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RESEARCH ARTICLE

# Poultry Chicken Price Forecasting Using GRU–LSTM-Based Hybrid Deep Learning Model

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**Abstract:** The precise poultry chicken price forecasting is necessary to maintain food security and market stability as well as protein demand mitigation in many countries. Existing machine learning-based forecasting models have problems with feature selection, hyper-parameter tuning, linear assumptions, lower accuracy values, and insufficient data integration. Additionally, they did not offer highly accurate and month-based poultry chicken price forecasts. A deep learning (DL)-based framework for 30-day broiler chicken price forecasting is presented in this work. This work makes use of daily data from multiple sources, such as retail prices, feed costs, and macroeconomic variables. The proposed method combines ensemble feature selection, resilient feature engineering, and sophisticated data preparation, and it is optimized using walk-forward cross-validation and Bayesian optimization using Optuna. This work proposed a hybrid DL ensemble technique for monthly poultry price forecasting that combines Long Short-Term Memory (LSTM) networks with the Gated Recurrent Unit method. The proposed model outperforms previous studies by obtaining at least 2% lower MAPE and 10% higher $R^2$ value, with a MAPE score of 3.69% and R-squared value of 0.832. The feature contribution is explained in this work for forecasting using SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) methods.

**Keywords:** poultry price forecasting, deep learning, LSTM, explainable AI

## 1. Introduction

The growing demand for reasonably priced animal protein around the world emphasizes how crucial accurate broiler chicken price forecasting is to maintaining market stability and food security. Because of its low cost and broad appeal, broiler chicken has become a mainstay in many cuisines around the world, especially in developing countries like Bangladesh, where its consumption is continuously increasing [1]. However, due to a complex interaction of factors like feed costs, supply chain interruptions, and macroeconomic indicators, prices in this sector show a great deal of volatility [2, 3]. For many stakeholders like poultry farm owners and general buyers, accurate and trustworthy broiler price forecasting models are not only advantageous but also essential [4, 5]. Accurate understanding of future supply and demand dynamics aids market planners in maintaining market equilibrium and minimizes the need for costly interventions or possible instability that raises operating expenses [4]. With accurate estimates, developers, farmers, and investors can determine the best locations for future chicken farms, guaranteeing higher returns on investment. In areas like Bangladesh, where changes in food prices can have a major influence on household purchasing power and living standards, the issue is especially pressing [1].

It is intrinsically difficult to forecast broiler chicken prices across short timeframes (such as 30 days) and under a variety of market situations, particularly in a dynamic nation like Bangladesh. Accurately handling these complications calls for sophisticated methodologies. The limitations of current forecasting techniques stem from their dependence on univariate historical data, frequently neglecting a variety of external factors such as macroeconomic interactions and feed cost indexes [5]. They mostly employ linear statistical models, such as AutoRegressive Integrated Moving Average (ARIMA) and Structural Time Series Models (STSM), which are deficient in sophisticated machine learning (ML) or deep learning (DL) approaches and have trouble with nonlinear dynamics [5–7]. Additionally, due to geographically focused datasets, these methods struggle to generalize across diverse locations, fail to adequately address nonlinear relationships and complex patterns in volatile agricultural prices, and exhibit limited feature engineering beyond basic lags and seasonality [8–11]. Furthermore, certain ML-based techniques that have already been developed [3, 5–7, 9] lack transparency in model interpretation and thorough feature integration. The current poultry chicken price forecasting model has very low accuracy and large MAE and MAPE error levels. The monthly poultry chicken price predictions with high accuracy and advanced feature selection method were not simultaneously demonstrated in the previous works [12–15]. Existing works [16–19] did not explain feature contributions to the final result using explainable AI (XAI)-based methods (e.g., SHAP, LIME). Additionally, they

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failed to gather accurate data on poultry item prices from trustworthy sources [20–22]. This paper delivers a hybrid DL-based monthly poultry chicken forecasting system with improved accuracy and error values in order to address these problems. This work's primary contributions are listed below:

1) This study creates a multi-source dataset that incorporates broiler retail prices, comprehensive feed costs, and important macroeconomic factors for the purpose of forecasting broiler chicken prices in Bangladesh.
2) A wide range of engineered features, such as price dynamics, custom lagged indicators, rolling statistics, derived feed cost metrics (such as USD impact features and protein-weighted index), detailed holiday features unique to Bangladesh, and interaction terms, are developed and applied by the proposed feature engineering method.
3) Using a multi-criteria ensemble feature selection methodology, this paper integrates the Recursive Feature Elimination (RFE) method, Granger causality, Principal Component Analysis (PCA), mutual information, and correlation analysis. By methodically identifying the most pertinent features, this work lowers dimensionality and improves the interpretability and performance of the model. After analyzing many ML and DL models, the best forecasting model is selected for a 30-day broiler price prediction. To attain the best model performance, hyperparameter optimization is carried out utilizing Bayesian optimization with Optuna and walk-forward cross-validation.
4) The proposed DL-based forecasting model, which uses a hybrid ensemble of Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM) models, is compared to previous studies in terms of accuracy and error metric value. The significance and impact of the features on the model choice are explained using XAI techniques (SHAP and LIME).

Related studies on poultry chicken price forecasting are highlighted in Section 2. The proposed system model for forecasting poultry chicken prices is covered in Section 3. The results of the performance review are described in full in Section 4. The work's conclusion, including key findings and recommendations for further research, is presented in Section 5.

## 2. Literature Review

A thorough analysis of the literary works on broiler chicken price forecasting is given in this section. Up to 70% of production expenses in Turkey are related to feed, and prices are heavily influenced by soybean and wheat prices [3]. Similar to this, feed costs account for over 65% of broiler production costs in Malaysia [2]. Overall pricing levels are significantly impacted by general economic factors, such as inflation and producer price indices, which also have an effect on consumer purchasing power and company profitability [1].

In economies like Sri Lanka and Indonesia, seasonal demand patterns—which are frequently linked to holidays—also contribute to steady price increases [7, 18]. The article in [3] employed boosting regression, an ML ensemble method, to predict broiler chicken prices. They did not use any feature engineering and tuning techniques. This study in [4] used ARCH-GARCH models to predict broiler prices. An ARIMA model was used in [5] to forecast Egypt's monthly broiler prices. For price forecasting, the previous works did not, however, make use of elements like comprehensive feed cost indexes or particular macroeconomic dynamics outside of inflation. The STSM technique for monthly chicken meat price forecasting with trend and seasonal components was the main focus of the study in [6]. The ARIMA and SARIMA models for broiler, curry chicken, and egg prices were the primary models used in the paper in [7]. In order to analyze the price of chicken products in Sri Lanka, they primarily concentrate on nominal and real prices as well as fundamental time series components. Linear statistical models were the main focus of their work. They didn't employ any sophisticated DL and ML methods. They didn't employ any appropriate feature engineering methodology. In [8], Vector Autoregression (VAR) Models and Autoregressive (AR) models for forecasting wholesale broiler prices were compared.

