CHAPTER I
INTRODUCTION

1.1. Background

Chicken is one of the most widely consumed sources of animal protein in Indonesia due to its high nutritional value and relatively affordable price. Its protein and essential amino acid content makes it crucial for meeting the nutritional needs of the community. Broiler chicken meat, also known as broiler chicken, is the main choice because of its abundant availability, easy access to the market, and its tender texture and ease of processing, making it widely consumed both in households and culinary businesses [1].

Official statistics published by the Central Statistics Agency (BPS), per capita chicken consumption in Indonesia continues to increase. In 2023, chicken consumption was recorded at 7.46 kg per capita per year for household consumption and 12.58 kg per capita per year for non-household consumption. Meanwhile, per capita chicken consumption reached approximately 11.41 kg per year in 2024 [2]. This increase in consumption coincides with a corresponding rise in production. In 2024, broiler chicken production reached approximately 3.83 million tons and is projected to increase by 10.95% to 4.25 million tons in 2025, according to the National Food Balance Projection by the National Food Agency (NFA) [3]. The high level of consumption and production makes broiler chicken a strategic national food commodity that requires price stability to remain affordable, especially for lower-middle income communities [4].

East Java Province is a significant contributor to the national broiler chicken industry, both as a producer and consumer. Official statistics published by the East Java Statistics Agency (BPS), broiler chicken meat production in 2024 was recorded at 510,176.96 tons, an increase of approximately 3.40% compared to the previous year [5]. This large contribution makes East Java one of the regions that influences price dynamics at the national level.

Data from the National Strategic Food Price Information Center (PIHPS) reveals that broiler chicken prices in East Java have fluctuated significantly. In 2024, broiler chicken prices rose to around Rp38,338/kg, and in 2025, prices fluctuated again, reaching a peak of around Rp38,500/kg [6]. Unpredictable price fluctuations can impact people's purchasing power when prices rise, and cause losses for livestock breeders and business owners when prices fall due to surplus production.[7]. PIHPS provides food price data obtained through daily surveys in traditional markets and represents average prices at the regional level, thus reflecting actual market price dynamics. In addition to PIHPS, food price data is also available through the Staple Food Availability and Price Development Information System (Siskaperbapo), an information system managed by local governments to monitor the availability and price development of staple foods in various markets. However, this study used PIHPS data because its data collection method is more consistent through surveys of regular traders, making it more suitable for time series data modeling. Therefore, a scientific approach through time series data-based price modeling and prediction is needed to assist livestock farmers, business actors, and policymakers in making more precise and accurate decisions.

Recent years have seen the growing adoption of machine learning algorithms across increasingly applied in various research fields, such as classification, clustering, and prediction. This approach leverages historical data to build predictive models that are more adaptive to changing patterns, including predicting chicken prices [8]. Conventional statistical forecasting techniques, including Autoregressive Integrated Moving Average (ARIMA) and Double Exponential Smoothing, are still widely used in predicting commodity prices. However, research by Agustiyani et al. shows that although ARIMA provides the best results among conventional methods, the model still has limitations in capturing nonlinear patterns and complex price fluctuations [9].

The advancement of deep learning has opened new opportunities in time series data modeling. Long Short-Term Memory (LSTM), as one of the Recurrent Neural Network (RNN) architectures, has the advantage of modeling long-range dependencies and nonlinear patterns in sequential data. Research by Septiajayanti et al. (2025) shows that the LSTM model produces better predictive performance than SARIMA, with a MAPE value of 20.31%, while SARIMA produces a MAPE of 38.6% and is less adaptive to sharp price fluctuations. However, this study still uses standard hyperparameter configurations and does not apply systematic model optimization [10].

The superiority of LSTM has also been demonstrated in various other food commodity prediction studies. Gunawan, Andriani, and Ujianto (2025) demonstrated that LSTM performed better than Support Vector Regression (SVR) and Random

Forest in predicting seasonal chili prices, with an R^2 value of 0.861 [11]. Jaelania et al. (2022) found that LSTM produced a significantly lower error rate than linear regression in predicting national sugar production, making it more effective in capturing long-term temporal patterns [12]. Similar findings were also shown by Hidayat and Wibisonya (2024) in rice price prediction, where LSTM was able to capture long-term trends better with an RMSE value of 0.054 [13].

