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Leveraging of recurrent neural networks architectures and SMOTE for dyslexia prediction optimization in children

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ABSTRACT

Dyslexia in children are serious problems that need to be addressed early. Many previous studies have focused on the detection/prediction of dyslexia. However, in the prediction process, there is often an imbalance in the dataset used (between patients with dyslexia and non-dyslexia). Therefore, we are trying to build a system using recurrent neural networks architectures that can quickly and accurately predict the possibility of a child having dyslexia. To overcome the data imbalance between dyslexics and non-dyslexics, we also apply the synthetic minority oversampling technique (SMOTE) method to the dataset. SMOTE will synthesize dyslexic data to balance the numbers with non-dyslexic data. This study used a dataset of 3640 participants (392 dyslexic and 3248 non-dyslexics). For the process of predicting dyslexia, several algorithms such as simple recurrent neural networks (RNN), long short term-memory (LSTM), and gate recurrent units (GRU) are used. As a result, there is an increase in prediction accuracy when SMOTE is applied (compared to without SMOTE) in the dyslexia forecasting process using RNN (92.68% for training and 91.16% for testing), LSTM (94.81% for training and 93.16% for testing), and GRU (96.43% for training and 92.24% for testing). Using SMOTE+RNN architecture in this research increased the accuracy of dyslexia prediction by up to 5% compared to without SMOTE.

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1. INTRODUCTION

Dyslexia (learning disorder) has become a problem that needs serious attention today. According to the International Dyslexia Association, the number of people with dyslexia ranges from 15-20% of the world's population [1]. In Europe alone, people with dyslexia range from 5-12% (37.3-89.5 million people) of the entire European population [2], while in the United States, it is estimated that more than 35 million people have dyslexia even though only 2 million people are detected [3]. The Indonesian Dyslexia Association also states that around 5 million Indonesian children are indicated to have dyslexia [4]. The signs of someone with dyslexia have started to be seen since childhood [5]. It is characterized by reading abilities much lower than their age, difficulty processing and understanding what they hear, difficulty remembering the sequence of events and finding the right words or sentences to answer questions [6]. If dyslexia in children is not paid attention to, these habits will carry over into adulthood and cannot be changed. Therefore, early detection and treatment related to dyslexia urgently needs to be done immediately. Dyslexia is a learning difficulty in children that disrupts their learning to spell, read and write [7]-[10]. Learning disorders (dyslexia) are caused by nerve damage in the brainstem [11]-[13]. Learning disorders (dyslexia) are caused by nerve damage in the brainstem [8]. This condition stems from differences in electrical activity in the human brain [9]. The brainstem regulates the language processing centre in humans. Even though this is classified as an incurable disease, detection and treatment from an early age have proven effective in improving the ability of sufferers to learn to spell, read, and write [14]. To diagnose dyslexia, psychiatrists will usually assess people suspected of having dyslexia [15]. The assessment can be done through a question-and-answer session with the person concerned/family and several tests (medical, psychological, and academic tests) [16]. Questions in the assessment usually relate to family living conditions and a history of family members who also have learning disorders. Nervous function tests are carried out to check whether dyslexia experienced is related to disturbances in the brain's nerves, vision, and hearing [17]. Psychological tests are used to understand a child's mental condition and rule out the possibility of a learning disorder related to anxiety or depression [12]. At the same time, academic tests are carried out by spelling, reading, and writing certain words/sentences. At this time, academic tests are the easiest thing to do to predict and recognize dyslexia. Then the results of this test will be analyzed by experts in their field and become the basis for determining whether a person has dyslexia [18]. However, if the test results are analyzed manually, the time required will be long, and the prediction/diagnosis results are also not necessarily accurate.

