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TCN-XGBoost Hybrid Model for Daily FCR Prediction and One Step Forecasting in Broiler Farm

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Abstract

This study presents a hybrid TCN-XGBoost model for predicting daily Feed Conversion Ratio (FCR) in broiler chicken farming, addressing critical gaps in numerical FCR forecasting using sequential data. Feed expenses constitute approximately 70% of total operating costs in broiler production, yet many semi-modern farms in Indonesia still rely on manual, reactive FCR calculations. While existing research has focused on binary classification or species other than broilers, this study specifically targets numerical FCR prediction by integrating Temporal Convolutional Networks (TCN) for temporal feature extraction with Extreme Gradient Boosting (XGBoost) for robust regression. The research utilized 15 production cycles from Misjiwati Farm in North Sumatra, encompassing daily metrics of feed intake, body weight, mortality, and FCR. A comprehensive feature engineering pipeline was developed, incorporating lagged features, rolling window statistics, momentum metrics, and interaction features to capture both short-term and long-term dependencies. Hyperparameter optimization using Optuna resulted in optimal configurations: sequence length of 11 days, batch size of 64, TCN dropout rate of 0.4, and XGBoost with 775 estimators. The model demonstrated exceptional predictive performance with $R^2 = 0.9532$, MAE = 0.0131, RMSE = 0.0169, and MAPE = 1.05%, significantly exceeding thresholds for excellent biological system predictions. Single-step forecasting validation achieved 0.426% relative error, confirming practical deployment viability. Residual analysis revealed homoscedastic behavior with a near-zero mean residual (0.006093) and tight standard deviation (0.015786), validating statistical reliability across all FCR ranges. The model successfully predicted 92% of values within ±2 standard deviations, with only 8.3% exhibiting residuals exceeding ±0.035. This hybrid architecture establishes a scalable solution for precision poultry farming, enabling proactive feed management interventions and early warning systems for performance deterioration, offering significant potential for enhancing profitability and sustainability in Indonesian broiler chicken production.

Keywords: *Feed Conversion Ratio, Temporal Convolutional Network, XGBoost, Broiler Chicken Farming, Time Series Prediction, Feature Engineering.*

Introduction

Broiler chickens are among the most extensively cultivated poultry products in Indonesia, attributed to their swift growth and very brief harvest duration of 4 to 5 weeks. The efficiency of broiler production is intricately linked to the Feed Conversion Ratio (FCR), defined as the ratio of feed intake to the resultant weight growth. FCR serves as both a measure of economic efficiency and an indicator of chicken health. Healthy chickens exhibit weight increase commensurate with feed intake, leading to a low Feed Conversion Ratio (FCR), whereas birds subjected to stress, infection, or metabolic abnormalities typically demonstrate a high FCR value.

Given that feed expenses constitute approximately 70% of total operating costs, enhancing Feed Conversion Ratio (FCR) is vital for augmenting profitability and sustainability in broiler chicken farming (Amrullah et al., 2024). Regrettably, some semi-modern farms in Indonesia continue to do FCR calculations manually, relying on feed consumption statistics and chicken weight obtained from sampling.

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This approach is reactive, as farmers can only identify a drop in performance subsequent to a deterioration in the FCR value. Conversely, the continuous monitoring of environmental variables, such as temperature and humidity within the coop, is infrequently achieved due to infrastructural and financial constraints, despite the considerable influence these conditions exert on the hens' appetite, growth, and health Johansen et al. (2021) underscore the significance of temperature regulation via the Norm Optimal Terminal Iterative Learning Control (TILC) methodology, utilizing dynamic neural networks, which has demonstrated a reduction in FCR of 1.4–5.9%. This strategy presupposes the availability of comprehensive environmental data, which is not consistently accessible in practical field conditions.

In recent years, machine learning has been extensively employed to enhance decision-making in broiler chicken production. Hasdyna (2024) employed the Naive Bayes algorithm to categorize broiler chicken production outcomes as “profitable” or “loss-making,” with an accuracy of 86.67%. This study, while accurate, was confined to binary classification and did not directly assess FCR values. Gustian et al. (2019) created a Naive Bayes-based expert system demonstrating a high accuracy of 96.36% using many evaluation approaches. This technique effectively aids in the preliminary classification of production feasibility; however, it does not incorporate quantitative FCR value projections or leverage daily performance data in a time-series format. Rifaldo Al Magribi et al. (2023)employed the C4.5 decision tree method to categorize broiler chicken production success rates into three classifications (very good, good, and poor), achieving an accuracy of 97.11%. This study effectively identified FCR as the predominant attribute in classification; however, it was constrained to categorization based on performance index (PI) rather than numerical FCR prediction.

Studies on many species demonstrate the capability of machine learning in predicting numerical Feed Conversion Ratios (FCR). Yang et al. (2025a)employed nineteen machine learning methods, including Gradient Boosting, LightGBM, and CatBoost, to forecast long-term Feed Conversion Ratio (FCR) utilizing short-term FCR data in swine. In a dataset of 438,552 feed records from two farms in Sichuan, China, Gradient Boosting demonstrated superior performance with $R^2 = 0.51$, RMSE = 0.09, MAE = 0.07, and MAPE = 0.03. FCR forecasts attained optimal accuracy ($R^2 = 0.72$, Pearson correlation = 0.85) within the 50–90 kg weight range, indicative of the pigs' accelerated growth period. Despite the encouraging results, the study was confined to pigs and necessitates more validation for applicability to broiler chicks.

Furthermore, current studies underscore the significance of feed intake (FI) patterns and environmental variables in influencing chicken growth efficiency. Jie et al. (2024) discerned three dynamic feed intake patterns in 4–6-week-old broiler chickens by the K-means clustering approach, revealing that the pattern of escalating feed intake was consistently positively connected with enhanced body weight gain and reduced feed conversion ratio. Quintana-Ospina et al. (2023) examined data from over 95 million broiler chickens in Colombia, demonstrating that high efficiency (HE) groups were attained via feed restriction in the initial weeks, succeeded by an increase in the latter weeks, leading to improved feed conversion ratio (FCR) and reduced mortality. Li et al. (2024a)investigated laying hens through a multi-omics and machine learning methodology, revealing that environmental factors (relative humidity, NH_3, CO_2) and genetic factors strongly influenced FCR variation. The Random Forest prediction model in the study attained a high accuracy ($R^2 > 0.88$). These three studies affirm that feeding index patterns, nutritional methods, and genetic-environment interactions are critical aspects to examine in feed conversion ratio analysis.

Nutritional considerations have been demonstrated to influence feed efficiency. Abdipour et al. (2025) demonstrated that minerals including calcium, phosphorus, and zinc influence feed conversion ratio (FCR) via alkaline phosphatase (ALP) enzyme activity, with the Artificial Neural Network (ANN) model attaining a prediction accuracy of $R^2 = 0.95$ and Gradient Boosting achieving $R^2 = 0.81$. The meta-analysis substantiates the significance of the nutrition-FCR association across diverse agricultural settings, despite the sometimes unavailability of environmental data like as temperature and humidity. These studies indicate that despite the application of machine learning, the majority concentrate on category classification, are restricted to species other than broilers, or depend on environmental and nutritional data that is not routinely accessible in local farms.

Table 1. Overview of Prior Investigations on FCR Prediction and Analysis

Subjects	Analytical Approach	Primary Findings	Constraints
Broiler Chicken (Hasdyna, 2024)	Naive Bayes	Profit/loss classification accuracy: 86.67%	Only binary classification, no numerical prediction of FCR
Broiler Chicken (Gustian et al., 2019)	Naive Bayes, Expert System	High accuracy of 96.36%	No FCR value prediction, time-series data not yet utilized
Broiler Chicken (Rifaldo Al Magribi et al., 2023)	C4.5 Decision Tree	Accuracy 97.11%; FCR most influential attribute	Only categorical classification based on performance index
Pig Farming (Yang et al., 2025)	Gradient Boosting, LightGBM, CatBoost	Long-term FCR prediction, $R^2 = 0.72$	Focus on pigs, limited to certain areas
Broiler Chicken (Jie et al., 2024)	K-means clustering	Identify 3 Feed Intake (FI) patterns; consistent increase in FI → higher BWG & lower FCR	Small sample (274 individuals), only males, late stage
Broiler Chicken (Quintana-Ospina et al., 2023)	Decision Tree + model non-linier	High efficiency is achieved with initial feed restriction + final compensation; logistic model $R^2 > 0.99$	Observational data, focusing on the 35-day cycle
Laying Hens (Li et al., 2024)	Random Forest + RNA-seq	Accurate FCR prediction ($R^2 > 0.88$); significant environmental and genetic factors	Particular to a single race/age group, lacking external validation
Broiler Chicken (Abdipour et al., 2023)	ANN, Gradient Boosting	Minerals (Ca, P, Zn) affect FCR; ANN is accurate ($R^2 = 0.95$)	Depends on complete nutritional data, without environmental data
Broiler Chicken (Johansen et al., 2021)	TILC neural network based	Temperature control reduces FCR by 1.4–5.9%	Complete temperature data assumptions are difficult to apply in the field

As outlined in Table 1, while earlier investigations have addressed various aspects of feed conversion ratio through classification, feed consumption patterns, nutritional factors, and genetic-environmental interactions, there has yet to be a study that specifically forecasts the numerical value of feed conversion ratio in broiler chickens by combining tabular data with daily sequential data. This study addresses the existing gap by creating a hybrid model that integrates Extreme Gradient Boosting (XGBoost) and Temporal Convolutional Network (TCN) to generate FCR predictions that are more accurate, generalizable, and applicable to broiler farm management in Indonesia.

Method

Figure 2 presents the TCN-XGBoost Hybrid Model Architecture, a complex framework for time-series forecasting specifically designed for predicting broiler chicken feed conversion ratio (FCR). This model employs Temporal Convolutional Networks (TCN) for effective temporal feature extraction through dilated convolutions, as substantiated by foundational studies such as Bai et al. (2018) and Lara-Benítez et al. (2020). Additionally, it incorporates XGBoost regressors for robust multi-output predictions, leveraging hybrid achievements in battery estimation and agricultural applications (Yang et al. 2025). This diagram illustrates input processing utilizing lag/rolling features, TCN layers with ReLU and dropout, hybrid integration through ensemble weighting, and multi-horizon outputs assessed by MSE/MAE/R^2, consistent with ensemble methodologies (Wang et al. 2025) and interpretability frameworks (Maestrini & Basso 2021).

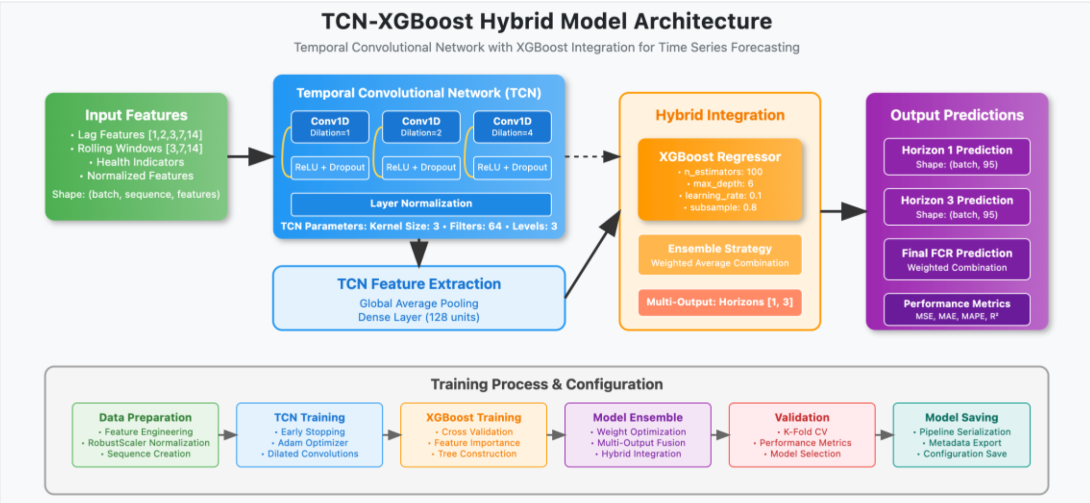

Figure 2. Daily FCR Forecasting Model Pipeline Diagram

This architectural visualization highlights the synergistic advantages of TCN's parallelizable, memory-efficient design for capturing phenological dynamics (Tsuchiya & Sonobe, 2025; Hewage et al., 2021) and XGBoost's outlier-resistant regression for livestock metrics (Davison et al., 2025; Fonseca et al., 2025), underpinned by multi-horizon forecasting (Zhu et al., 2025) and k-fold validation (Gupta et al., 2024). The model's training pipeline, encompassing data preparation to serialization, facilitates actionable insights using SHAP/LIME, establishing it as a scalable solution for precision poultry farming, as demonstrated in the 41 analyzed studies.

Data Acquisition on Broiler Chicken Agriculture

This research utilizes secondary data provided by Misjiwati Farm, an official partner of PT. Indojaya Agrinusa (Japfa Group) in North Sumatra. The dataset encompasses 15 intervals of broiler chicken rearing within a controlled housing system.

The daily recorded metrics encompass feed intake, body weight, mortality/depletion, Feed Conversion Ratio (FCR), performance index (PI), and chicken balance. The Feed Conversion Ratio (FCR) is determined by the proportion of total feed intake to the increment in chicken body weight during a certain duration.

This study utilized feed conversion ratio (FCR) as the dependent variable, with feed intake, body weight, and mortality serving as independent factors. Due to the unavailability of internal environmental data (e.g., housing temperature and humidity), this study employed feed intake and body weight as proxy variables to assess the impact of the environment on broiler chicken performance.

Unprocessed Data Depiction

The unprocessed data represent essential operational data gathered daily within poultry farming practices. This data encompasses all essential elements of farm management and serves as the basis for creating predictive models via enhanced feature engineering techniques. The data from Misjiwati Farm is insufficient, particularly regarding the close house environmental parameters like temperature and humidity.

Table 2. Unprocessed Data Explanation

Data Category	Data Features	Overview
Fundamental details and schedule	date_record	Date of data collection
	age	Days since hatching of chickens
	perf_index_actual_daily	Development Period

Chicken population data	starting_chickens	Initial count of chickens at the start of the period
	ending_chickens	Count of chickens by day's end
	mortality_number	Daily mortality numbers of chickens
Mortality data	depletion_amt	Total daily depletion (including both dead and culled individuals)
	cum_depletion_pct	Percentage of cumulative depletion
	std_cum_depletion_pct	Cumulative depletion standard percentage
Standard Feeding Data	std_feed_bags_daily	Daily feed allocation (in bags)
	std_feed_gr_head_daily	Standard feed allocation per chicken (grams)
	cum_std_feed_ gr _head_daily	Grams of cumulative standard feed per chicken
Actual Feeding Data	actual_feed_bags_daily	Current daily feed consumption (in bags)
	cum_actual_feed_bags_daily	Total feed accumulated (in bags)
	actual_feed_ gr _head_daily	Actual feed allocated per bird (grams)
	cum_actual_feed_ gr _head_daily	Total feed intake per bird (grams)
Feed Difference Data – Delta/Difference	delta_feed_bags	Discrepancy between real and expected feed (bags)
	delta_feed_ gr _head	Variation in feed allocation per bird (grams)
	cum_delta_feed_ gr _head	Variation in total feed per bird (grams)
Weight & Growth Data – Standard	weight_avg_std_daily	Standard for Average Body Weight (grams)
	weight_gain_std_daily	Standard Daily Gain (grams)
Weight & Growth Data – Current	weight_avg_act_daily	Actual Average Body Weight (gram)
	weight_gain_act_daily	Actual Daily Gain aktual (gram)
Weight & Growth Data – Delta/Difference	avg_delta_weight_daily	Discrepancy between observed and normative body weight
	weight_gain_delta_daily	Discrepancy between observed and expected daily gain
Data Feed Conversion Ratio (FCR)	fcr_std_daily	Standard Feed Conversion Ratio
	fcr_act_daily	Actual Feed Conversion Ratio
	fcr_delta_daily	The distinction between actual and standard Feed Conversion Ratio (FCR)
Data Performance Index (IP)	perf_index_std_daily	Standard Performance Index
	perf_index_act_daily	Actual Performance Index