In addition to model architecture selection, predictive performance is significantly influenced by hyperparameter configuration. Manual hyperparameter determination is often suboptimal, necessitating efficient optimization methods. Particle Swarm Optimization (PSO) is a swarm intelligence-driven optimization technique that is effective in finding optimal hyperparameter combinations in LSTM models. A study conducted by Tanjung et al. (2025) demonstrates that PSO integration substantially enhances the accuracy of agricultural commodity price predictions relative to LSTM without optimization [14]. Furthermore, the application of feature engineering constitutes a salient determinant in augmenting the predictive capacity of forecasting models. Research by Mohammad Tami and Amani Yousef Owda (2024) demonstrates that the incorporation of time-series-derived features, including lag variables, moving averages, and price volatility, can represent price dynamics more informatively and significantly improve the accuracy of LSTM predictions. [15]. On the other hand, model evaluation strategies are also important in time series research. Hutama et al. (2025) showed that Walk-Forward Validation produces more realistic evaluations because it preserves temporal order and prevents look-ahead bias [16].

Although LSTM has been shown to be superior to conventional methods in predicting food commodity prices, most studies still use standard hyperparameter configurations and have not integrated optimization, feature engineering, and specific evaluation strategies for time series data such as Walk-Forward Validation. Furthermore, studies combining LSTM, Particle Swarm Optimization (PSO), feature engineering, and Walk-Forward Validation for broiler chicken price prediction in East Java Province are still limited. Based on this description, this study proposes the application of an LSTM algorithm optimized using PSO, supported by feature engineering, and evaluated with Walk-Forward Validation to predict broiler chicken prices in East Java Province. This approach is expected to produce accurate and stable price predictions, supporting price stability and food security.

1.2. Formulation of the problem

In light of the aforementioned background, the research problem is formulated as follows:

1. How can the Long Short-Term Memory (LSTM) model be employed to predict broiler chicken meat prices in East Java Province?
2. How is the performance Long Short-Term Memory model (LSTM) in predicting broiler chicken prices in East Java Province when assessed using the MAE, RMSE, and MAPE performance measures?
3. How does hyperparameter optimization through Particle Swarm Optimization (PSO) influence the predictive performance of the LSTM model in predicting broiler chicken prices in East Java Province?

1.3. Research purposes

1. Building and implementing a broiler chicken price prediction model using an algorithm Long Short-Term Memory (LSTM).
2. Evaluating model performance Long Short-Term Memory (LSTM) in predicting broiler chicken prices in East Java Province based on MAE, RMSE, and MAPE assessment measures.
3. Analyzing the contribution of hyperparameter optimization facilitated by Particle Swarm Optimization (PSO) to the predictive efficacy of the LSTM architecture in forecasting broiler chicken prices in East Java Province.

1.4. Benefits of research

This study is anticipated to yield the following contributions:

1. Theoretical Benefits
    a. Providing scientific contributions in the development of the application of LSTM and PSO algorithms in food commodity price prediction.
    b. Serves as an academic reference for hyperparameter optimization and feature engineering applications on time series data.
2. Practical Benefits
    a. Providing information on predicted prices for broiler chicken meat as a consideration for breeders and business actors in production and marketing planning.

b. To be a supporting material for local governments in formulating policies on price stabilization and food security.
c. Provide an overview of broiler chicken price trends to the public and relevant stakeholders.

1.5. Scope of problem

The scope and limitations of this study are delineated as follows:

1. This study focuses on predicting the price of broiler chicken meat prices across East Java Province using the LSTM algorithm with PSO optimization.
2. The data used is historical broiler chicken price data sourced from the National Strategic Food Price Information Center (PIHPS) for the period January 2018 to January 2026.
3. The variables used in this study do not include external economic variables such as substitute commodity prices or livestock feed costs, but are limited to features engineered from historical broiler chicken meat price data and calendar information.
4. Evaluation of the LSTM-PSO model was carried out through the implementation of the Walk-Forward Validation framework employing an expanding window strategy.
5. Model performance measurements were performed using evaluation metrics comprising Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE).