I. INTRODUCTION

Rice is the primary food source for the Indonesian population, with over 95% of individuals consuming it as their staple food [1]. Additionally, a significant proportion of the Indonesian population derives their livelihood from rice cultivation [2]. Rice production provides income for approximately 20 million households, or 100 million individuals, in Indonesia [2]. This is corroborated by the fact that the area dedicated to rice cultivation in Indonesia reaches 10 million hectares per year, which is three times the size of the corn harvest area and eight times the size of the soybean harvest area [2]. The size of the harvest area makes Indonesia the third-largest rice-producing country in the world [3]. The substantial quantity of rice production is accompanied by a multitude of risks, including drought, pests, and diseases [4]. These challenges can be mitigated through the application of current agricultural technology and insurance [4]. However, one factor that is difficult to handle is the price of rice [4].

Rice prices tend to change over time [4]. Significant fluctuations in rice prices can influence the decisions of farmers, particularly those engaged in large-scale production [5]. An increase in the price of rice can result in greater profits for farmers [5]. Nevertheless, a decline in rice prices may also result in a reduction in the farmer's profit margin [5]. Therefore, rice price prediction is important because it can help large farmers organize their strategies to maximize their profits [6].

The prediction of rice prices is typically conducted using conventional statistical methods, such as exponential smoothing and Box-Jenkins or Autoregressive Integrated Moving Average (ARIMA) methods [7]. However, conventional statistical methods often prove ineffective when directly applied [7]. These methods necessitate theoretical prerequisites, such as stationarity in the data [7]. Consequently, the data must undergo complex and time-consuming processing before it can be utilized in these conventional statistical methods [7]. In recent years, machine learning and deep learning methods have been employed extensively to predict rice prices. In 2019, Zaw et al. utilized the Back Propagation Neural Network (BPNN) method to predict rice prices in Pyapon village, Myanmar, achieving a prediction accuracy of over 80% [8]. In 2022, Rathod et al. predicted rice prices in India using the Extreme Learning Machine (ELM) method and achieved a mean absolute percentage error (MAPE) value of 0.82 [9]. In 2022, Sanusi et al. predicted local rice prices in Nigeria using the artificial neural network (ANN) method and obtained a root mean square error (RMSE) value of 5628 [10]. In 2021, Wibowo et al. employed the Ridge Regression (RR) method to predict rice prices in Indonesia, resulting in an RMSE value of 0.04 [11]. In 2019, Verma et al. utilized the Neural Network Regression method to predict rice prices in India, with an RMSE value of 105.2 [12].

The results of the literature survey indicate that while some models are already quite effective at predicting rice prices, there is still potential for improvement in the prediction performance of these models. The issue of rice price prediction can be addressed through the Temporal Fusion Transformer (TFT) method. TFT represents a specific instance of the Transformer model employed to forecast time series data. TFT employs a deep neural network (DNN) architecture designed to perform multi-horizon predictions concerning temporal dynamics [13]. TFT employs known covariates as input data when performing multi-horizon prediction [14]. Subsequently, the algorithm uses multi-horizon prediction outcomes to analyze the temporal dynamics [14]. The TFT model exhibits high prediction performance in both short-term and long-term prediction scenarios [14].

TFT is a neural network-based method that requires the setting of hyperparameters. The parameters of the neural network layer significantly influence the accuracy of the predictions. Consequently, hyperparameter optimization in neural networks is essential for achieving optimal prediction accuracy. One method for optimizing hyperparameters is through the use of an architecture optimization algorithm [15]. Optimization algorithms are frequently employed in machine learning and deep learning models to facilitate feature reduction and architectural optimization processes. One optimization algorithm that can be employed for architecture optimization is the Grey Wolf Optimizer (GWO) [16].

The objective of this study is to implement the TFT-GWO algorithm to predict rice prices in Bandung Regency. The GWO algorithm is employed to optimize the architecture of TFT to enhance prediction accuracy, preventing it from becoming trapped in a local minimum. The GWO algorithm functions by emulating the hierarchy and hunting behaviors of grey wolves [16]. The GWO algorithm has been successfully applied in a variety of fields due to its robustness and strong search ability in solving optimization problems [16]. Meanwhile, the TFT model serves as the primary model for predicting rice prices in the Bandung Regency.