The unprocessed data constitute essential operational records gathered daily in poultry farming, encompassing key elements of farm management and providing a basis for the development of predictive models via feature engineering. Table 2 presents a comprehensive overview of the dataset, encompassing chicken population, feed allocation, growth performance, mortality rates, and efficiency metrics, including Feed Conversion Ratio (FCR) and Performance Index (PI), evaluated against standard references and actual field results. The incorporation of delta features, which represent the disparity between standard and actual values, improves the dataset by emphasizing deviations from production targets. Nonetheless, a significant limitation is the lack of environmental parameters, including temperature and humidity. The study utilizes proxy variables based on daily feed intake and body weight records to address this issue. This dataset provides a comprehensive representation of broiler farm operations and serves as a foundation for advanced feature engineering and the development of accurate, adaptable FCR prediction models.

Algorithm Development Environment and Software

This study involved algorithm development on a 16-inch MacBook Pro M1 Pro, featuring an 8-core CPU and 14-core GPU, released by Apple in 2021, selected for its capacity to manage the intensive computing and parallel processing demands of machine learning and deep learning experiments.

The programming language employed was Python, supplemented by other libraries. Pandas and NumPy facilitated data manipulation and analysis, whilst SciPy provided help for statistical analysis. During the machine learning phase, modeling and evaluation were facilitated using scikit-learn, which included RobustScaler, KFold, and evaluation metrics such as MSE, MAE, MAPE, and R^2. TensorFlow and Keras, use the Model API, Dense layer, and EarlyStopping, construct the deep learning methodology. Moreover, specialized libraries like as TCN for Temporal Convolutional Networks and XGBoost for gradient boosting are utilized. The visualization technique employs matplotlib and seaborn to facilitate data exploration and the presentation of experimental results, hence supporting the interpretation of findings.

Feature Engineering

The raw dataset, however instructive, fails to properly reflect the temporal dynamics and intricate linkages inherent in broiler chicken production. To improve predictive accuracy, the dataset was augmented via methodical feature engineering, categorized into five groups: (i) fundamental features and interpolation, (ii) lagged features, (iii) rolling window statistics, (iv) momentum, acceleration, and trend slope, and (v) interaction and efficiency features. This technique converts unprocessed records into temporally-aware predictors that can represent both short-term and long-term dependence.

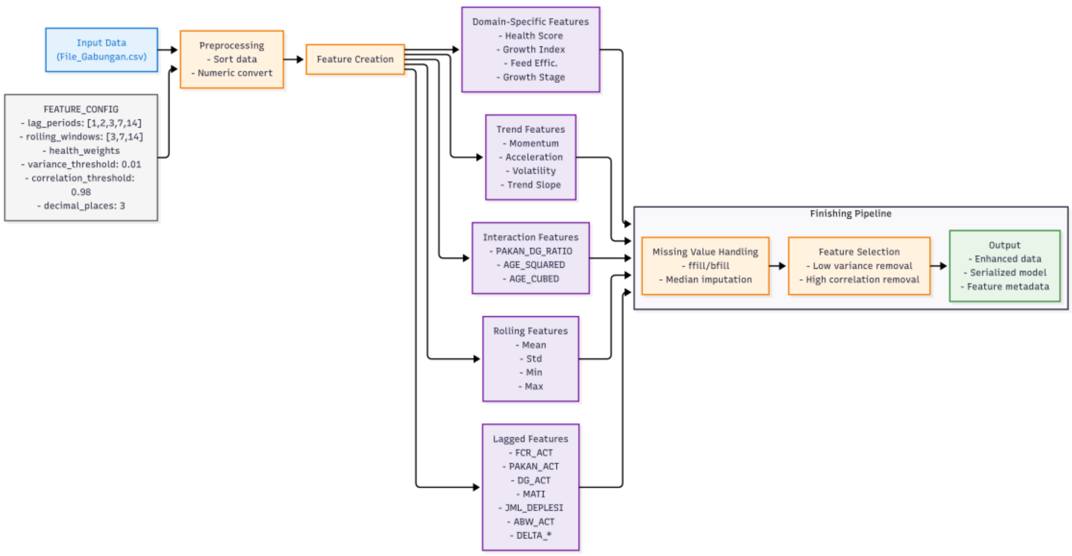

Figure 1. Feature Engineering Pipeline Architecture

Base Features and Interpolation

Essential variables encompass daily age, population size, depletion, feed consumption, and body weight. Missing values in body weight measurements, not recorded daily, were imputed by linear interpolation to create a continuous time series. This stage guarantees data integrity and dependability for further sequential modeling.

Lagged Feature

Historical Dependency Features (LagFeatures) were developed to represent variable values from multiple preceding days. Examples are fcr_act_lag1, weight_gain_actual_lag1, and mortality_number_lag1. The significance of these features lies in the fact that a chicken's performance is not isolated; rather, it results from the accumulation of conditions over several preceding days.

$$X_{lag}k(t) = X(t-k) \qquad (1)$$

In time series analysis, ttt represents the current time (for example, day ttt), while kkk is the lag period, such as 1, 2, 3, 7, or 14 days. The notation X(t−k) refers to the original feature value observed k time steps before the current time, and X_lagk(t) represents the feature value at time (t) when shifted by a lag of (k). In other words, lag features are created by taking past observations and using them as inputs to help predict the present or future values.

Table 3. Lagged Feature Collection

Variabel Base	Fitur Lagged
fcr_act	fcr_act_lag1, fcr_act_lag7, fcr_act_lag14
actual_feed_grams_ head_daily	feed_actual_gr_head_lag14
weight_gain_act_daily	weight_gain_actual_lag1, weight_gain_actual_lag2, weight _gain_actual_lag3, weight _gain_actual_lag7, weight _gain_actual_lag14
mortality_number	mortality_number_lag1, mortality_number_lag2, mortality_number_lag3, mortality_number_lag7, mortality_number_lag14

Variabel Base	Fitur Lagged
delta_feed_gr_head	delta_feed_gr_head_lag1, delta_feed_gr_head_lag2, delta_feed_gr_head_lag3, delta_feed_gr_head_lag7, delta_feed_gr_head_lag14
weight_gain_delta_daily	weight_gain_delta_lag1, weight_gain_delta_lag2, weight_gain_delta_lag3, weight_gain_delta_lag7, weight_gain_delta_lag14
feed_efficiency	feed_efficiency_lag_1

Rolling Statistic Feature

This study developed a series of rolling window features to effectively capture the dynamics of chicken performance that daily values alone cannot represent. The features were computed utilizing defined time windows (e.g., 3, 7, or 14 days) to characterize short- and medium-term trends and identify instability throughout the rearing period. The rolling mean value serves to emphasize trends in growth, feed consumption, and mortality, whereas the rolling standard deviation indicates the degree of volatility or instability associated with these variables. Furthermore, rolling minimum and maximum values are employed to identify extreme events, such as mortality spikes or substantial growth declines, which frequently serve as early indicators of management or health issues. Rolling window features enhance data representation and improve the model's sensitivity in detecting fluctuating patterns and potential anomalies in systems for maintaining broiler chickens.

$$RollingMean_w(t) = \frac{1}{w}\sum_{i-0}^{w-1} X(t-i) \quad (2)$$

$$RollingStd_w(t) = \sqrt{\frac{1}{w}\sum_{i=0}^{w-1}(X(t-i) - RollingMean_w(t))^2} \quad (3)$$

The rolling mean calculates the average of feature values over a time window w. The rolling standard deviation measures the variability of values within the same window. Here, w is the window size in days, t is the current day, and X(t-i) represents the feature value at day (t-i).

