor based feature selection for regression and its application to neural activity. *Neural Information Processing Systems, 18*, 996–1002. https://papers.nips.cc/paper/2848-nearest-neighbor-based-feature-selection-for-regression-and-its-application-to-neural-activity.pdf

Pijewska, E., Zhang, P.-F., Meina, M., Meleppat, R. K., Szkulmowski, M., & Zawadzki, R. J. (2021). Extraction of phase-based optoretinograms (ORG) from serial B-scans acquired over tens of seconds by mouse retinal raster scanning OCT system. *Biomedical Optics Express, 12*(12), 7849. https://doi.org/10.1364/boe.439900

Porrazzo, R., Cipollina, A., Galluzzo, M., & Micale, G. (2013). A neural network-based optimizing control system for a seawater-desalination solar-powered membrane distillation unit. *Computers & Chemical Engineering, 54*, 79–96. https://doi.org/10.1016/j.compchemeng.2013.03.015

Ruchay, A., et al. (2022). A comparative study of machine learning methods for predicting live weight of Duroc, Landrace, and Yorkshire pigs. *Animals, 12*(9), 1152. https://doi.org/10.3390/ani12091152

Ruchay, A., Kober, V., Dorofeev, K., Kolpakov, V. I., Gladkov, A., & Guo, H. (2022). Live weight prediction of cattle based on deep regression of RGB-D images. *Agriculture, 12*(11), 1794. https://doi.org/10.3390/agriculture12111794

Ruchay, A., Kober, V., Dorofeev, K., Kolpakov, V. I., & Miroshnikov, S. A. (2020). Accurate body measurement of live cattle using three depth cameras and non-rigid 3-

D shape recovery. *Computers and Electronics in Agriculture, 179*, 105821. https://doi.org/10.1016/j.compag.2020.105821

Sant'Ana, D. A., et al. (2021). Weighing live sheep using computer vision techniques and regression machine learning. *Machine Learning With Applications, 5*, 100076. https://doi.org/10.1016/j.mlwa.2021.100076

Setiawan, A., Andalantama, Y., Sidiq, M., & Kusrini. (2023). Predictive analysis of monthly flood variables in the Palangkaraya area using multiple regression methods and MLR, NN, KNN, Random Forest, SVM algorithms. In *Proceedings of the 2023 6th International Conference on Information and Communications Technology (ICOIACT)* (pp. 224–229). IEEE. https://doi.org/10.1109/ICOIACT59844.2023.10455906

Setiawan, A., & Ariatmanto, D. (2024). Application of certainty factor in an expert system to diagnose cow diseases. In *Proceedings of the 2024 IEEE International Conference on Artificial Intelligence and Mechatronics Systems (AIMS)* (pp. 1–6). IEEE. https://doi.org/10.1109/AIMS61812.2024.10513343

Setiawan, A., & Utami, E. (2024). Predicting the weight of livestock using machine learning. In *Proceedings of the 2024 IEEE International Conference on Artificial Intelligence and Mechatronics Systems (AIMS)* (pp. 1–6). IEEE. https://doi.org/10.1109/AIMS61812.2024.10512610

Setiawan, A., Utami, E., & Ariatmanto, D. (2024). Cattle weight estimation using linear regression and random forest regressor. *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi), 8*(1), 72–79. https://doi.org/10.29207/resti.v8i1.5494

Setiawan, A., Atina, V., & Hartanti, D. (2022, June). Sistem pakar diagnosa penyakit infeksius hewan ternak sapi. In *Prosiding Seminar Nasional Teknologi Informasi dan Bisnis* (pp. 320–326).

Van Der Heide, E. M. M., Veerkamp, R. F., Van Pelt, M. L., Kamphuis, C., Athanasiadis, I. N., & Ducro, B. J. (2019). Comparing regression, naive Bayes, and random forest methods in the prediction of individual survival to second lactation in Holstein cattle. *Journal of Dairy Science, 102*(10), 9409–9421. https://doi.org/10.3168/jds.2019-16295

Wełeszczuk, J., Kosińska-Selbi, B., & Cholewińska, P. (2022). Prediction of Polish Holstein's economical index and calving interval using machine learning. *Livestock Science, 264*, 105039. https://doi.org/10.1016/j.livsci.2022.105039