They talked about how, especially for individual chicken parts, simpler AR models frequently perform better than VAR. Additionally, they talked about how VAR's increased complexity does not always result in more accurate forecasts, particularly for short-term projections (up to three months), as accuracy tends to decline after that. The study in [9] used a linear trend forecasting method to predict poultry chicken meat price. For monthly chicken meat prices in Malaysia, this study in [9] used the STSM model, which included trend and seasonal components. Their approach yields extremely poor accuracy results. For forecasting, they didn't use sophisticated ML and DL approaches. They didn't use multi-source feature engineering methodologies with various features, like holiday impacts and feed component ratios. In order to study and anticipate the production and export volumes of poultry meat, the work in [17] employed a number of time series models. SARIMA frequently performed better than the other models in their work. The study in [20] forecasted weekly broiler purchase costs in Poland using the random walk and creeping trend models. They only use adaptive statistical techniques in their work. They didn't forecast prices using sophisticated DL algorithms. Additionally, they did not employ a thorough multi-source feature integration or an appropriate feature selection method. Their price forecasting results have relatively poor accuracy. The study in [23] obtained an Root Mean Squared Error (RMSE) value of 0.295 by predicting broiler weight using an LSTM model. The paper in [24] forecasted cattle prices using GRU with an attention mechanism. Their primary focus was on the prices of beef, mutton, and pork. The LSTM model was employed by the authors in [25] to forecast the growth of broiler chickens. They did not, however, offer any performance analysis value for correctness or mistakes. The study in [26] created a chicken behavior prediction method based on Support vector machine (SVM) and attained a respectable accuracy level of more than 90%. Using the GRU model for food commodity price forecasting, the paper in [27] obtained a MAPE value of 1.2 percent. They didn't forecast the poultry chicken monthly price. In [28], the mortality rate of broiler chickens is predicted using time series models. The study in [29] predicted poultry chicken sickness using a Convolutional Neural Network (CNN) approach based on mobile nets. The work in [30] and [31] used SHAP and LIME techniques for drop coalescence prediction in a microfluidics device. Several crucial features required for projecting poultry prices were not used in the previous works. Their efforts lack sophisticated feature selection and hyperparameter approaches. Additionally, their work's prediction accuracy and error results are insufficient. Additionally, they did not explain how features contributed to the result using XAI methodologies. This study offers a hybrid DL-based monthly poultry price forecasting technique with sophisticated feature selection and explanation capabilities to address these problems.

## 3. Proposed Hybrid DL-Based Poultry Chicken Price Forecasting Framework

This section will cover the system model for the suggested poultry chicken price forecasting scheme.

### 3.1. System design

The proposed system model for poultry chicken price forecasting begins with the gathering of raw daily poultry chicken price data from multiple sources, such as feed costs, broiler prices, and macroeconomic factors, as shown in Figure 1. To ensure a clean dataset, these raw input data are subjected to thorough preprocessing to address noise, missing values, and inconsistencies. Rich predictive signals are then extracted and categorized into rolling statistics, cyclical, lag, and interaction features during a thorough feature engineering phase. To avoid data leakage and guarantee realistic evaluation, the preprocessed data were categorized chronologically into training sets, validation sets, and testing sets.

In order to understand intricate temporal patterns, the hybrid ensemble DL architecture employing GRU and LSTM then takes over, digesting the sequential and multivariate input characteristics with skill. This work uses ensemble feature selection for advanced hyperparameter adjustment and optimal feature selection. By evaluating its performance against other base models, the suggested hybrid model with a high R-squared value and low error rates (such as MAPE) is chosen for forecasting the price of chicken. A strong and transparent forecasting tool is created by this straightforward procedure. The proposed forecasting method combines two different kinds of DL models in the methodology such as a GRU network and an LSTM network.

By combining the advantages of both designs, this ensemble approach enables the system to identify more intricate and varied patterns in the price data for broiler chickens. As a result, forecasts for broiler chicken prices over the following 30 days become more solid, trustworthy, and accurate. The full image of our broiler chicken price forecasting system's operation is shown in Figure 2. The painstakingly preprocessed and manufactured raw data is the

**Figure 1**
**Overview of proposed system for poultry price forecasting**

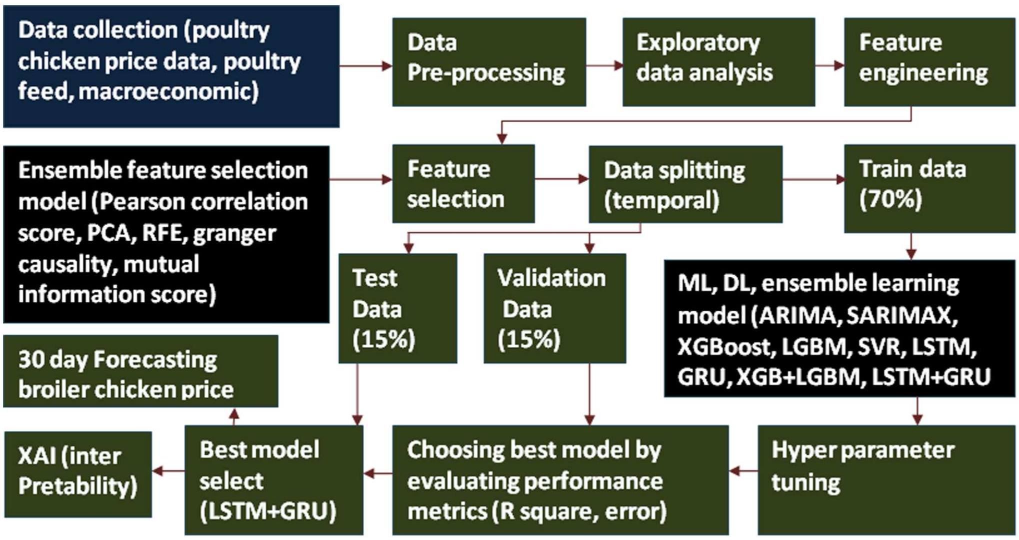
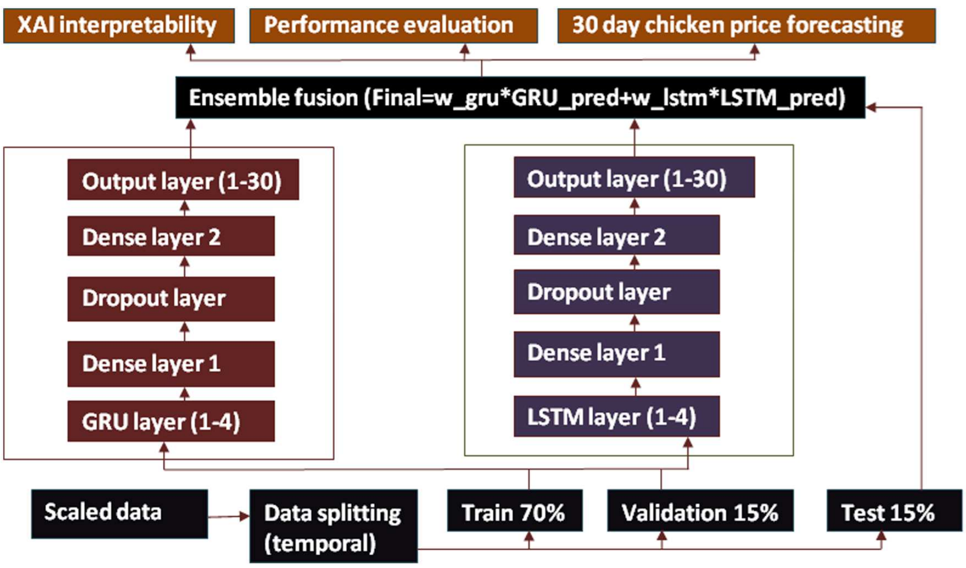



**Figure 2**
**Proposed ensemble DL model**



first step, followed by the training of each individual model and a 30-day ensemble projection. The data is subjected to extensive preprocessing, temporal separation, feature engineering, feature selection, and data transformation. Both the GRU and LSTM models employ the test data for the final performance evaluation after processing the prepared training and validation data in parallel and learning on their own. Both the LSTM and GRU models are designed for regression with multiple outputs. This indicates that all 30 future daily broiler chicken prices are concurrently predicted by each model. Both models produce all 30 predictions as a single vector rather than generating predictions one day at a time (recursive forecasting). In order to maximize the distinct advantages of each model while minimizing their individual drawbacks, hybridization of GRU and LSTM models and ensemble fusion are required in poultry chicken price forecasting. This will enhance the overall accuracy, robustness, and stability of predictions in the unstable poultry chicken price market. The complicated, nonlinear, and volatile nature of poultry chicken prices time series data will be addressed by this hybridization of GRU and LSTM.