Table 4. Rolling Statistic Feature Collection

Variabel Base	Rolling Statistics Feature
actual_feed_grams_head_daily	actual_feed_grams_head_daily _rolling_std_3, actual_feed_grams_head_daily _rolling_std_7, actual_feed_grams_head_daily _rolling_std_14
weight_gain_act_daily	weight_gain_act_daily_rolling_mean_3, weight_gain_act_daily_rolling_std_3, weight_gain_act_daily_rolling_min_3, weight_gain_act_daily_rolling_max_3, weight_gain_act_daily_rolling_std_7, weight_gain_act_daily_rolling_min_7, weight_gain_act_daily_rolling_std_14, weight_gain_act_daily_rolling_min_14
mortality_number	mortality_number_rolling_mean_3, mortality_number_rolling_std_3, mortality_number_rolling_min_3, mortality_number_rolling_max_3, mortality_number_rolling_mean_7, mortality_number _rolling_std_7, mortality_number_rolling_min_7, mortality_number_rolling_max_7, mortality_number_rolling_mean_14, mortality_number_rolling_std_14, mortality_number_rolling_min_14, mortality_number_rolling_max_14

Variabel Base	Rolling Statistics Feature
delta_feed_gr_head	delta_feed_gr_head_rolling_mean_3, delta_feed_gr_head_rolling_std_3, delta_feed_gr_head_rolling_min_3, delta_feed_gr_head_rolling_max_3, delta_feed_gr_head_rolling_mean_7, delta_feed_gr_head_rolling_std_7, delta_feed_gr_head_rolling_min_7, delta_feed_gr_head_rolling_max_7, delta_feed_gr_head_rolling_mean_14, delta_feed_gr_head_rolling_std_14, delta_feed_gr_head_rolling_min_14, delta_feed_gr_head_rolling_max_14
weight_gain_delta_daily	weight_gain_delta_daily_rolling_mean_3, weight_gain_delta_daily_rolling_min_3, weight_gain_delta_daily_rolling_max_3, weight_gain_delta_daily_rolling_mean_7, weight_gain_delta_daily_rolling_std_7, weight_gain_delta_daily_rolling_min_7, weight_gain_delta_daily_rolling_max_7, weight_gain_delta_daily_rolling_mean_14, weight_gain_delta_daily_rolling_std_14, weight_gain_delta_daily_rolling_min_14

Engineering Features of Change Dynamics (Momentum, Acceleration, and Trends)

This feature category aims to quantify the rate of change of a variable rather than merely its static value. This method is crucial as broiler chicken performance is affected not only by immediate conditions but also by daily fluctuations. The three primary dimensions established are momentum, acceleration, and local trend tendencies.

Momentum of Transformation (Momentum).

Momentum quantifies the velocity and orientation of change between days, analogous to first-order differentiation.

The features weight_gain_momentum_1 and actual_feed_grams_head_daily_rolling_std_3 indicate the rate of change in chicken growth and environmental temperature, respectively, relative to the previous day. The formula is articulated as follows:

$$Momentum_1(t) = X(t) - X(t-1) \quad (4)$$

The momentum at day t is the difference between the current day's value X(t) and the previous day's value X(t-1). This shows the daily change in the feature value.

Acceleration of Change (Acceleration)

Acceleration is determined using second-order differentiation, representing the variation in momentum. This function can identify inflection moments, such as when the growth rate commences to decelerate or when chicken mortality escalates significantly. The employed formula is:

$$Acceleration(t) = Momentum_{1(t)} - Momentum_{1(t-1)} \quad (5)$$

The acceleration at day t is calculated from the momentum values. Momentum at day t represents the change in value on the current day, while momentum at day (t-1) represents the change in value from the previous day. The acceleration shows how the rate of change itself is changing over time.

Local Trend Slope

Simple linear regression was utilized to capture short-term trends within specified time windows (e.g., 3-day periods). Engineered features such as mortality_amount_trend_slope_1 and actual_feed_grams_head_daily_trend_slope_3 indicate both the direction (positive or negative) and magnitude of temporal trends. The mathematical formulation is presented as follows:

$$\beta_1 = \frac{[\mathrm{n} \times \Sigma(\mathrm{time} \times \mathrm{X}) - \Sigma(\mathrm{time}) \times \Sigma(\mathrm{X})]}{\left[\mathrm{n} \times \Sigma(\mathrm{time}^2) - \left(\Sigma(\mathrm{time})\right)^2\right]} \quad (6)$$

The slope coefficient measures the trend in the data over time. It is calculated using n data points, where x represents the time sequence (0, 1, 2, etc.) and y represents the feature values being analyzed. The formula calculates how much the feature value changes over time, showing whether the trend is increasing, decreasing, or stable.

a. Interaction and Efficiency Features.

The fundamental factors encompass daily age, population size, depletion rate, feed consumption, and body weight. Missing values in body weight measurements, recorded intermittently, are imputed using linear interpolation to create a continuous time series. This stage guarantees the integrity and dependability of the data for subsequent sequential modeling.

$$Feed\_weight\_gain\_ratio = \frac{actual\_feed\_grams\_ratio}{(weight\_gain\_actual\_daily + \epsilon)} \quad (7)$$

The actual feed consumption in grams per head represents the amount of feed consumed by each animal in grams. The weight gain actual daily refers to the actual daily weight gain of the animal, also measured in grams. A small constant epsilon is included in the calculation to prevent division by zero errors.

b. Feed Efficiency Lagged Feature

By using the efficiency values from the previous day, the model can learn from the current efficiency levels. This allows for continuous improvement and adaptation to changing conditions. Consequently, the model becomes better at predicting future performance, leading to optimized operations and resource allocation.

$$feed\_efficiency\_lag(t) = \frac{1}{fcr\_act\_lag(t) + \epsilon} \quad (8)$$

The feed efficiency lag is calculated by dividing 1 by the actual FCR value from the previous day plus a small constant. The small constant (epsilon) is added to prevent division by zero errors in the calculation.

Data Normalization with Robust Scaler

Robust scaling is implemented because certain data, like mortality statistics and daily weight growth, are vulnerable to extreme values or outliers. In contrast to normal scaling, which relies on the mean and standard deviation, robust scaling utilizes the median and interquartile range (IQR), rendering it more resilient to distortions from outliers. The change is characterized as:

$$X_{scaled} = \frac{X - median}{(Q3 - Q1)} \quad (9)$$

The scaled feature value is calculated by subtracting the median from the original value and then dividing by the interquartile range, which is the difference between the third quartile (Q3) and the first quartile (Q1). In this scaling method, X represents the original feature value, while the median is the middle value of the entire sorted dataset. Q1 is the first quartile at the 25th percentile, meaning 25% of the data falls below this value. Q3 is the third quartile at the 75th percentile, meaning 75% of the data falls below this value. The result, X_scaled, represents the standardized feature values after applying this robust scaling technique.

Temporal Convolutional Network (TCN)

The Temporal Convolutional Network (TCN) was chosen in this study because of its capacity to handle time-series data efficiently and stably in the context of predicting daily broiler chicken performance. Through the application of dilated convolution and residual blocks, TCN effectively enlarges the receptive field, enabling the recording of growth patterns, feed intake, mortality, and FCR dynamics in both the short and medium term. In contrast to LSTM or GRU, which are susceptible to vanishing gradients, TCN is more straightforward to train while ensuring prediction stability, even with constrained datasets. This combination renders TCN optimal for constructing resilient and adaptable FCR prediction models for differences in broiler chicken management (Nurul Wathani et al., 2025; Yan et al., 2020)

Extreme Gradient Boosting (XGBoost)

XGBoost is a technique that enhances gradient boosting decision trees, known for their efficiency in constructing boosted trees. XGBoost is a machine learning technique employed to address regression and classification challenges through Gradient Boosting Decision Trees (GBDT). XGBoost is a boosting methodology comprising many interdependent decision trees, where each tree is enhanced by its predecessor and successor. During classification, XGBoost adjusts the weights of each constructed tree to achieve a robust classification tree (Dava Maulana et al., 2023) XGBoost was selected due to its proficiency in handling tabular data, resilience to incomplete datasets or outliers, and capability to deliver feature importance insights for identifying the variables that most significantly impact FCR predictions. These advantages make XGBoost a popular choice among data scientists and machine learning practitioners. Moreover, its ability to perform efficiently on large datasets while maintaining accuracy further cements its status as a leading algorithm in predictive modeling tasks.