To overcome this, many researchers have proposed methods or systems to predict dyslexia in children (using data obtained from assessments) based on artificial intelligence. In his research, Kaisar [19] conducted a literature survey to determine the development of a machine learning-based dyslexia detection system. He reviewed and presented 13 research papers (2015-2019) in his systematic paper review. In several papers he has reviewed, the assessment process to obtain data on dyslexic patients is based on simple game applications (such as listening to videos, spelling words, and constructing words/sentences). Learning machines often used for prediction include linear discriminant analysis (LDA), naive Bayes (NB), support vector machine (SVM), K-nearest neighbors (K-NN), neural networks (NN), and many others. However, for the dyslexia detection process, the best accuracy rate (80.24%) was obtained using the SVM method. In addition, Rauschenberger *et al.* [20] conducted a diagnosis of dyslexia in children using web-based games (listening to videos and constructing sentences). The assessment is carried out on children with native Spanish and German languages. Of the 313 children who participated in the study, 116 were dyslexic, and their data was processed using the random forest prediction method. The results obtained an accuracy value of 74% (for children whose native language is German) and 69% (for children whose native language is Spanish). At the same time, Rello *et al*. [21], tried to detect dyslexia in children based on linguistic computer applications. The number of participants who participated in the study was 267 children, and what this study tried to explore was related to language skills, perceptions, and children's memory. Based on the results of their research, the best accuracy value was obtained at 84.62% using the SVM (Gaussian kernel) algorithm.

However, the prediction systems that have been previously proposed still do not focus on solving the problem of class inequality in the dataset of people with dyslexia, which is used in the system training and testing process [22]. In this case, the amount of data in the dyslexic sufferer class tends to be less than the regular person data class, so the training and testing results will potentially lead to the majority data class. It should be avoided to make the prediction results more objective and accurate. So, to overcome this problem, a technique is needed to automatically synthesize data from patients with dyslexia so that the numbers are balanced with the data from regular people in the dataset. In addition, the execution time in medical data processing still needs to be considered. In the medical field, speed in health services is essential because it relates to the patient's benefit. The sooner the patient knows the diagnosis of the disease, the faster the treatment or therapy steps can be given to the person concerned. The accuracy and speed of processing/analyzing assessment data are crucial to building a system that can predict dyslexia well. Therefore, we are trying to build a system that can accurately predict the likelihood of a child having dyslexia. In this system, we use synthetic minority oversampling technique (SMOTE) to overcome class inequality in the dyslexia patient dataset so that prediction results become more objective and accuracy increases. In addition, this system is also expected to be able to provide fast prediction results because it utilizes the modified artificial neural network (ANN) algorithm. This study uses recurrent neural networks (RNN), long short term-memory (LSTM), and gate recurrent units (GRU) to predict children with dyslexia.

2. METHOD

An overview of the research method is presented in Figure 1. In this study, the data inequality of dyslexic and non-dyslexic patients in the dataset will be overcome by using SMOTE. So that the prediction results with and without SMOTE will be compared with the evaluation matrix values. The dyslexia dataset consists of patient information and a list of questions for assessment. The dataset will be weighted. After going through the weighting stage, the data will be divided into training data and testing data. In the dyslexia prediction process, several algorithms are used such as simple RNN, LSTM, and GRU. The performance of the prediction system will be observed from the evaluation matrix value.