## 3.2. Dataset collection, dataset preparation

A comprehensive and diverse dataset serves as the basis for a trustworthy broiler chicken price forecasting algorithm. The dataset is obtained from multiple websites and organizations; that's why we used the multi-source dataset term for this work. To obtain the raw data required for the Bangladeshi market, a multi-source data gathering technique (multiple websites, organizations, and poultry farms) was used for this thesis. The Trading Corporation of Bangladesh's (TCB) official website was used to gather daily retail prices for broiler chicken, the main goal variable (Price (BDT/100 kg)) [21]. The Provita Group, a major feed supplier in Bangladesh, issued official reports that included daily pricing for key feed ingredients such as soybean meal, feed wheat, feed barley, and maize gluten feed [22]. Through online scraping from Trading Economics, daily food inflation rates were gathered, capturing variations that affect the dynamics of the poultry market.

Trading Economics provided the daily data for the crude oil prices (BDT) and the USD/BDT exchange rate (BDT) via direct download. Local broiler prices are influenced by these global statistics, which have a major impact on the cost of importing feed materials and transportation [2, 3]. The forecasting assignment has a granular time series foundation thanks to the raw dataset, which spans from January 1, 2018, to May 30, 2025. Table 1 provides a preview of this dataset. There are 2707 records in the dataset overall. Table 2 displays the dataset's primary variables. A thorough validation procedure was carried out to guarantee the precision and dependability of the gathered dataset.

**Table 1**
**Portion of dataset**

| Serial | Date | Soybean meal (BDT) | Feed wheat (BDT) | Feed barley (BDT) | Maize gluten feed | Price (BDT/ 100 kg) | Food inflation rate | Crude (BDT) | Dollar (BDT) |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 1-1-18 | 4648 | 2429 | 2080 | 3431 | 12168 | 4.90 | 5897 | 84.70 |
| 1 | 2-1-18 | 4647 | 2427 | 2078 | 3430 | 11688 | 4.90 | 5845 | 84.70 |
| 2 | 3-1-18 | 4649 | 2426 | 2082 | 3429 | 11892 | 4.90 | 5668 | 84.70 |
| 3 | 4-1-18 | 4647 | 2428 | 2080 | 3430 | 11722 | 4.90 | 5528 | 84.70 |
| 2705 | 29-5-25 | 4765 | 3031 | 2507 | 2648 | 17250 | 8.60 | 7894 | 122.22 |
| 2706 | 30-5-25 | 4760 | 3030 | 2506 | 2645 | 17500 | 8.60 | 7859 | 122.22 |

**Table 2**
**Primary dataset variables**

| Variable name | Unit | Description (relevance) |
|---|---|---|
| Date | NA | The daily timestamp for each observation |
| Soybean meal (BDT) | BDT | Daily price of soybean meal in Bangladeshi taka |
| Feed wheat (BDT) | BDT | Daily price of feed wheat in Bangladeshi taka |
| Feed barley (BDT) | BDT | Daily price of feed barley in Bangladeshi taka |
| Maize gluten feed (BDT) | BDT | Daily price of maize gluten feed in Bangladeshi taka |
| Price (BDT/ 100 kg) | BDT | The daily retail price of broiler chicken in Bangladeshi taka per 100 kg |
| Food inflation rate | Percent | The daily food inflation rate (percentage) |
| Crude (BDT) | BDT | Daily price of crude oil in Bangladeshi taka |
| Dollar (BDT) | BDT | Daily exchange rate of US dollar to Bangladeshi taka |

The dataset was validated by the four-member expert committee. This dataset validation group's members include a poultry chicken salesman, a university professor, a trade specialist, and a farm owner. This study covered daily observations from January 1, 2018, to May 30, 2025, and performed a thorough Exploratory Data Analysis on the multi-source dataset for broiler chicken price predictions in Bangladesh. Figure 3 shows that the price of broiler chicken generally increased during the period under observation. Plotting moving averages (30-day and 90-day) revealed underlying patterns, indicating the existence of long-term movements as opposed to randomness. To show the nonstationarity and correlation of a time series, plots of the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) were created for each variable in this study.

A strong trend and nonstationarity in the series are indicated by the slow decay of the Broiler Chicken Price ACF plot (Figure 4(a)). With notable spikes mostly at lag 1, the PACF plot (Figure 4(b)) indicates a substantial initial autoregressive component. For many important variables, statistical tests for autocorrelation and stationarity were performed; the findings are compiled in Table 3. The ADF test produced a *p*-value of 0.0145 for Price (BDT/100 kg), which is marginally less than 0.05 and indicates weak stationarity. The ADF *p*-values for the majority of the other important variables, however, were substantially higher than 0.05, suggesting that they were not stationary.

The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test consistently produced a *p*-value of 0.0100 (at 5% significance) for all examined variables, which is below the cutoff and disproves the null hypothesis of stationarity, proving that the series were not. Price (BDT/100 kg), feed wheat (BDT), and crude (BDT) were categorized as inconclusive, whereas the majority of variables were found to be nonstationary when combining the results of ADF and KPSS. The Ljung-Box test consistently produced a *p*-value of 0.0000 for all variables, suggesting that the series had strong autocorrelation across several lags. An additive model was used to conduct a seasonal decomposition of the Price (BDT/100 kg)

