CHAPTER I
INTRODUCTION

1.1 Background

The stock market is a vital component of the financial system because it serves as a means of mobilizing public funds and a key indicator of a country's economic performance [1]. Through stock trading, investors seek to generate profits based on their expectations regarding a company's fundamentals, market sentiment, and other external factorsl [2]. Advances in information technology and the integration of global financial markets have led to a significant increase in stock price volatility, making forecasting increasingly complex and crucial in supporting investment decisions [3], [4]. Stock prices not only reflect a company's internal performance but are also influenced by monetary policy, geopolitical conditions, and the non-linear and ever-changing dynamics of the macroeconomy [3], [5].

Stock investment apps currently available generally provide market information, historical data, technical analysis, investment indicators, and various analytical tools that help investors evaluate market conditions and forecast potential stock price movements [6]. This information and these analytical tools serve as the basis for investment decision making [7]. However, most investment apps do not yet provide features capable of accurately predicting stock prices because stock price movements are influenced by various dynamic and complex factors. Buczynski et al. demonstrate that many stock prediction models that perform well in research environments may not necessarily maintain the same level of accuracy in real market conditions [8]. Therefore, the various information and analytical tools available in investment apps serve more as aids to support investment decision-making rather than as definitive predictors of future stock price movements [8].

Traditional statistical methods such as ARIMA and VAR, which were commonly used in the past, are unable to capture nonlinear relationships or structural changes in financial data, particularly under volatile market conditions [4], [9]. Conversely, advancements in machine learning and deep learning technologies have opened new opportunities for analyzing complex patterns in the stock market, with models such as LSTM, GRU, and Transformer proving superior at recognizing long term dependencies in time series data [10], [11]. Although

LSTM and GRU perform well, these models remain limited in interpretability and are less effective at handling large-scale multivariate data with dynamic relationships between variables [1]. To address this, the Temporal Fusion Transformer (TFT) model was developed, combining the sequence modeling capabilities of LSTM with the Self-Attention mechanism of the Transformer, thereby enabling it to capture both temporal and inter-feature patterns simultaneously [1]. The main advantages of TFT lie in two aspects: first, the Variable Selection Network, which can select the most relevant variables at each time point; and second, the interpretable attention mechanism, which can explain the contribution of each variable to the prediction results, making it ideal for financial applications that demand transparency [3], [12]. Previous studies have shown that TFT outperforms in various domains, such as multinational GDP forecasting and energy price movements, with improved accuracy compared to baseline models like LSTM and standard Transformers [13], [14].

In the context of the stock market, research by Hartanto et al. shows that the Temporal Fusion Transformer (TFT) is capable of achieving an SMAPE of 0.0022 on Indonesian stock data from Yahoo Finance, demonstrating superior performance in predicting short-term fluctuations [14]. Similar findings by Yang et al. and Laborda et al. also confirm the superiority of TFT in multi-horizon forecasting involving numerous dynamic features, making it an efficient and accurate model for predicting stocks in emerging markets [3], [4]. However, most previous studies have focused only on a single sector or a single time horizon, thus failing to test TFT's ability to generalize across different sectors and horizons [2]. In fact, investors require a short-term, multi-dimensional perspective for trading decisions and a medium-to-long-term perspective for portfolio management, which can be provided through a multi-horizon forecasting approach [1], [15]. On the other hand, state-owned enterprises in Indonesia play a strategic role in the national economy because they span various key sectors such as banking, energy, and telecommunications. Each sector has distinct volatility characteristics: the energy sector is influenced by global commodity prices, the banking sector by interest rates and monetary policy, while the telecommunications sector is shaped by digital transformation and infrastructure policy [16], [17], [18].