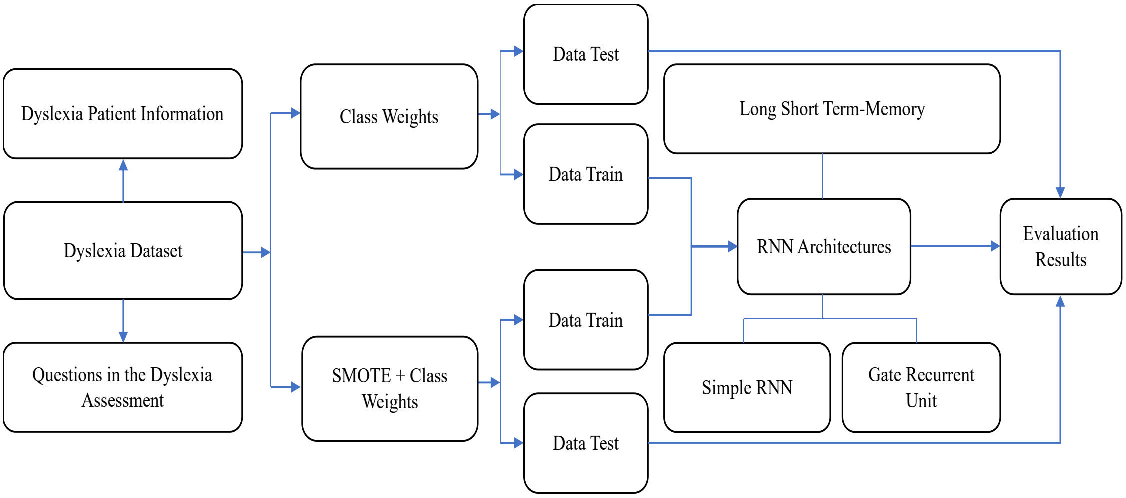

Figure 1. Method of the research

2.1. Dyslexia dataset

In predicting dyslexia, we used a dataset from research by Rello *et al*. [22] in which there were 3640 participants. Of the number of participants, there 392 were diagnosed with dyslexia and 3248 were without dyslexia. The participants' ages were between 7-17 years (with a mean of 10.47 and a standard deviation of 2.47). Apart from information related to age, some other information was extracted from the participants, such as gender (G), daily language (native Spanish or not), and fluency in language at school (fluent or not). Related data collection on participants was carried out using Spanish. There are 32 questions tested on participants. Questions 1-21 are related to distinguishing objects using sight and hearing. Questions 22-29 relate to constructing words and sentences. Questions 30-32 deal with remembering certain information sequentially. Based on data collection using these questions, calculations are then carried out related to the number of questions answered (NA), correct answers (CA), wrong answers (WA), the score of the correct answers (SCA), the ratio of CA to the number of questions answered (RCA), and the ratio of WA to the number of questions answered (RWA).

2.2. SMOTE

An unbalanced class is a condition of unequal distribution between classes in a dataset. One class has a massive amount of data (majority class) compared to other classes (minority class). Differences in a large amount of data between classes can result in the classification model being unable to predict the minority class correctly, so many test data that should be in the minority class are mispredicted by the classification model [23]. One method used to overcome the problem of unbalanced classes is sampling. The sampling method modifies the data distribution between the majority and minority classes in the dataset to balance the amount of data for each class. One of the sampling methods often used is the SMOTE. Therefore, we implemented SMOTE on the dataset for the dyslexia prediction process in this study. SMOTE is a method used to balance the amount of data that is not balanced between classes [24]. The imbalance of data between classes can cause the classifier algorithm to have difficulty correctly grouping data in the minority class and only focusing on the majority class compared to the minority class. So that the possibility of misclassification/prediction in the minority class is very high and finally makes the accuracy of the classification/prediction of machine learning algorithms not optimal [25].

2.3. Prediction algorithms

2.3.1. RNN

RNN is an algorithm that can process data sequentially. The working principle of an RNN is the same as a regular NN, but there is additional memory in the neurons [26]. The diagram depicts a RNN architecture (Figure 2), designed to process sequential data. The symbol "x" represents the input sequence. Each circle labeled "x" corresponds to a single element in the sequence, and the subscript "t" indicates the position of that element in the sequence. Hidden state is denoted in "h". This is the internal memory of the RNN. Each "h" circle represents the hidden state at a specific time step "t". The RNN updates this hidden state based on the current input and the previous hidden state. The double-circled "$h(\ldots)$" indicates that the hidden state at time "t" is affected by a history of past inputs. While the symbol "o" represents the output of the RNN at each time step. The "o" indicates the outputs corresponding to the inputs at each time step.