**Figure 3**
**Broiler chicken historical price (2018–2025)**

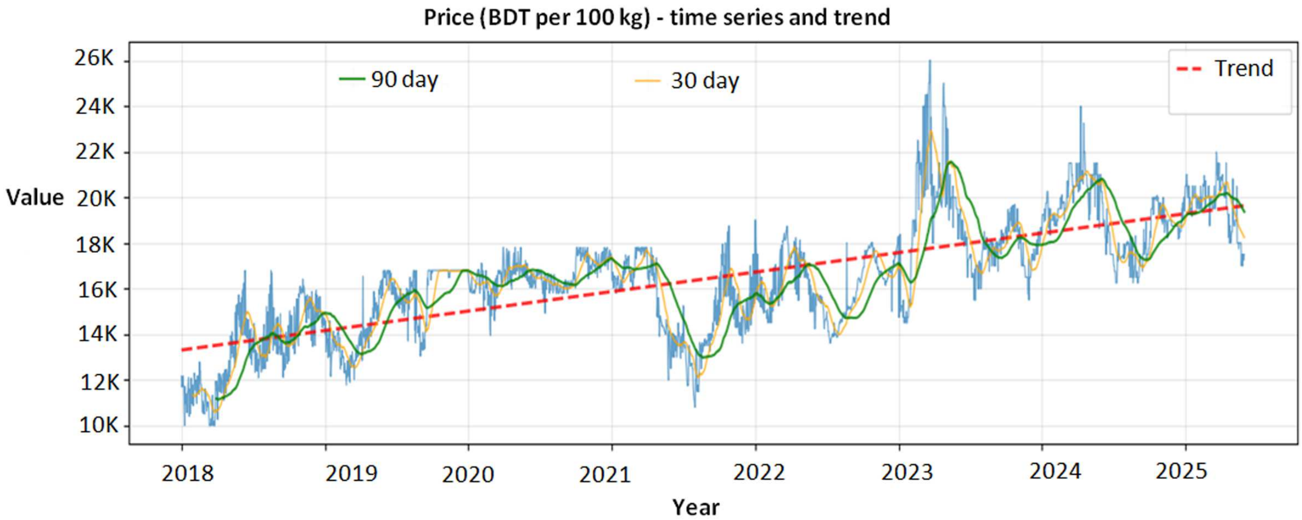



**Figure 4**
**(a) ACF plots for target variable and (b) PACF plots for target variable**

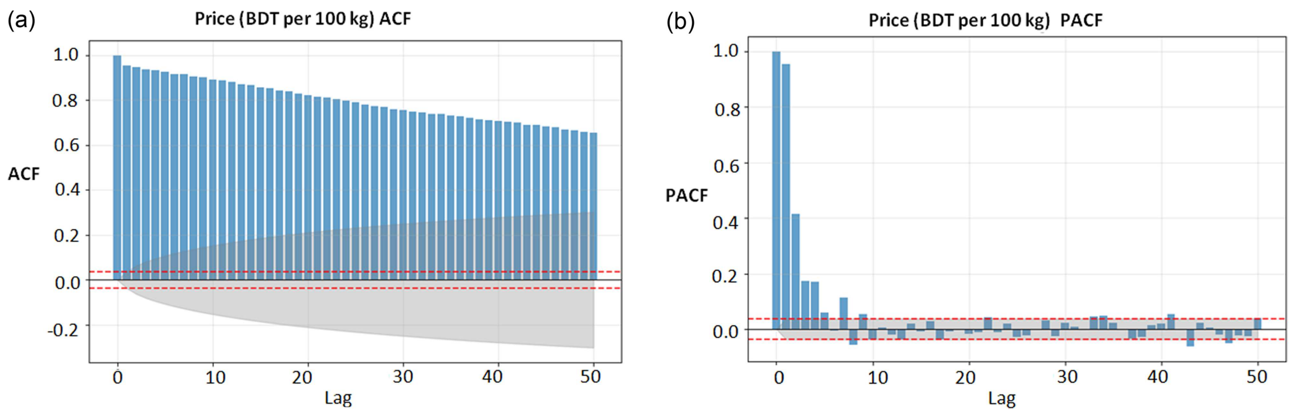


**Table 3**
**Stationary test results for key variables**

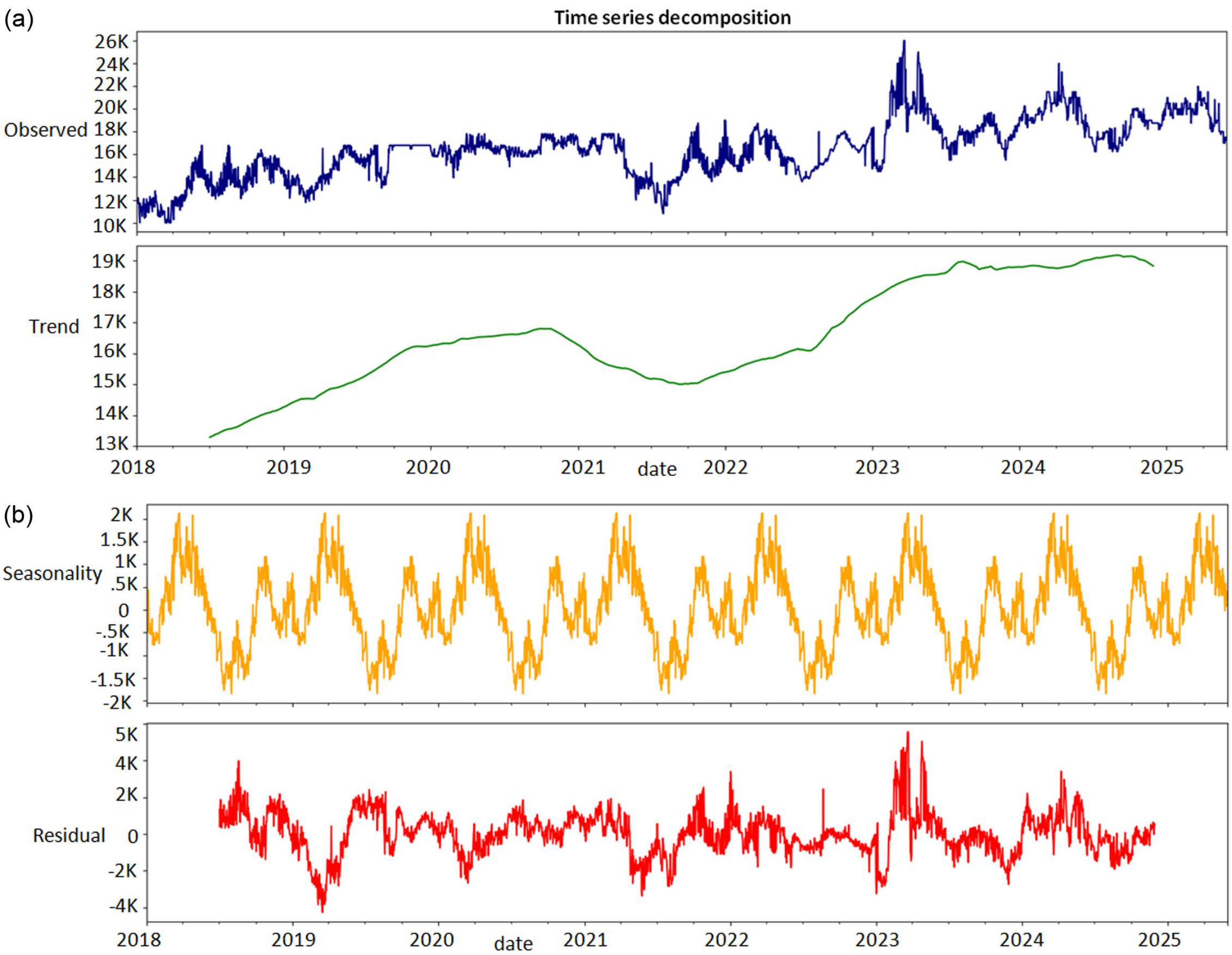
| Variable | ADF stat. | ADF *p*-value | KPSS stat. | KPSS *p*-value | L box *p*-value |
|---|---|---|---|---|---|
| Price (BDT/100 kg) | –3.3 | 0.01 | 0.24 | 0.01 | 0.00 |
| Soybean meal (BDT) | –2.3 | 0.16 | 0.57 | 0.01 | 0.00 |
| Feed wheat (BDT) | –2.9 | 0.03 | 0.22 | 0.01 | 0.00 |
| Maize gluten feed (BDT) | –1.8 | 0.33 | 0.70 | 0.01 | 0.00 |
| Feed barley (BDT) | –2.6 | 0.08 | 0.29 | 0.01 | 0.00 |
| Food inflation rate | –2.2 | 0.19 | 1.04 | 0.01 | 0.00 |
| Crude (BDT) | –3.4 | 0.01 | 0.23 | 0.01 | 0.00 |
| Dollar (BDT) | –1.5 | 0.48 | 0.71 | 0.01 | 0.00 |

feature during a 30-day period, as shown in Figure 5. The observed series was visually divided into its basic elements—trend, seasonality, and residuals—by this decomposition.

### 3.3. Data preprocessing, feature engineering

A uniform preprocessing workflow was used to guarantee data consistency, integrity, and suitability for DL models and time series analysis after the multi-source raw data was retrieved. A date time object was created from the Date column, which is necessary for feature engineering and appropriate time series indexing. Features with varying frequency, such as daily, weekly (like maize gluten feed), and monthly (like Food Inflation Rate) observations, were included in the raw dataset. All weekly and monthly features were transformed to a daily frequency in order to produce the constant, high-resolution daily time series required

**Figure 5**
**Broiler chicken price - time series decomposition**



for granular forecasting. The handling of missing data, which were mostly introduced during the development of rolling and lagging window features, was robust.