In the banking sector, previous research indicates that although Bank Mandiri (BMRI) and Bank Rakyat Indonesia (BBRI) are both state-owned banks listed on the Indonesia Stock Exchange, they possess distinct fundamental characteristics and risk profiles, particularly regarding credit portfolio structure, market segments, and sensitivity to macroeconomic conditions [19]. A comparative study by Sasono et al. indicates that differences in indicators such as Return on Assets (ROA) and Net Interest Margin (NIM) reflect variations in business models and performance stability among these state-owned banks [19]. Therefore, Bank Mandiri was selected to represent the banking sector in this study because it has a more balanced portfolio across retail, commercial, and corporate segments, thereby better representing the general characteristics of the banking sector and minimizing subsectoral bias in the evaluation of cross-sector forecasting models [19].

In the telecommunications sector, the most representative state-owned enterprise (SOE) for which data is available for stock price analysis in the capital market is PT Telekomunikasi Indonesia (Persero) Tbk (Telkom). Telkom is the largest telecommunications company in Indonesia and plays a strategic role in the national economy through the provision of communication services and digital infrastructure [20]. Telkom shares are listed on the Indonesia Stock Exchange under the ticker symbol TLKM, making them suitable for use as the subject of stock price time series analysis [20]. In this study, shares of PT Perusahaan Gas Negara Tbk (PGAS) were selected to represent Indonesia's energy sector because it is one of the major energy companies listed on the Indonesia Stock Exchange, with stock prices that reflect the volatility dynamics of the energy market—influenced by global commodity prices, energy demand, and national energy policies. This makes PGAS a suitable subject for evaluating the performance of forecasting models in a sector characterized by high volatility [21], [22]. These differences require a model capable of adapting to cross-sectoral data heterogeneity to ensure that the resulting predictions remain accurate [12], [23].

In addition to differences in fundamental characteristics across sectors, the patterns of stock price movements also exhibit varying dynamics within each sector, reflecting that the relationships among stocks are heterogeneous and depend on the structure of the sectoral market [24]. Energy sector stocks tend to experience sharp fluctuations with high volatility due to sensitivity to global commodity prices such as oil and gas, as well as other market uncertainty factors [25]. Meanwhile, the banking sector generally exhibits more stable movements but is responsive to changes in monetary policy, interest rates, and macroeconomic indicators that affect profitability and investor expectations within the sector [26]. On the other hand, the telecommunications sector often exhibits lower volatility compared to other sectors due to its more stable business nature, driven by technological factors and long-term infrastructure policies [27].

These differences in price movement patterns mean that a forecasting model performing well in one sector may not demonstrate the same stability when applied to another sector, particularly when dealing with heterogeneous and complex time-series data [28]. Therefore, it is important to evaluate not only the accuracy of predictions but also the stability and consistency of the model's performance in the face of cross-sector stock price dynamics, including the model's ability to capture both short- and long-term temporal patterns [29]. This testing is relevant for assessing the extent to which the Temporal Fusion Transformer (TFT) can adapt and maintain its performance on data with heterogeneous fluctuation characteristics, as the TFT is a deep learning architecture specifically designed for multivariate time series forecasting [14]. In addition to cross-sectoral aspects, the time dimension is also a critical factor in stock forecasting research. Prediction errors generally increase as the time horizon lengthens due to the accumulation of errors and unpredictable market fluctuations [3], [13]. Therefore, models capable of maintaining performance stability across various time horizons, such as the TFT, offer a potential solution to this challenge [1], [4]. Recent studies, such as those conducted by Lim et al. and Bai et al., show that multi-view and spatio-temporal Transformer approaches can improve the reliability of predictions for many stocks simultaneously, but they have not yet been widely applied in the Indonesian market. In addition, research conducted by Pinyu et al. demonstrates that combining technical data and financial news can improve model interpretability; however, this approach has not yet leveraged the more stable TFT architecture in a multi-horizon setting [30].