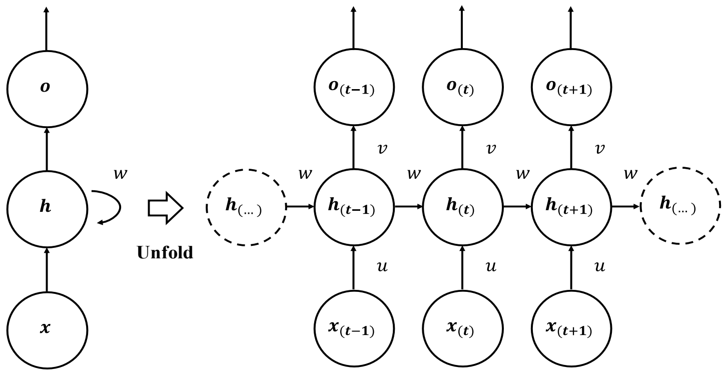

Figure 2. Architecture of RNN

2.3.2. LSTM

LSTM is designed to overcome these RNN weaknesses. LSTM also maintains the advantages that exist in the RNN to provide more accurate predictions based on the latest information. The architecture of LSTM is explained in Figure 3. The diagram shows a single LSTM cell, which consists of three main components: the cell state, the input gate, the output gate, and the forget gate [27]. The cell state, denoted by c_t, is the internal memory of the LSTM cell, which stores information over long periods of time. The three gates, denoted by i_t, o_t, and f_t, control the flow of information into and out of the cell state. The forget gate, denoted by f_t, is responsible for deciding what information to discard from the previous cell state. It takes the previous hidden state $h_{(t-1)}$ and the current input x_t as inputs, and outputs a vector of values between 0 and 1, indicating how much of each piece of information to forget. The forget gate is like a filter that removes unnecessary information from the cell state.

The input gate, denoted by i_t, is responsible for deciding what new information to add to the cell state. It takes the previous hidden state $h_{(t-1)}$ and the current input x_t as inputs, and outputs a vector of values between 0 and 1, indicating how much of each piece of new information to add to the cell state. The input gate is like a filter that selects the most relevant information to add to the cell state. The output gate, denoted by o_t, is responsible for deciding what information to output from the cell state. It takes the updated cell state c_t and the previous hidden state $h_{(t-1)}$ as inputs, and outputs a vector of values, which is the final output of the LSTM cell. The output gate is like a filter that selects the most relevant information to output from the cell state.

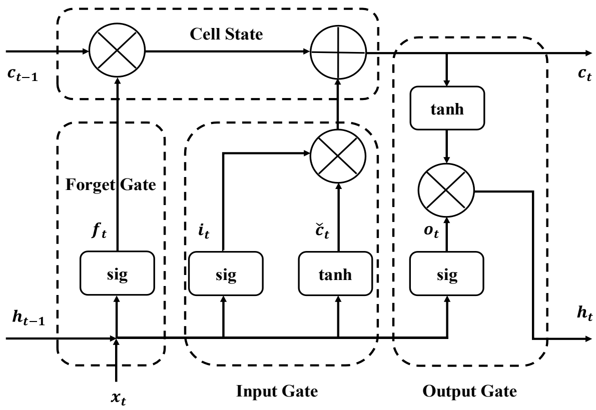

Figure 3. Architecture of LSTM

2.3.3. GRU

Besides LSTM, GRU is a modified form of RNN. The advantage of GRU (compared to LSTM) is that the computation is much simpler. Even though the computation is much faster, the accuracy produced by GRU is still on par with LSTM. In addition, it is still quite effective for dealing with gradient descent problems during data training (Vanishing Gradient) [28]. The Figure 4 shows a single GRU cell, which consists of two main components: the reset gate and the update gate. The reset gate, denoted by r_t, is responsible for determining how much of the previous hidden state to forget. The update gate, denoted by z_t, is responsible for determining how much of the new information to add to the hidden state. Both gates take the previous hidden state $h_{(t-1)}$ and the current input x_t as inputs. The candidate hidden state is a combination of the previous hidden state and the current input. It is computed using the reset gate and the current input. The candidate hidden state is used to compute the final hidden state.

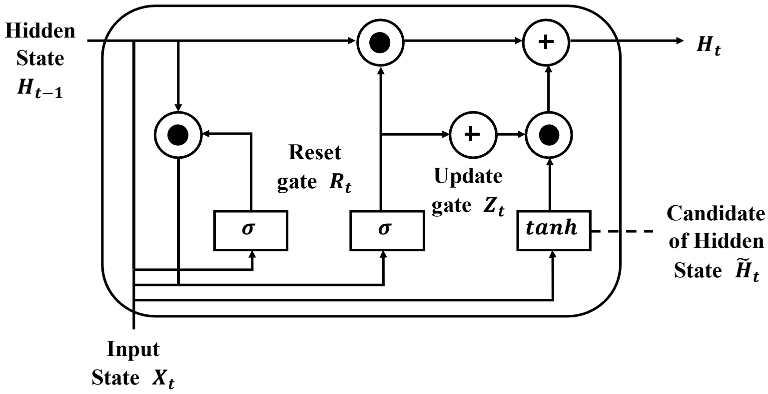

Figure 4. Architecture of GRU

3. RESULTS AND DISCUSSION

RNN, LSTM, and GRU-based dyslexia prediction involves using NN architectures and their advanced variants to identify complex patterns in data that may indicate the presence of dyslexia in an individual. Dyslexia is a learning disorder that affects a person’s reading, writing, and spelling abilities. RNN, LSTM, and GRU are types of NN architectures capable of modeling data sequences well, so they can be used to learn sequential patterns in dyslexic data [29]. RNN is a NN that handles sequential data by remembering previous information through a recursive loop. In the context of dyslexia prediction, RNNs can be used to model sequences of patient data, such as cognitive test results, learning history, or reading behavior, to identify dyslexia-associated patterns [30]. However, RNNs may encounter the problem of widening gradient movement when processing long sequences.