The median of each feature column was used to impute missing values throughout the feature selection preparation stage. Because it is less susceptible to outliers than mean imputation, median imputation is a reliable technique that works well with skewed data distributions, which are typical in economic time series. To capture the dynamics of broiler chicken pricing, a wide range of predictive features—including market prices, feed costs, macroeconomic factors, and temporal elements—were developed. Core price features include volatility (e.g., Price_volatility_30d, rolling 30-day standard deviation), absolute changes (e.g., Price_abs_change_1d, 1-day difference), momentum (e.g., Price_momentum_7d, difference from 7-day prior price), and percentage changes of the broiler chicken price feature (30-day percent change). This paper used lagged features based on autocorrelation (ACF) and partial autocorrelation (PACF) analysis to capture temporal interdependence in the data. These contain the 30-day lagged values of the crude BDT and food inflation rate, as well as the 7- and 30-day lags for feed component costs. Short-term trends are summarized by rolling window features. For feed components (such as soybean meal and the 30-day rolling mean), these include the 30-day rolling mean, standard deviation, minimum, and maximum. Feed_Meal_BDT, Feed_Wheat_BDT, Feed_Barley_BDT, and Maize_Gluten_Feed_BDT are the four main feed components whose average costs are combined in the Feed_Cost_Index. Month, Quarter, DayOfYear, WeekOfYear, and DayOfWeek are examples of seasonal features. Bangladesh Features of the Holiday were made in order to provide the holiday effects. These comprise the seven days prior to the festival, the seven days after the holiday, and the holiday itself. Polynomial interactions between feed components are produced for the Statistical and Interaction Features. Inflation_Price_Interaction, for instance, multiplies the rate of inflation for food by price_pct_change_7d. In feature engineering, NaN values are frequently introduced at dataset boundaries by lag and rolling window procedures. This study used a multi-stage imputation technique that included Time-Aware Interpolation, Linear Interpolation, Ratio/Derived Features, and Fallback Imputation to guarantee data completeness for model training.

A number of competitive feature selection techniques, including PCA, Granger causality analysis, correlation analysis, mutual information analysis, and RFE, were used to choose the most pertinent features for training. In order to systematically find the most discriminative predictors for price forecasting, this study made use of a wide range of statistical and model-based feature selection strategies, all of which have their roots in fundamental mathematical concepts. An ensemble aggregation strategy was used to mitigate the specific limitations of the feature selection techniques under consideration (such as Pearson's limitation to linear relationships or PCA's incapacity to directly rank original features) while leveraging their complementary strengths. To generate a final score for every feature, feature rankings from all methods were combined. A collection of highly influential features was methodically selected after this thorough study because of their consistently high scores across all selection criteria. Table 4 provides detailed documentation of the resulting feature subset, which consists of the top 30 features. These features are utilized for final model training and are the result of our ensemble feature selection process. The score is the ensemble feature selection score by checking all feature selection methods. The scores are combined using borda count aggregation.

### 3.4. Model selection, hyperparameter tuning, comparison with existing works

Each split is subject to minimum viable sizes in order to guarantee that there is enough data for reliable training and

**Table 4**
**Top features selection (ensemble feature selection)**

| Feature | Score | Feature | Score |
|---|---|---|---|
| USD feed spread | 0.83 | Maize gluten feed rolling mean 30 | 0.48 |
| Price (30dma) | 0.75 | Price momentum 30d | 0.47 |
| Feed price ratio | 0.74 | Soya bean meal BDT (lag7) | 0.45 |
| Dollar (BDT) | 0.67 | Soya bean meal (BDT) rolling STD 30 | 0.42 |
| Soybean meal BDT (lag30) | 0.60 | Maize gluten feed (lag30) | 0.38 |
| Food inflation rate (lag30) | 0.59 | Days of year | 0.38 |
| Soybean meal BDT (rolling mean 30) | 0.55 | Soya wheat ratio | 0.33 |
| Price volatility (30d) | 0.53 | Week of year | 0.33 |
| Price pct change (30d) | 0.48 | Days of year (sin) | 0.32 |
| Days since last eid) | 0.48 | Feed cost (USD) | 0.32 |
| Feed cost (volatility 30d) | 0.31 | Feed momentum 7d | 0.29 |
| Dollar feed cost index | 0.31 | Soybean mean (BDT) feed wheat (BDT) | 0.29 |
| USD momentum 7d | 0.30 | Feed volatility 30d | 0.28 |
| Price abs change 30d | 0.30 | Feed wheat (rolling mean 30) | 0.28 |
| Feed momentum 30d | 0.29 | Days of year (cos) | 0.28 |

assessment. The datasets for the training, testing, and validation splits are distributed as follows: 70%, 15%, and 15%, respectively. For feature scaling, "StandardScaler" from "scikit-learn" is used. The target broiler prices (for the 30-day forecast horizon) are scaled to a predetermined range (e.g., 0 to 1) using "MinMaxScaler" from "scikit-learn." In regression tasks, this is especially advantageous for neural network output layers. Every benchmark model and the elements of our suggested hybrid ensemble underwent a specific hyperparameter-tweaking procedure to guarantee competitive performance.

To determine the optimal configurations for the benchmark models (ARIMA, SARIMAX, Support Vector Regression (SVR), XGBoost, and LightGBM), extensive optimization was conducted using Optuna with walk-forward cross-validation. Table 5(a) displays the optimal hyperparameters for every benchmark model. Table 5(b) displays the hyperparameters for the suggested hybrid model (GRU and LSTM model) with the NADAM optimizer. To capitalize on the complementary advantages of the GRU and LSTM architectures, this work employs a parallel ensemble technique. This indicates that the LSTM and GRU models are trained concurrently and entirely independently of one another.

During their training phases, they are exposed to the same input data but do not exchange any information. The final ensemble prediction is obtained by combining the 30-day forecasts generated by each model following independent training. Dynamically weighted averaging is the method used to fuse the predictions from the GRU and LSTM models. This approach gives each model a varied weight depending on how well it performed on the validation data, as opposed to just averaging the forecasts equally. The comparison of various models for projecting the price of chicken and poultry is displayed in Table 6. By comparing the performance measures (R-squared, RMSE, MAPE, and MAE) of several learning techniques (e.g., ARIMA, SARIMAX, GRU, LSTM, and hybrid ensemble that combines both GRU and LSTM), the optimal forecasting model is chosen. For poultry chicken price predictions, the hybrid ensemble model (GRU and LSTM) performed the best, with the lowest RMSE (790.74), MAE value (621.80), and MAPE value (3.69%), as well as the highest $R^2$ value (0.832). This supports the idea that integrating different DL architectures can take advantage of their complementary advantages to provide forecasts that are more reliable and accurate. The training and validation loss curves for the GRU and LSTM models in the hybrid ensemble are theoretically

**Table 5(a)**
**Hyperparameters selection for different models**

| Method | Parameters | Values |
|---|---|---|
| XGBoost | N_estimators, maxdepth, learning rate, subsample ratio, colsample, reg_alpha, Reg_lambda | 429, 6, .01, .72, .84, 2.1e$^{-6}$, 5.9e$^{-8}$ |
| ARIMA | Best model orders | (0, 1, 1) |
| SARIMAX | Best model orders | (0, 1, 1) |
| SVR | Kernel, C, Gamma, Epsilon | Linear, 99.60, .01, .28 |
| LGBM | N_estimators, maxdepth, learning rate, subsample, colsample, reg alpha, reg lambda | 249, 4, .03, .83, .81, .01, .02 |