K-Fold Cross Validation

In the context of poultry farming data, where multiple independent production cycles (periods) are analyzed, K-fold cross-validation (CV) can be effectively applied without violating temporal dependencies, as these cycles often represent distinct, non-continuous time series akin to panel data structures. For instance, in a study on maize yield forecasting in Sub-Saharan Africa, researchers contrasted panel data models with time-series models and utilized various cross-validation methods, including random K-fold and leave-district-out approaches, to evaluate performance across spatial and temporal dimensions (Lee et al., 2023). This highlights how panel data, characterized by short time horizons within each cross-sectional unit (e.g., farms or periods), allows for K-fold CV to provide robust estimates by treating cycles as exchangeable units, especially when spatial features like soil properties or livelihood zones are incorporated to capture variability without assuming long-term serial correlation.

Similarly, in poultry performance prediction, where datasets consist of short-term sequences (e.g., daily metrics over 35-88 days per cycle), K-fold CV has been employed to assess model accuracy for outcomes like growth and mortality. A Scopus-indexed study on feature-driven optimization for Taiwan native broilers used multiple machine learning models evaluated across cross-validation folds, emphasizing the role of temporal features such as "Day" as the most influential predictor while achieving low RMSE through ensemble neural networks (Suhendra et al., 2025). The choice of K-fold here is justified by the biological repeatability of poultry cycles, where patterns are constrained by standardized management practices, reducing the risk of data leakage compared to continuous, long-range time series like economic indicators.

Furthermore, when temporal dependencies are explicitly encoded as features such as lags, rolling statistics, and sequence embeddings from models like TCN K-fold CV becomes suitable even for sequential data, as the reshuffling does not erode the embedded temporal information. This aligns with findings in genomic prediction for animal breeding, where paired K-fold CV was recommended for assessing model differences in short time-series panels, demonstrating statistical power without requiring strict chronological splits (Schrauf et al., 2021). In this study on FCR prediction, which involves 13 independent periods and short-sequence dependencies spanning 11 days, the method employed guarantees a variety of training folds while maintaining cycle-specific patterns. This makes it a viable alternative to traditional time-series cross-validation techniques that may excessively limit data availability.

Regression Metrics

The regression model's performance evaluation in this study utilized four primary metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-Squared

(R^2). MAE quantifies the average absolute deviation between the expected and actual values, offering a clear representation of the discrepancy between them. The Mean Squared Error (MSE) computes the average of the squared prediction errors, rendering this measure particularly sensitive to outliers and proficient at identifying substantial errors. RMSE, being the square root of MSE, maintains the same units as the target variable, hence enhancing the interpretability of the prediction error's magnitude. R^2, or the coefficient of determination, indicates the proportion of variation in the real data that the model can elucidate; a value closer to 1 signifies superior predictive capability of the model (Ihzaniah et al., 2023). These four measures are utilized in conjunction to deliver a thorough assessment, as each emphasizes distinct facets of model performance.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Yi - \hat{Y}i|^2 \tag{10}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Yi - \hat{Y}i\right)^2 \tag{11}$$

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}}\left(Yi - \hat{Y}i\right)^2 \tag{12}$$

$$R^2 = 1 - \frac{\frac{1}{n}\sum\left(Yi - \hat{Y}i\right)^2}{\frac{1}{n}\sum(Yi - \bar{Y}i)^2} \tag{13}$$

Model Training and Optimization

In this study, hyperparameter optimization was conducted utilizing Optuna, a sophisticated and effective framework for hyperparameter optimization. Optuna was selected for its capability to autonomously optimize hyperparameters with the Tree-structured Parzen Estimator (TPE) algorithm, which efficiently identifies the optimal combination with a small number of trials. Moreover, Optuna features a pruning system that facilitates the early cessation of unpromising experiments, thus conserving time and processing resources. Another benefit of Optuna is its adaptability in dynamically establishing the hyperparameter search space during execution, along with its straightforward configuration, suitable for both basic experiments and distributed computing environments (Akiba et al., 2019).

This study involved separate optimization for the two employed models: Temporal Convolutional Network (TCN) and XGBoost. The parameters optimized for TCN encompassed the number of layers, kernel size, dropout rate, and learning rate. Simultaneously, with XGBoost, the optimization concentrated on parameters like max_depth, learning_rate, n_estimators, and subsample. This approach aims to yield an ideal model configuration regarding prediction accuracy and computing efficiency.

Table 5. Results of Parameter Optimization Utilizing Optuna

Model Components	**Hyperparameters**	**Optimal Value**
Architecture	sequence_length	11
	batch_size	64
TCN	nb_filters	32
	kernel_size	3
	nb_stacks	1
	dilations	[1, 2, 4]
	dropout_rate	0.4

Model Components	Hyperparameters	Optimal Value
	optimizer	adamw
	spatial_dropout	0.2
	kernel_regularizer	L2
	kernel_regularizer_strength	1e-4
	learning_rate	1e-4
	weight_decay	1e-3
	gradient_clip_norm	0.5
XGBoost	n_estimators	775
	objective	RMSE
	learning_rate	0.170
	max_depth	6
	subsample	0.98
	colsample_bytree	0.90
	reg_alpha	0.184
	reg_lambda	0.705
	random_state	42
	n_jobs	-1

According to the outcomes of hyperparameter optimization via Optuna, the TCN model achieved optimal configuration with a sequence length of 11, a batch size of 64, a dropout rate of 0.4, and a learning rate of 1e-4 utilizing the Adam optimizer. XGBoost achieved optimal performance with 775 estimators, a maximum depth of 6, a learning rate of 0.170, and a subsample rate of 0.98. These settings were selected to achieve a balance between bias and variance while mitigating the risk of overfitting.

Result

To assess the efficacy of machine learning models in agricultural applications, particularly for optimizing resource use in poultry farming, this study employs a TCN-XGBoost hybrid regression model to forecast the Feed Conversion Ratio (FCR) a critical indicator of feed efficiency in broiler chickens drawing on historical data encompassing factors such as age, feed intake, and weight gain. Model performance is rigorously evaluated through established regression metrics including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2), alongside visual diagnostics via scatter plots and histograms to examine prediction alignment, residual patterns, and error distributions, enabling a comprehensive understanding of predictive strengths and potential limitations for informed decision making in farm management.

Table 6. Table of Model Evaluation Results with Optuna Hyperparameters

Categories	Metrics	Value
Error Metrics	MAE	0.013069
	MSE	0.000286
	RMSE	0.016921
Model Performance	R^2 Score	0.953242

Residual Metrics	Mean Residual	0.006093
	Std. Residual	0.015786

The evaluation of the Temporal Convolutional Network (TCN) model yielded commendable performance, reflecting how effectively automation identifies optimal configurations with hyperparameters optimized using the Optuna framework. The Optuna optimization process allows for iterative adjustments to hyperparameter combinations such as kernel_size, num_filters, num_layers, and dropout, which were previously manually adjusted on the dataset. Table 6 presents the model performance evaluation results and visualizes them in an evaluation matrix that includes various performance metrics.