LSTM is a development of RNN specifically designed to handle the problem of widening gradient movement. LSTM can remember long-term information and ignore irrelevant information in sequence data. In addition, LSTM in dyslexia detection can help avoid local minima during the data training process and improve the overall performance of the system [31]. Thus, LSTM can model long-range patterns in dyslexia data and identify signs that traditional RNN models might miss [30]. GRU has a more straightforward structure than LSTM but is still effective in handling long-range information in sequence data. GRU uses gate updates and gate resets to regulate the flow of information in recurrence cells, allowing the model to retain relevant information over extended periods. In the context of dyslexia prediction, GRU can be used to model complex patterns in patient data and identify signs that indicate the presence of dyslexia [32]. In practice, RNN, LSTM, and GRU-based dyslexia prediction involves processing patient data, training the model using training data for which dyslexia status is known, and testing the model using never-before-seen test data [33]. The model results can be used to predict the likelihood of dyslexia in individuals based on the patterns found in their data.

When combined with SMOTE, the main advantages of RNN, LSTM, and GRU architectures become more prominent. SMOTE helps address the problem of class imbalance in dyslexia datasets by increasing minority class representation [30]. By increasing the number of samples from the minority class, SMOTE enriches the training data used by the RNN, LSTM, or GRU model, allowing the model to learn better patterns from the minority class and produce more accurate predictions [34]. Additionally, this combination helps prevent overfitting. By providing more synthetic samples for training, SMOTE helps the model be more general and understand patterns in the data, thereby reducing the risk of overfitting the training data [35]. It allows the model to predict dyslexia on never-before-seen test data better, as it can understand variations that may exist in accurate patient data. Combining RNN, LSTM, or GRU with SMOTE can also help improve model generalization [36]. By introducing additional variations in the training data through SMOTE, the model becomes better able to understand the variations that may exist in actual patient data, thereby increasing the generalization capabilities of the model. Thus, this combination helps improve the overall performance and effectiveness of dyslexia prediction models [32], [33]. The following accuracy values are obtained based on the prediction results of dyslexia using RNN, LSTM, and GRU algorithms combined with the SMOTE.

There is a significant difference in the accuracy value when the dyslexia prediction process is carried out using datasets that have implemented SMOTE and without implementing SMOTE. This result occurs when the prediction uses several predictor algorithms, including RNN, LSTM, and GRU (Figures 5-7). When dyslexia prediction was carried out using the RNN algorithm, the accuracy values (training and testing) without SMOTE reached 91.66% and 90.01% (Figure 5). However, if predictions are made using SMOTE, the accuracy values (training and testing) increase to 92.68% and 91.16% (Figure 5). The application of SMOTE to the dyslexia dataset will synthesize the amount of data in the minor class (the class that has less data) until the amount is almost equal/balanced with the amount of data in the major class (the class that has more data) [37]. Data balance is one of the factors that affect the accuracy of the forecasting algorithm. If the amount of data between classes is the same, then the forecasting algorithm will have no difficulty distinguishing data patterns from minor classes [38]. Therefore, the prediction error can be minimized.

The increase in the accuracy of dyslexia predictions does not only occur when forecasting is done using the RNN. However, the same thing also happens when the prediction of dyslexia is made with the LSTM. When predictions are made using the LSTM algorithm, the accuracy values (training and testing) without SMOTE reach 93.56% and 92.77% (Figure 6). Meanwhile, if predictions are made using SMOTE, the accuracy values (training and testing) increase to 94.81% and 93.16% (Figure 6). It is proven that the prediction accuracy using LSTM is much better than RNN. It is because the LSTM algorithm can store past information in the long term compared to RNN [39]. So the prediction results are more accurate than the RNN.