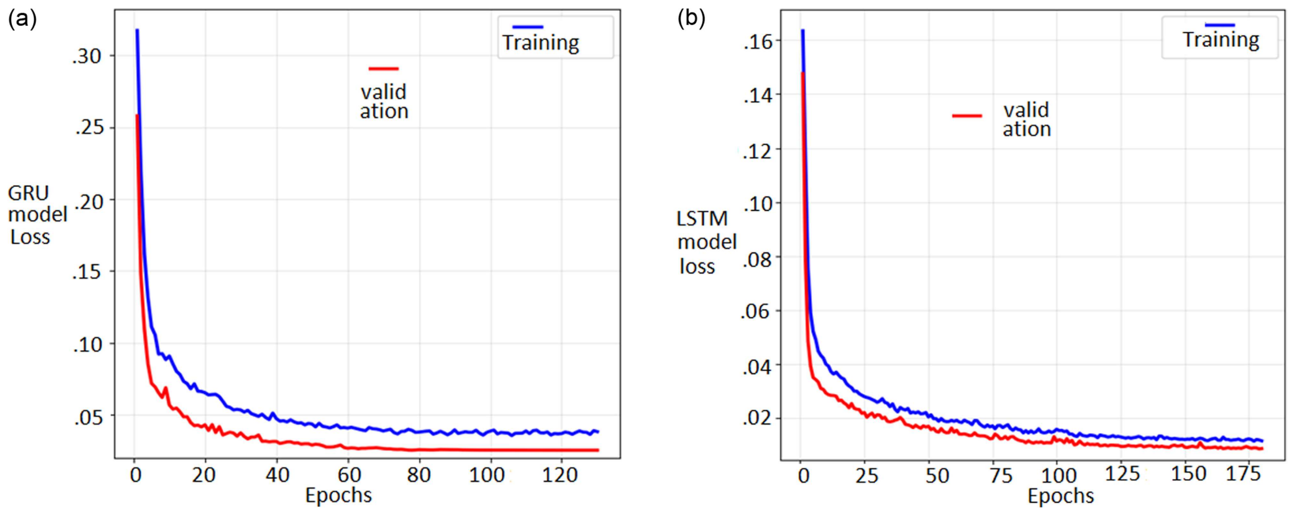
**Table 5(b)**
**Hyperparameters for GRU and LSTM**

| Parameters | GRU | LSTM |
|---|---|---|
| Input layers, recurrent layers, layers (1, 2, 3, 4), dropout, recurrent dropout, dense layer, dense layer (1, 2), dense dropout, output layer | Window size and number of feature, 4, varying (96, 48, 32, 48), .10, .20, 2 layer ReLu, varying (128 and 32), .10, 30 unit (linear activation) | Window size and number of feature, 3, varying (96, 48, 32, 48), .20, .00, 2 layer ReLu, varying (128 and 48), .20, 30 unit (linear activation) |
| Optimizer, learning rate, loss function, batch size, epochs, early stopping, Linear Regression (LR) reduction factor, LR reduction patience | NADAM, .01, MSE, 16, 175, 35, .40, 11 | NADAM, .01, HUBER, 16, 175, 35, .40, 11 |

**Table 6**
**Comparative analysis of forecasting models**

| Model | MAE | MAPE | R-squared | RMSE |
|---|---|---|---|---|
| ARIMA | 1235.70 | 8.35 | 0.59 | 1430.20 |
| SARIMAX | 1170.50 | 7.95 | 0.62 | 1375.30 |
| SVR | 890.60 | 6.30 | 0.69 | 1012.40 |
| XGBoost | 750.50 | 5.69 | 0.74 | 860.35 |

**Figure 6**
**(a) GRU model loss curve and (b) LSTM model loss curve**




depicted in Figures 6(a) and 6(b), respectively. Effective learning is shown by a usually steady decrease in training loss in both models. Additionally, the validation loss first declines before stabilizing, indicating that the models perform well when applied to new data. By stopping training when the validation loss no longer improves noticeably, early stopping mechanisms successfully prevent overfitting and make sure the models don't just memorize the training data. Reliable models are produced by a healthy and controlled training process, as seen by the convergence and stabilization of both training and validation loss. Histograms of the prediction errors (residuals) and a visual comparison of actual and predicted broiler chicken prices are shown in Figure 7. The accuracy of the hybrid ensemble and the distribution of prediction errors over different forecast periods are clearly understood thanks to this image. Longer forecasting horizons typically result in a larger spread of mistakes, as evidenced by the natural increase in prediction dispersion as the forecast horizon moves into the medium and long periods. In spite of this, there is consistently a substantial positive connection between actual and anticipated values throughout all time periods. The residuals are mostly centered on zero, according to the prediction error histograms, indicating that the model makes predictions that are objective. The ensemble model's ability to follow actual broiler chicken prices over a 30-day period within the test set is demonstrated in Figure 8. The main advantage of the suggested hybrid ensemble model, aside from past performance, is its ability to produce future forecasts. The ensemble model shows better forecasts than others. A 30-day poultry chicken price forecast for a future period generated by the proposed ensemble model is shown in Figure 9. By providing a clear forecast of anticipated price movements, this visualization helps stakeholders foresee future market conditions and make appropriate plans. The SHAP analysis for the Day 30 forecast is shown in the next figure. The summary plot (Figure 10) displays feature impacts. The feature importance bar plot (Figure 11) ranks their contributions. Features that represent longer-term patterns, economic cycles, and basic supply-demand balances are what drive the model's