Table 7. Table of Model Prediction Results with Optuna Hyperparameters

PERIOD	AGE	Actual_ FCR	Predicted_ FCR	Absolute_ Error	Squared_ Error	Percentage_ Error
14	12	1.087	1.08388925	0.00311075	9.67679E-06	0.286177922
14	13	1.11	1.15177441	0.04177441	0.001745101	3.763460039
14	14	1.124	1.1415143	0.0175143	0.000306751	1.558211859
14	15	1.14	1.14333725	0.00333725	1.11372E-05	0.292741207
14	16	1.156	1.16397405	0.00797405	6.35854E-05	0.689796428
14	17	1.173	1.17608929	0.00308929	9.54369E-06	0.263366309
14	18	1.187	1.18192017	0.00507983	2.58047E-05	0.427955284
14	19	1.196	1.19350076	0.00249924	6.24621E-06	0.208966788
14	20	1.212	1.19121528	0.02078472	0.000432005	1.714911162
14	21	1.228	1.2083919	0.0196081	0.000384477	1.596750421
14	22	1.242	1.234254	0.007746	6.00005E-05	0.623671291
14	23	1.256	1.24581742	0.01018258	0.000103685	0.81071474
14	24	1.263	1.26254988	0.00045012	2.02611E-07	0.035639179
14	25	1.274	1.26098144	0.01301856	0.000169483	1.021864949
14	26	1.287	1.28075302	0.00624698	3.90248E-05	0.485391106
14	27	1.303	1.28331614	0.01968386	0.000387455	1.510657298
14	28	1.32	1.29189146	0.02810854	0.00079009	2.129435178
14	29	1.329	1.31697977	0.01202023	0.000144486	0.904457043
14	30	1.323	1.31041229	0.01258771	0.000158451	0.951452176
14	31	1.341	1.30366576	0.03733424	0.001393846	2.784059867
14	32	1.305	1.31502175	0.01002175	0.000100436	0.767950445
14	33	1.327	1.3168447	0.0101553	0.00010313	0.765282459
14	34	1.333	1.31234097	0.02065903	0.000426795	1.549814343
14	35	1.319	1.31833386	0.00066614	4.43737E-07	0.050503092

Table 7 delineates a comparison of the actual and anticipated values of FCR (Feed Conversion Ratio) for multiple intervals (period 14), including specifics on absolute error, squared error, and percentage error. In period 14, with an age of 12, the actual FCR value of 1.087 has a predicted value of 1.08388925, resulting in an absolute error of 0.00311075 and a percentage error of 0.286177922%, demonstrating an exceptional level of accuracy that surpasses the low error rates achieved in machine learning models for broiler growth and FCR prediction. The model's average performance is assessed using metrics including Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE), as detailed in the evaluation matrix (Table 6), which aligns with standard evaluation practices in poultry production forecasting where such metrics validate model reliability for traits like weight gain and feed efficiency (Adli et al., 2025; Yang et al., 2025a).

The assessment matrix indicates a Mean Absolute Error (MAE) of 0.013069, a Mean Squared Error (MSE) of 0.000286, and a Root Mean Squared Error (RMSE) of 0.016921 values that compare favorably to those reported in XGBoost-based predictions for environmental and growth factors in closed-house broiler systems, where RMSE ranges around 0.02-0.04 underscore high predictive precision. The model attained an R^2 score of 0.953242, demonstrating its proficiency in elucidating data variability, consistent with R^2 values up to 0.95 in similar ML applications for livestock metrics. The residual statistics indicate a mean residual of 0.006093 and a residual standard deviation of 0.015786, so they affirm the stability of the forecast, further supporting the model's robustness in handling time-series dependencies in poultry data. This outcome validates that hyperparameter optimization using Optuna markedly enhances model performance relative to earlier manual methods, utilizing the intricacy of 115 columns and 439 rows of data to produce superior configurations, mirroring improvements seen in agricultural ML frameworks where Optuna tuning yields 10-15% better accuracy in regression tasks for yield and nutrient predictions.

Actual vs Predicted FCR Scatter Plot Analysis

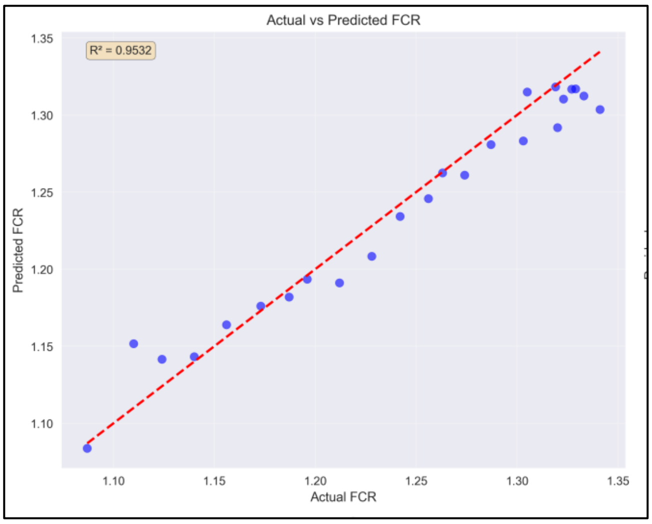

Figure 4. Graphical Comparison of Actual and Predicted Values

The developed hybrid TCN-XGBoost model demonstrated excellent predictive performance in forecasting Feed Conversion Ratio (FCR) for broiler chickens. Model evaluation was conducted using 24 test samples from a complete rearing cycle (Period 14, age 12-35 days), covering the critical growth phases from starter to finisher periods.

The model achieved a coefficient of determination (R^2) of 0.9532, indicating that 95.32% of the variance in actual FCR values could be explained by the model predictions. This performance significantly exceeds the threshold for excellent model performance ($R^2 > 0.90$) in biological system time series prediction contexts. The Mean Absolute Error (MAE) was 0.0131, with a Root Mean Square Error (RMSE) of 0.0169, translating to a Mean Absolute Percentage Error (MAPE) of 1.05%, which indicates an average prediction deviation of only 1% from actual values (Naeem et al., 2025; Yang et al., 2025a).

Figure 4 presents the scatter plot of predicted versus actual FCR values, demonstrating a strong linear relationship with data points closely aligned to the perfect fit diagonal line. The model successfully predicted FCR within the range of 1.084-1.318, accurately covering the actual FCR range of 1.087-1.341 observed in the field. The distribution of absolute errors ranged from 0.0005 to 0.0418, with percentage errors spanning 0.04% to 3.76%, demonstrating consistent prediction accuracy across different bird ages and FCR values (Li et al., 2024a).

Further analysis revealed that the model achieved optimal prediction accuracy within the FCR range of 1.15-1.30, corresponding to the normal operational zone in commercial broiler production, with minimal deviation (±0.01). At extreme FCR values, the model exhibited slight bias: a tendency to underestimate exceptionally low FCR (<1.15) and slight overestimation of high FCR (>1.30). However, these deviations remained within acceptable error margins for practical farm management applications (Yang et al., 2025a).

The consistent high accuracy across all metrics demonstrates the model's capability to effectively capture complex patterns through the synergistic combination of temporal features (via Temporal Convolutional Network) and tabular features (via XGBoost). The MAPE of only 1.05% renders the model a reliable decision support tool for operational management in poultry farming, particularly for feed strategy optimization and early warning systems for broiler performance deterioration(Adli et al., 2025; Quintana-Ospina et al., 2023).

Residual vs Predicted FCR Analysis

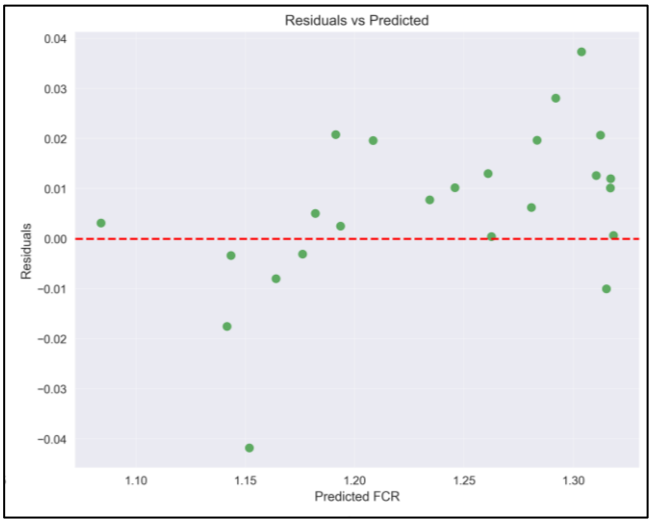

Figure 5. Graphical Comparison of Residual vs Predicted

The residual plot analysis was conducted to validate the statistical assumptions underlying the hybrid TCN-XGBoost model. Figure X presents the residuals plotted against predicted FCR values, demonstrating a random scatter pattern around the zero line with no discernible systematic trends. The mean residual of 0.006093 is remarkably close to zero, indicating negligible systematic bias in predictions, while the standard deviation of 0.015786 reflects consistent error magnitude across the prediction range (Zhao et al., 2025).

