1. Pendahuluan (*Introduction*)

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition that affects early childhood communication skills, such as responsiveness and eye contact [20]. Failure to address these challenges, as highlighted by Harumi et al. [9], can lead to adverse outcomes like depression and suicidal thoughts, underscoring the urgency of providing effective interventions and support for individuals with ASD.

In 2018, the Centers for Disease Control and Prevention (CDC) reported that approximately one in forty-four children in the United States, totaling an estimated five million, were diagnosed with autism. The male-to-female ratio for autism diagnoses was found to be four to one [7]. Indonesia currently lacks official documentation regarding the prevalence of autism. However, according to a report released by Statistics Indonesia (Badan Pusat Statistik), approximately 140,000 individuals under seventeen in 2016 were diagnosed with autism. [30].

The conventional approach for diagnosing autism involves administering questionnaires such as the Autism Spectrum Quotient (AQ-10) and the Quantitative Checklist for Autism in Infants (Q-CHAT-10) [3, 2, 21, 16]. Relying solely on questionnaires is deemed inadequate for confirming a diagnosis. Therefore, it is imperative to integrate machine learning algorithms to guarantee precise evaluation.

Facial recognition methodologies have been utilized to identify autism within image datasets, including those procured from Kaggle. The images undergo processing by extracting colors, resizing to a standardized resolution, and partitioning into the train, validation, and test sets. Diverse algorithms and configurations are employed in the field, with research consistently indicating that convolutional neural network (CNN) models such as VGG16, VGG19, and MobileNet implemented in Keras exhibit superior accuracy compared to conventional machine learning algorithms [5, 11, 1].

The Long-Short Term Memory (LSTM) algorithm is a Recurrent Neural Network (RNN) type that has gained recognition for its high precision in classifying sequential datasets. The technique, as mentioned earlier, has been effectively implemented in diverse fields, including but not limited to arrhythmia detection [6], voice-to-text conversion [29], and identification of COVID-19 from X-ray images [14]. The comprehensive architecture of the LSTM model is illustrated in Fig. 1 of Khalil's scholarly article [17]. Nonetheless, applying direct LSTM algorithms for autism detection via facial recognition has been subject to limited research, as evidenced by Saranya's recent study [26]. Previous investigations have reported comparatively lower accuracy rates for LSTM-based approaches in contrast to non-LSTM methods [11, 1].

Numerous research studies have conducted comparative analyses of various algorithms to classify autism. According to the research conducted by Alsaadee and Alzahrani [5], Xception exhibited the most superior accuracy, specificity, and sensitivity levels. In their study, Rabbi et al. conducted a comparative analysis of various algorithms and determined that the Convolutional Neural Network (CNN) exhibited the highest level of accuracy [22]. Ghazal and Sadik employed transfer learning methodologies to enhance the precision of their study, with Ghazal attaining a satisfactory level of 87.7% accuracy, as reported in their respective works [8, 25]. Lu attained a high level of accuracy by utilizing the VGG19 model in merging facial image datasets, as documented in [18].

This study presents a proposed Keras-LSTM architecture, i.e., VGG16-LSTM, VGG19-LSTM, and MobileNet-LSTM, for transfer learning and conducts a comparative analysis. This architecture is simple and robust and can achieve high accuracy with minimal modifications. This study aims to investigate the performance of Keras-LSTM to detect autism and non-autism classes from the facial image dataset.

This paper is structured as follows: The subsequent discourse segment delves into the Kaggle dataset, the framework of the suggested models, and the evaluative criteria employed. The experimental findings, comparative evaluation of the deep learning framework, and its advantages are presented in the third section. The ultimate segment of the manuscript serves as a conclusion and proposes potential avenues for future research.