**Figure 7**
**Forecast of actual vs. predicted prices and residual analysis plots**

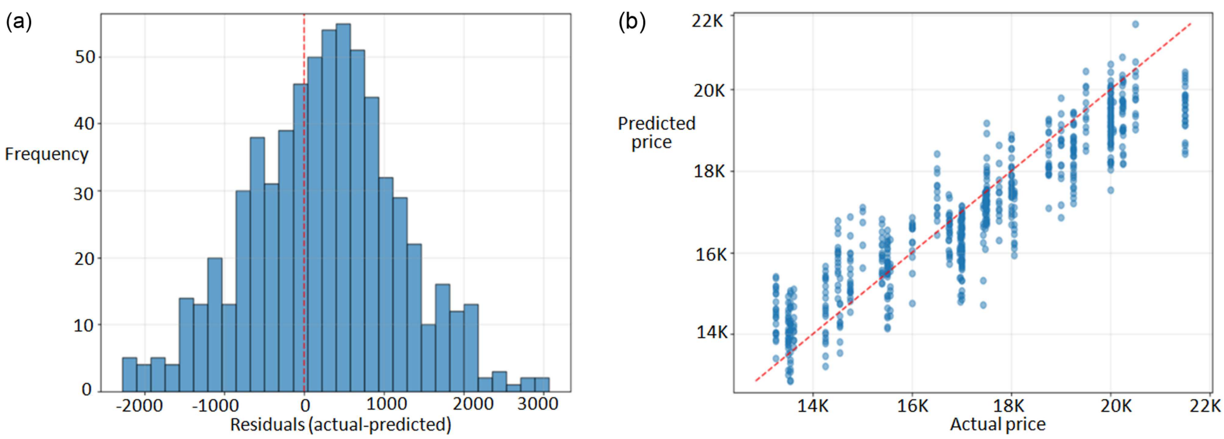


**Figure 8**
**Actual vs. predicted broiler chicken price over time**

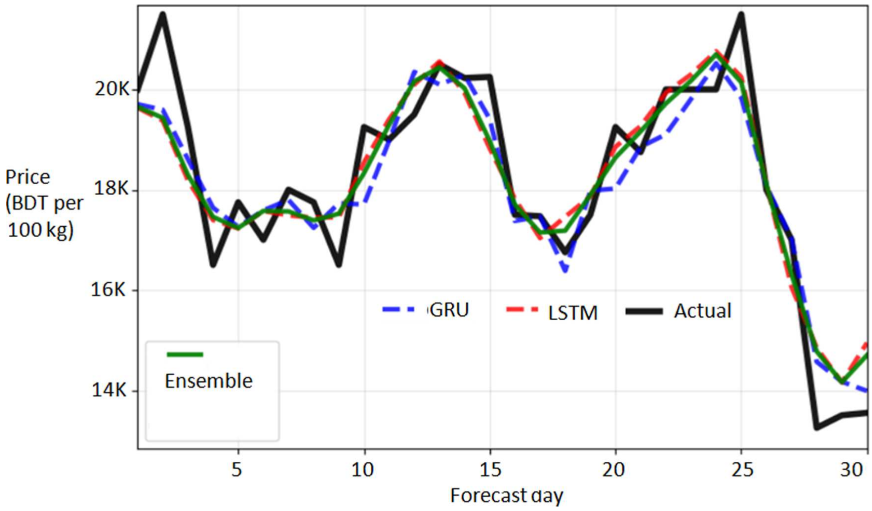
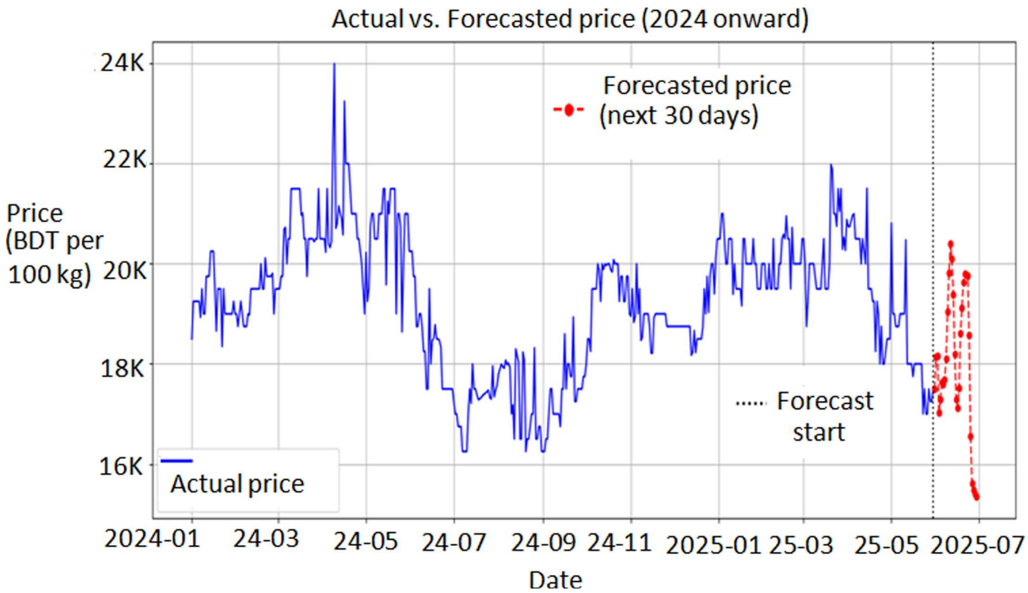



**Figure 9**
**Example of a 30-Day future broiler chicken price forecast**




forecasts at Day 30. Features that have a significant impact include Price_30d_ma, Food_Inflation_Rate_lag_30, Dollar_BDT, and other aggregated feed cost metrics or spreads. Predictable demand changes might also be captured by seasonal cyclical elements (such as the time of year) and particular holiday indicators associated with forthcoming celebrations. This illustrates how the model may incorporate macrolevel variables and extrapolate patterns to produce longer-term forecasts. Figure 12 displays the LIME explanations over the whole 30-day forecast horizon. The influence of longer-term historical price trends (Price_30d_ma), the cumulative macroeconomic consequences of these variables (Food_Inflation_Rate_lag_30, Dollar_BDT), and the impact of certain event-related features like Days_Since_Last_Eid are frequently highlighted in LIME explanations for Day 30. This demonstrates that the model may incorporate more fundamental, wider market dynamics for monthly forecasts. Figure 9 shows the forecast of actual vs predicted prices and residual analysis plots. Each split is subject to minimum viable sizes in order to guarantee that there is enough data for reliable training and assessment.

## 4. Evaluation Results

Table 7 illustrates the comparison results. The proposed DL-based ensemble approach (GRU and LSTM) is contrasted with a few previous studies (e.g., [2, 3, 17]). Three widely used metrics are included in the evaluation: the coefficient of $R^2$, Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The low MAPE of 3.69%, MAE of 621.80, and $R^2$ of 0.832 all demonstrate the improved performance of our hybrid ensemble model using GRU and LSTM. Compared to other

**Figure 10**
**SHAP summary plot for broiler price forecast on Day 30**

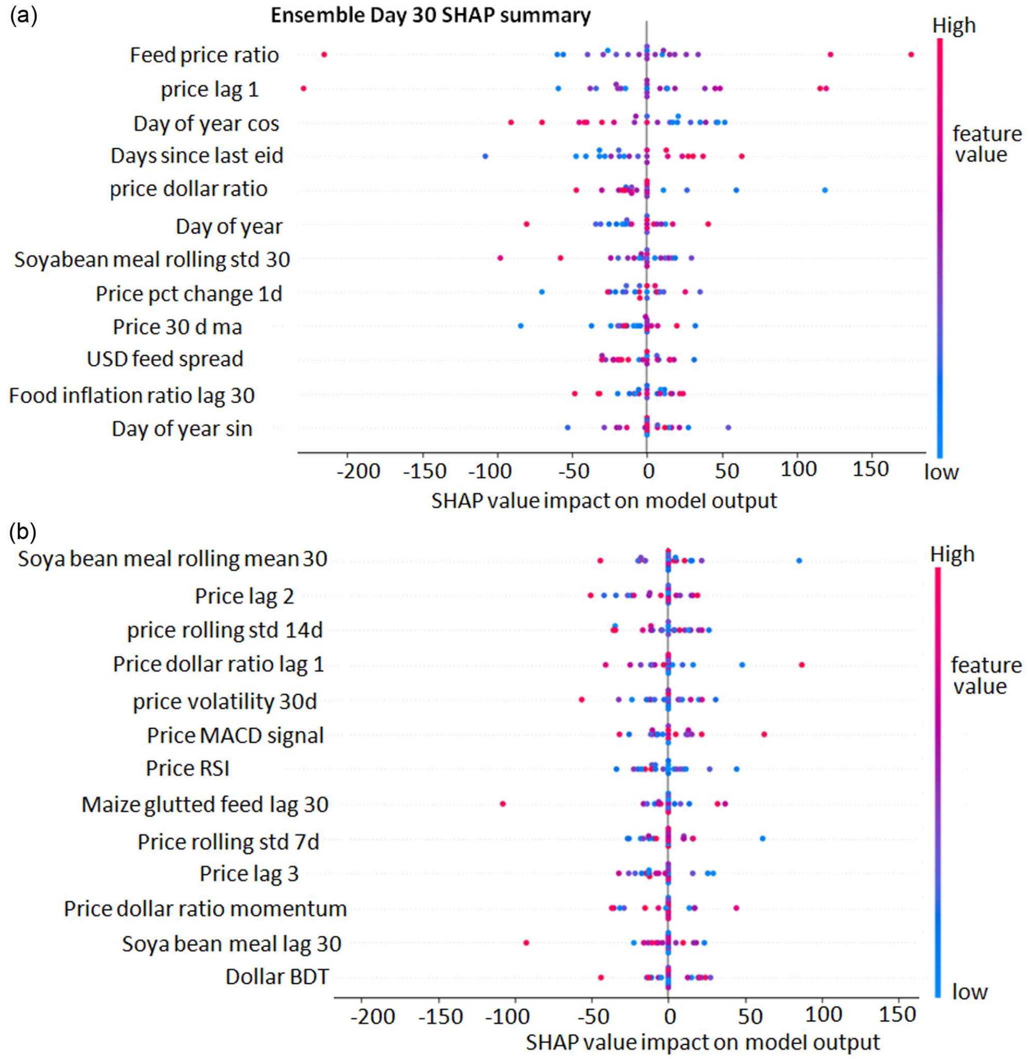
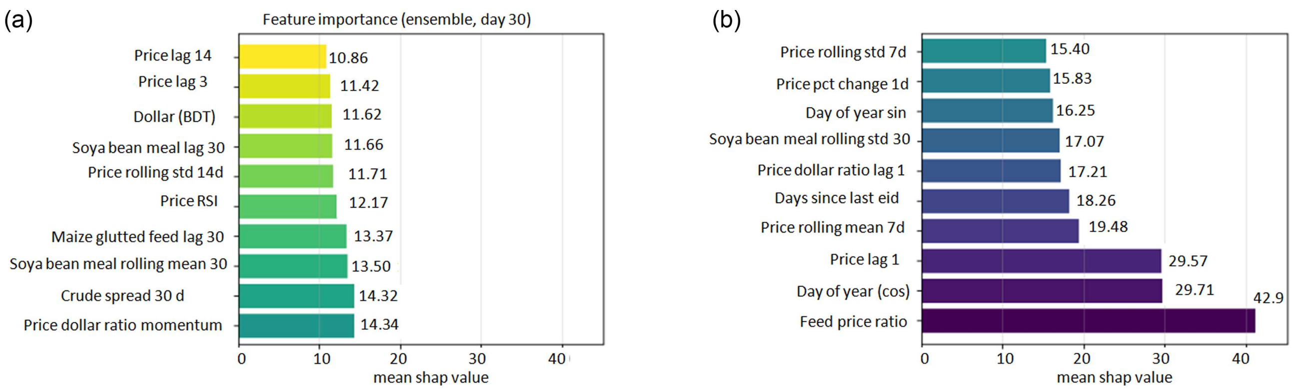



