I. INTRODUCTION

Social media today not only serves as a platform for sharing information but also reflects various sentiments in society. Twitter, which is now known as X, is one of the leading social media platforms that are being used to express aspirations, ideas, criticism, and even political agendas [1]. With over 327.9 million active users and one of the most frequently used social media platforms [2], X has become highly influential in shaping public sentiment.

The diversity of public sentiments makes the X platform a highly potential source for sentiment analysis. Sentiment analysis is a method of identifying positive and negative opinions [3]. Sentiment analysis can be applied not only to movie reviews [4], [5], [6], and hotel reviews [7], [8] but also to public opinions on Presidential Elections [9], [10], [11].

Several studies on sentiment analysis have implemented deep learning methods such as CNN[12], [13], achieving accuracy rates of 89.39% and 87%, while BiLSTM achieved an F1-score of 92.18% [7]. Moreover, hybrid deep learning models combining both CNN-BiLSTM have been applied for sentiment analysis. For example, research [14] employed CNN-BiLSTM with Word2Vec as word embedding, and another study [9] utilized CNN-BiLSTM with Glove as word embedding, both achieving accuracies of 91.48% and 95%, respectively. In [14], the combination of CNN and BiLSTM outperformed other individual models like LSTM, CNN, and BiLSTM. This is because the combinations of both methods use each model's advantage. CNN excels at extracting local features as much as possible from the text, while BiLSTM, unlike LSTM, can capture local distance dependencies in both directions, from front to back and back to front. BiLSTM also can keep the chronological order between words and documents, making BiLSTM ignore unnecessary words using the delete gate [15].

From the recent use of word embedding, the objective of implementing word embedding is to reduce the word mismatches caused by character limitations in writing tweets. Word embedding may serve as a feature expansion and potentially enhance sentiment analysis accuracy [16]. FastText, Glove, and Word2Vec are frequently employed as word embeddings; however, FastText achieved the highest precision value of 83.83% [17]. Besides word embedding, CNN-BiLSTM as hybrid deep learning uses optimization such as Particle Swarm Optimization [18].

As mentioned earlier, research related to sentiment analysis has applied hybrid deep learning with the use of word embedding. This significant contrasts with research on sentiment analysis related to presidential elections, which still uses machine learning approaches such as Gradient Boosting and Stacked Ensemble [9], achieving 88.20% accuracy, SVM [10], [11] with 79.94% and 60% accuracy, and Naïve Bayes Classifier [10] with 44.94% accuracy.

Considering that, to the best of our knowledge, there is a gap in the application of sentiment analysis methods related to the Indonesian Presidential Election which still predominantly uses machine learning. In contrast, other topics have advanced to deep learning and hybrid techniques with optimization and feature expansion. It is important to update the sentiment analysis methodology on this topic to keep pace with the existing advancements

Therefore, the main contribution of this research is the implementation of sentiment analysis using a comprehensive model that incorporates hybrid deep learning, feature expansion, optimization, and hyperparameter tuning on a dataset of Indonesian language tweets for the 2024 Indonesian Presidential Election. This research uses a hybrid deep learning model that combines CNN and BiLSTM, with FastText being employed for feature expansion. Additionally, PSO in this research is used for optimization to enhance the model's performance, and hyperparameters can be used to determine the optimum model parameter setting.

The paper is structured as follows: Section II presents the result from related work. Section III describes the research methodology that outlines the model architecture, crawling data stage, labeling data, data preprocessing steps, feature extraction using TF-IDF, and feature expansion with FastText. The results and discussion are explained in Section IV. Last, the results of the research and suggestions for further research are provided in Section V.