In addition to model architecture design, the hyperparameter optimization process also plays a crucial role in improving the performance of deep learning models for stock price forecasting tasks. Parameters such as learning rate, batch size, number of hidden units, and attention heads significantly influence prediction results [31]. One effective recent approach is Optuna, an automated hyperparameter optimization framework based on Bayesian Optimization and the Tree-structured Parzen Estimator (TPE) that can adaptively find optimal parameter combinations [32]. Research by Shekar et al. and Stefano et al. demonstrates that using Optuna can significantly improve the accuracy of Transformer and LSTM models compared to conventional grid search [33], [34]. Therefore, the integration of Optuna Optimization with the Temporal Fusion Transformer architecture in this study is expected to yield the best model configuration for each time horizon, thereby enhancing the stability and accuracy of cross-sector stock price predictions. Thus, this study aims to apply and evaluate the Temporal Fusion Transformer (TFT) model optimized using Optuna for multi-horizon stock price forecasting for state-owned enterprises (SOEs) across various sectors in Indonesia using data from Yahoo Finance. The approach involves training the model separately for each stock from different sectors to evaluate the performance and stability of predictions within each sector. The objective is to test the model's ability to generalize across sectors while measuring the stability of performance across different time horizons.

1.2 Research Questions

Based on the background described above, the research questions to be examined in this study can be formulated as follows:

1. How can the Temporal Fusion Transformer (TFT) model be applied and optimized using Optuna to forecast stock prices of state-owned enterprises across sectors in Indonesia?
2. How does the TFT model perform in multi-horizon forecasting, specifically predicting stock prices in the short, medium, and long term?
3. How does the predictive performance compare across SOE sectors to assess the model's generalization ability regarding different sector characteristics?

1.3 Research Objectives

The objectives of this study are designed to address the research questions outlined above, as follows:

1. Apply and optimize the Temporal Fusion Transformer (TFT) through hyperparameter tuning using Optuna for multi-horizon forecasting of stock prices across various sectors of state-owned enterprises.
2. To evaluate the performance of the TFT model across various time horizons using evaluation metrics such as MAE, MAPE, SMAPE, and RMSE.
3. To analyze differences in prediction results across sectors to assess the model's generalization ability regarding distinct sector characteristics.

1.4 Research Benefits

This study is expected to provide several benefits, including:

1. Making an academic and methodological contribution through the application of the Temporal Fusion Transformer (TFT) model, optimized with Optuna, for stock price forecasting in Indonesia.
2. Providing practical insights for investors, capital market analysts, and financial system developers in utilizing deep learning models to support data-driven investment decision-making.
3. Demonstrating the potential of multi-horizon forecasting as a more comprehensive approach to projecting stock prices over different time horizons.

1.5 Scope of the Study

To ensure that this study is well-directed and focused, the following scope limitations have been established:

1. The research data used consists of historical daily stock price data for state-owned enterprises (SOEs) listed on the Indonesia Stock Exchange (IDX), namely PT Telkom Indonesia (Persero) Tbk (TLKM) from the telecommunications sector, PT Bank Mandiri (Persero) Tbk (BMRI) from the banking sector, and PT Perusahaan Gas Negara Tbk (PGAS) from the energy sector. The data was obtained through the Yahoo Finance platform.

https://finance.yahoo.com/quote/TLKM.JK/
https://finance.yahoo.com/quote/BMRI.JK/
https://finance.yahoo.com/quote/PGAS.JK/

2. This study uses only technical variables namely open, low, high, close, adjusted close, and volume along with temporal features, without incorporating macroeconomic factors.
3. The tested forecast horizons include short-term, medium-term, and long-term periods in accordance with the concept of multi-horizon forecasting.
4. The model used is limited to the Temporal Fusion Transformer (TFT) as the primary model and does not compare it with all other deep learning models beyond the selected baseline.
5. The data period is limited to the last 5 years, so the forecast results only reflect patterns during that period and do not incorporate older historical data.
6. This study focuses solely on predicting closing stock prices as the target variable; therefore, it does not include predictions of opening prices, high prices, low prices, or intraday movements.
7. Stock price predictions in this study are limited to the next 15 days based on available historical data.
8. The visualization of the prediction results was developed and run in a local environment (localhost) using a Streamlit-based application and does not include deployment or hosting on a server or cloud platform.