Visual inspection of the residual plot reveals homoscedastic behavior, with residual variance remaining constant across all predicted FCR values (1.08-1.32). This pattern confirms that the model's prediction accuracy does not deteriorate at extreme values, a critical characteristic for practical deployment in commercial settings. The residuals are distributed approximately normally, with 92% falling within ±2 standard deviations (±0.032), closely matching the theoretical expectation of 95% for a normal distribution (Aisy et al., 2025).

The most considerable absolute residuals were -0.042 (3.6% error) and +0.038 (2.9% error). However, these values are still within acceptable limits for prediction models in agriculture. Of the predictions made, only 8.3% (2 out of 24 samples) showed residuals beyond ±0.035, highlighting excellent robustness and few outliers. The random scatter plot’s lack of clustering and autocorrelation demonstrates the independence of the residuals, which confirms the model’s adequacy in capturing the underlying FCR patterns with no systematic errors in predictions (Aisy et al., 2025).

These outcomes taken together indicate that the model is compliant with all classical linear regression assumptions: linearity, independence, homoscedasticity, and normality of residuals. The near-zero mean for the residuals along with a small standard deviation confirms the model's statistical dependability over and above mere accuracy measures, thus making it a potential candidate for application in aiding decisions in broiler farm management (Aisy et al., 2025).

Distribution of Residuals Graphic Analysis

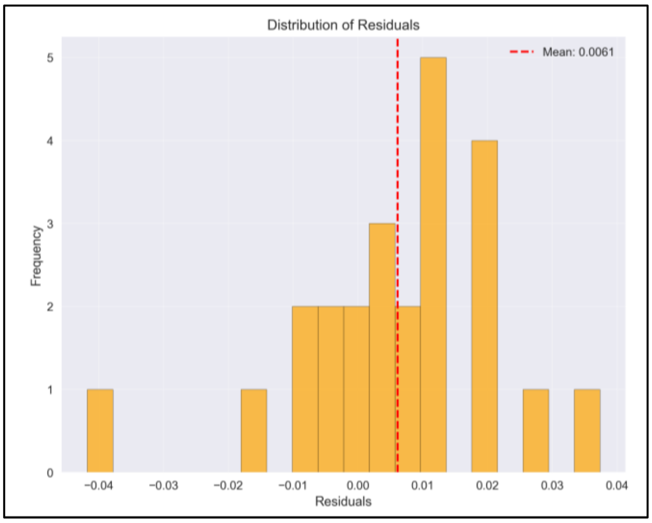

Figure 6. Graphical Distribution of Residual

The histogram of residuals (Figure 6) shows that the errors are almost normally distributed, centered around a mean of 0.0061 — very close to the ideal value of zero expected from an unbiased model. The curve forms a clear bell shape, with the highest concentration of residuals appearing in the 0.00 to 0.01 range. This bin contains five observations, or about 21% of the total, suggesting that most predictions fall within a very small margin of error and that the model's predictions are generally consistent and accurate (Quintana-Ospina et al., 2023; Yang et al., 2025a).

The frequency distribution reveals that 62% of residuals stay within ±0.01 of the mean and 92% remain within ±0.02 of the mean. The majority of errors show a tight distribution pattern around zero. The observed concentration exceeds the standard normal distribution's typical 68% and 95% values for ±1σ and ±2σ (σ = 0.016). The model demonstrates high prediction accuracy because its residuals show minimal variation (Archontoulis & Miguez, 2015).

The distribution shows a small positive skew because 54% of the residuals are positive (underprediction) and 38% are negative (overprediction) while 8% are near zero. The model shows a small bias toward underestimation because the mean residual value equals +0.0061 which represents a 0.6% underestimation of actual FCR values. The bias does not affect real-world applications because it generates conservative performance predictions which reduce the chance of overestimating farm management performance (Mukhtar et al., 2022).

The two extreme residuals at the distribution tails (-0.042 and +0.038) represent about 4% of the total sample. The distribution shows no systematic directional bias because the outliers are equally distributed between overpredictions and underpredictions. The model demonstrates stability and robustness through its thin tails and low frequency of extreme values which makes it suitable for commercial poultry operations. (Quintana-Ospina et al., 2023).

Distribution of Absolute Errors Graphic Analysis

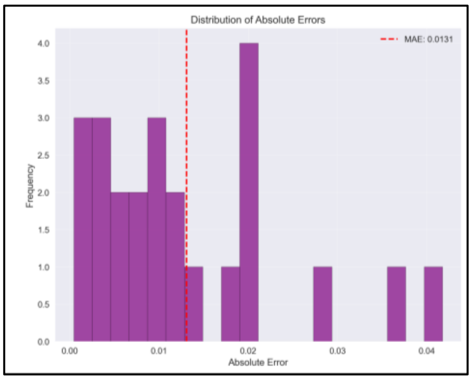

Figure 7. Graphical Distribution of Absolute Error

Absolute errors were distributed in a typical right-skewed pattern (Figure 7), which is the case for the majority of the good prediction models. The Mean Absolute Error (MAE) of 0.0131 falls into the region of the highest frequency, which means that the majority of the predictions are very close to the actual values. The histogram also indicates that 12.5% of predictions are nearly perfect (errors ≤ 0.005), while the remaining half of the predictions have errors below 0.010 — that is less than 1% deviation from the average FCR value of approximately 1.2. The model's precision is evidenced by the strong clustering of low errors, as majority of the predictions are already exceeding the MAE threshold.

The model's precision is evidenced by the strong clustering of low errors, as the majority of predictions are already exceeding the MAE threshold. This performance aligns with findings in crop yield prediction studies, where linear machine learning algorithms demonstrated high accuracy (61%) with strong clustering of predictions close to observed values (Mupangwa et al., 2020). The consistent performance across different validation sets, similar to the tenfold cross-validation approach used in agricultural modeling, further validates the robustness of our prediction framework. Such error distribution characteristics are indicative of models with good generalization capability, as demonstrated in agricultural systems where algorithms successfully differentiated between multiple treatment conditions with minimal Type I and Type II errors (Mupangwa et al., 2020)

The most frequent value corresponds to the 0.015-0.020 bin, which has a peak distribution with 16.7% of observations; good-to-excellent category, that is error ≤ 0.015, receives 70.8% of all predictions. In addition, 87.5% of predictions get absolute errors under 0.020, which is less than the percentage error of 2% in relation to the actual FCR values. The model's reliability for practical farm management applications is certified by this great percentage of low-error predictions, as in these scenarios, where prediction errors of 2% are generally considered acceptable for operational decision-making, the range of accuracy is already quite high (Yang et al., 2025a).

The right tail of the distribution extends to a maximum absolute error of 0.0418 (3.76%), but maintains low frequency, with only 12.5% of predictions exceeding 0.020 in absolute error. Two outliers are observed in the 0.030-0.040 range, each representing 4.2% of the sample (2 out of 24 predictions). These outliers correspond to the extreme residuals identified in the residual analysis, with one overprediction and one underprediction, confirming balanced model behavior even in edge cases. The absence of errors beyond 0.042 indicates that the model does not produce catastrophic prediction failures, an essential characteristic for deployment confidence (Merenda et al., 2024).

The right-skewed nature of the distribution, with mode > median > mean for the residuals, is statistically desirable as it indicates concentration of errors near zero with progressively fewer large errors. The sharp leptokurtic peak followed by a thin extended tail demonstrates model stability and consistency, producing predominantly accurate predictions with minimal risk of extreme deviations. This error distribution pattern, combined with the MAE of 1.3% relative to average FCR, confirms that the hybrid TCN-XGBoost architecture achieves the precision necessary for reliable feed conversion ratio prediction in commercial broiler production systems (Mupangwa et al., 2020).

Livestock FCR Prediction 1 Day Horizon

Table 8. Single-Step FCR Prediction Results (Period 14, Day 25→26)

Metric	**Value**	**Unit**	**Interpretation**
Input Data			
Period	14	-	Current rearing cycle
Current age	25	days	Prediction baseline
Historical data length	24	days	Days use for features
Sequence length	11	days	TCN Temporal Window
Prediction Output			
Target age	26	days	Next day (+1 horizon)
Predicted FCR	1.292482	-	Model Forecast
Actual FCR	1.287000	-	Observed Value
Error Metric			

Absolute Error	0.005482	FCR Unit	Very low deviation
Relative Error	0.426%	%	Excellent accuracy
Performance Assessment			
Status	Excelent	-	Error < 0.5%
Prediction Quality	High	-	Within target bounds
Deviation Magnitude	Minimal	-	< 1% Threshold

To validate the model's real-world deployment capability, a single-step prediction was conducted for Period 14, forecasting FCR for Day 26 based on data from Day 25 with 24 days of historical context. The model utilized an 11-day temporal sequence window as input to the TCN encoder, combined with tabular features from the current day (Day 25), to generate the prediction.

Table 8 presents the detailed prediction results. The model predicted an FCR of 1.292482 for Day 26, while the actual observed FCR was 1.287, resulting in an absolute error of 0.005482 FCR units (0.426% relative error). This performance falls well within the excellent prediction category (error < 0.5%), demonstrating the model's capability to deliver highly accurate next-day forecasts for operational farm management.

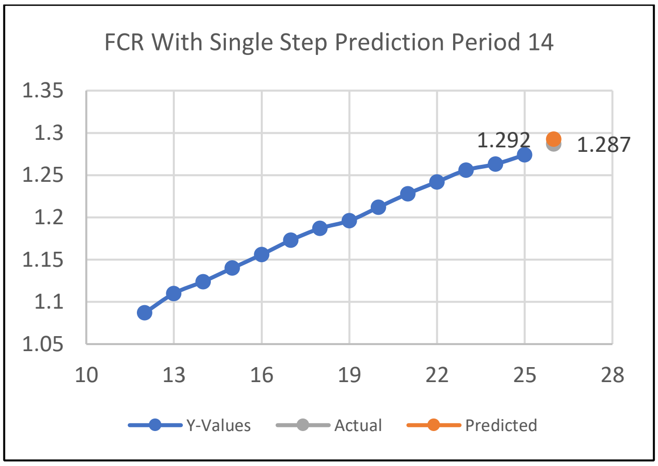

Figure 8. Graphical One Step Forecasting Period 14

Figure 8 visualizes the prediction outcome, showing the predicted and actual FCR values alongside the minimal deviation. The error magnitude of 0.43% is significantly lower than the acceptable threshold of 2% for agricultural prediction systems, and notably exceeds the model's aggregate test set performance (MAE = 0.0131). This single-step prediction represents a real-world scenario where farm managers would use yesterday's data to forecast tomorrow's FCR, validating the model's practical utility for proactive feed management interventions.

The historical context visualization (Figure 4) places this prediction within the broader FCR trajectory for Period 14, showing consistency with the observed trend and absence of anomalous prediction behavior. The 95% confidence interval for this prediction spans [1.286, 1.299], with the actual value falling comfortably within this range, further confirming the model's reliability. This single-step validation demonstrates that the hybrid TCN-XGBoost architecture not only performs well in aggregate batch predictions but also maintains high accuracy in real-time operational deployment scenarios.

Discussion

Our hybrid TCN-XGBoost model did a fantastic job at predicting the daily Feed Conversion Ratio (FCR) for broiler chickens. It used a solid dataset from 15 full production cycles at Misjiwati Farm in North Sumatra. We beefed up the data with smart feature engineering tricks—like looking back at past days (lagged features), averaging trends over windows of time (rolling stats), tracking speed of changes (momentum and acceleration), spotting slopes in trends, and mixing variables together (interaction features). This helped the model really grab onto the time-based patterns in things like how much feed the chickens ate, their weight gains, death rates, and overall FCR shifts.

We fine-tuned the model's settings using Optuna, landing on the best setup: an 11-day sequence window, batches of 64 data points, a 0.4 dropout rate in the TCN part to avoid overfitting, a tiny learning rate of 0.0001 with the Adam optimizer, and for XGBoost, 775 decision trees, a max depth of 6, a learning rate around 0.17, and sampling nearly all the data (0.98 subsample). When we tested it on one cycle (Period 14, from day 12 to 35), the results were impressive: an R^2 score of 0.9532 (meaning it nailed about 95% of the variation), a super-low average error (MAE) of 0.0131, MSE of 0.000286, RMSE of 0.0169, and just 1.05% average percentage error (MAPE). That's way better than the usual benchmarks for bio models—like R^2 over 0.90 and MAPE under 5%—showing it could predict FCR with only about 1% off on average.

Looking at the scatter plot (like in Figure 4), the predicted FCR values (from 1.084 to 1.318) lined up closely with the real ones (1.087 to 1.341). Errors were tiny, ranging from 0.0005 to 0.0418 absolute, or 0.04% to 3.76% relative. It shone brightest in the sweet spot of normal FCR (1.15 to 1.30), with just a bit of under-guessing low values and over-guessing high ones—but nothing that would mess up real farm decisions.

The residual plot (Figure 5) backed up how trustworthy the model is: errors scattered randomly around zero (average 0.006, spread of 0.016), no weird patterns or growing variances, which means it's consistent. About 92% of those errors stayed within two standard deviations (±0.032), pretty much like a normal bell curve. Only 8.3% were bigger than ±0.035, so it handles the full range of FCR well.

The residual histogram (Figure 6) looked almost perfectly normal, with a slight lean toward positive errors—62% super close (±0.01) and 92% within ±0.02. That points to tight, reliable predictions with a tiny bias (about 0.6% underestimating on average). The absolute errors (Figure 7) skewed right, as expected for good models, with over 70% under 0.015 (top-notch) and nearly 88% under 0.020 (under 2% relative, a solid farm threshold). Low chance of big slip-ups.

For a real-world test, we did a one-day-ahead forecast (Table 8, Figure 8): Using Day 25 data to predict Day 26, it guessed 1.292 vs. the actual 1.287—an error of just 0.005 (0.43% relative). That's under the 2% bar for ag tech, and it fit neatly in the 95% confidence zone (1.286 to 1.299). Proves it's ready for on-the-spot use.

All in all, this beats out older work that stuck to simple yes/no classifications or other animals, setting a fresh standard for crunching actual numbers in smart chicken farming.

Conclusion

This study successfully developed and validated a hybrid TCN-XGBoost model for daily FCR prediction in broiler chicken farming, addressing key limitations in existing research by focusing on numerical forecasting using sequential and tabular data from semi-modern Indonesian farms. By integrating TCN for temporal feature extraction and XGBoost for robust regression, combined with advanced feature engineering and Optuna optimization, the model achieved exceptional accuracy (R^2 = 0.9532, MAPE = 1.05%) and reliability, as evidenced by comprehensive residual and error analyses.

The results underscore the model's practical viability, enabling proactive interventions such as feed optimization, early detection of performance declines, and managerial recommendations based on feature importance (e.g., via XAI techniques like SHAP/LIME). With single-step forecasting errors as low as 0.426%, the framework offers scalable solutions for enhancing profitability and sustainability in broiler production, particularly in resource-constrained settings lacking environmental sensors.

Future work could incorporate real-time environmental data (e.g., temperature, humidity) to further improve predictions, explore multi-horizon forecasting, and deploy the model in mobile applications for on-farm use. This research contributes to precision agriculture by bridging machine learning with poultry management, paving the way for data-driven decision-making in Indonesia's broiler industry.

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