**Figure 11**
**SHAP based feature importance analysis for broiler price forecast on Day 30**




works, the proposed ensemble DL technique delivers a minimum of 10% higher R-squared value and 2% lower MAPE value.

Its sophisticated multivariate analysis, which successfully captures intricate relationships between several factors affecting poultry pricing, is responsible for this. Furthermore, careful feature engineering and selection improve the model's capacity to recognize and rank the most pertinent predictors. The proposed method effectively manages the dynamic and nonlinear price changes that conventional approaches, such as SARIMA

**Figure 12**
**LIME explanation for broiler price forecast on Day 30**

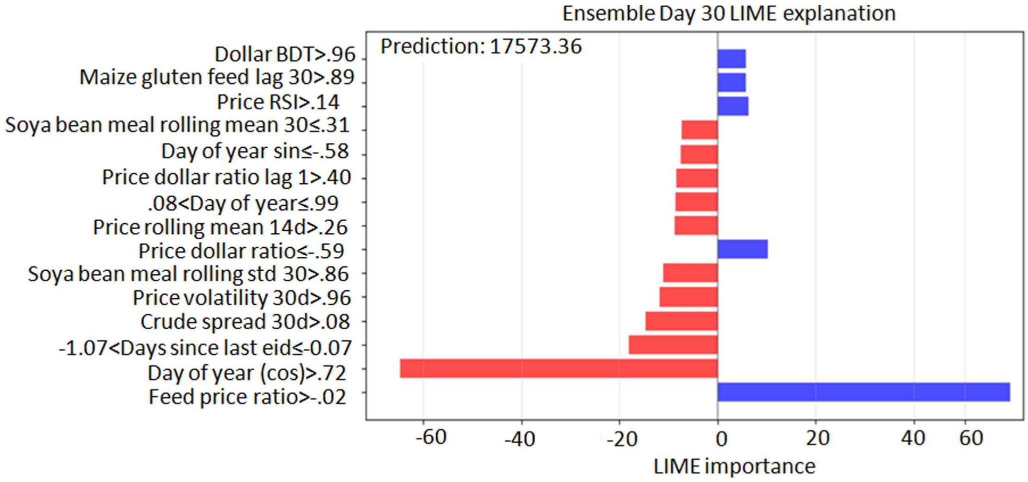



**Table 7**
**Comparison results**

| Study name | Model | MAPE | RMSE | $R^2$ |
|---|---|---|---|---|
| Arikanet al. [3] | Boosting regression | 5.50 | 765.20 | 0.73 |
| Klaharn et al. [17] | SARIMA | 8.33 | 1182.50 | 0.59 |
| Rose et al. [2] | STSM | 7.68 | 995.80 | 0.67 |
| Proposed method | Hybrid Ensemble of GRU+LSTM | 3.69 | 621.80 | 0.83 |

and STSM, frequently find difficult to precisely model by incorporating DL techniques.

## 5. Conclusion

Using a multi-source dataset, this paper developed a hybrid ensemble DL-based framework for broiler chicken price forecasting that combines GRU and LSTM techniques. To guarantee high accuracy and interpretability, the proposed method integrated sophisticated DL architectures, reliable preprocessing and feature engineering methods, the Ensemble feature selection approach, and XAI tools like SHAP and LIME. With a MAPE of 3.69% and an $R^2$ value (accuracy) of 0.832, the proposed hybrid DL ensemble model outperformed all benchmark models—including conventional statistical and classical ML techniques by a substantial margin. Throughout the 30-day forecast horizon, the proposed model's accuracy remained constant, demonstrating its generalizability and dependability for short-term operational planning in the poultry sector. The proposed hybrid DL-based ensemble model outperforms the current works by at least 10% in terms of $R^2$ (accuracy) and at least 2% in terms of MAPE. The incorporation of SHAP- and LIME-based XAI tools improved the model's interpretability and usefulness by offering clear insights into the dynamic influence of important features. The ML model's statistical connections, rather than actual causal relationships in the creation of poultry prices, are reflected in the features that SHAP and LIME identified as influential. Instead of explaining the real-world cause-and-effect relationship, these approaches describe how a model uses features to create a prediction.

Future research challenges could include, among other things, transformer-based poultry market trend analysis, blockchain-based broiler chicken sales data security enhancement, AI and Large Language Model (LLM)-based broiler chicken price inflation reason detection, and IoT and DL-based fraud detection. When applied to poultry markets in other nations, the performance of a hybrid GRU–LSTM model would probably change slightly and could need to be retrained or adjusted to take into consideration various economic drivers and data architectures (e.g., different datasets, data availability, feature importance, model standardization, fine-tuning models, generalizability). Although the hybrid model is excellent at capturing intricate nonlinear time series patterns, there are a number of obstacles to its transferability across various foreign marketplaces. To perform well in new poultry markets, the hybrid GRU–LSTM model would essentially need extensive customization and thorough validation, utilizing the strength of local data and domain experience to adjust to new circumstances. Essentially, even if the hybrid GRU–LSTM architecture is superior to individual models, it is necessary to incorporate external, real-time data to account for the disruption of past price patterns in order to anticipate during unusual events with reliability.

## Recommendations

This work investigated that the hybrid DL model using GRU and LSTM models is suitable for poultry chicken price forecasting work.

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## Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

## Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

## Data Availability Statement

The data that support the findings of this study are openly available in Kaggle at https://www.kaggle.com/datasets/mhchowdhury37/poultry-chicken-dataset-new.

## Author Contribution Statement

**Mohammad Yasin Arafat:** Methodology, Software, Validation, Formal analysis, Investigation, Resources. **Mahfuzulhoq Chowdhury:** Conceptualization, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

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