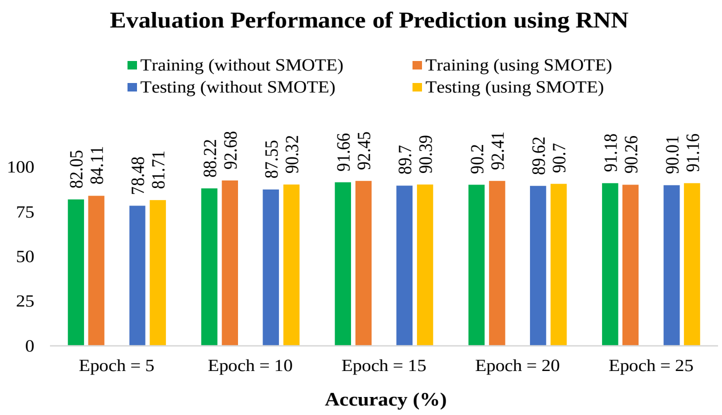

Figure 5. Evaluation performance of prediction using RNN

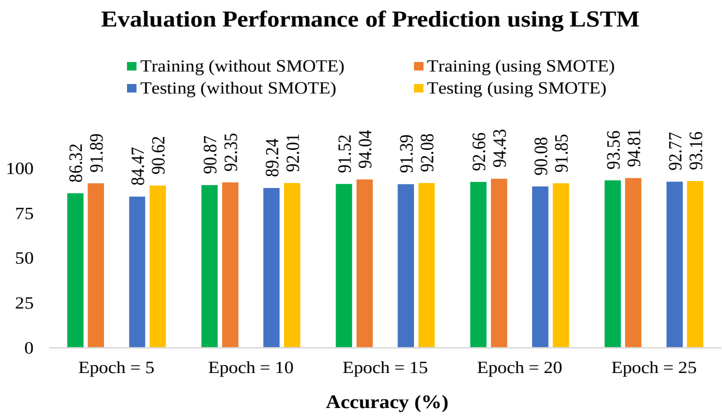

Figure 6. Evaluation performance of prediction using LSTM

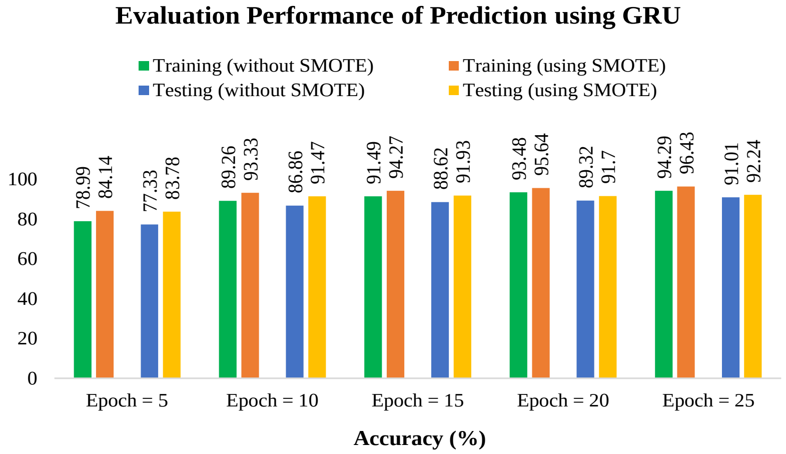

Figure 7. Evaluation performance of prediction using GRU

In addition to predictions using RNN and LSTM, dyslexia forecasting is also done using GRU. When dyslexia prediction was carried out using the GRU algorithm, the accuracy values (training and testing) without SMOTE reached 94.29% and 91.01% (Figure 7). However, if predictions are made using SMOTE, the accuracy values (training and testing) can increase to 96.43% and 92.24% (Figure 7). It is proven that the prediction accuracy value of GRU tends to be almost the same as that of LSTM. Although in this study, the training accuracy of GRU was slightly higher than that of LSTM, its testing accuracy was slightly lower than that of LSTM. It is because the architecture of the GRU is not as complex as LSTM (memory in the GRU architecture is limited) to reduce computation time [28]. So that only essential information is stored by the GRU in its architecture.

The LSTM architecture provides more accurate accuracy results compared to the other two architectures on both testing datasets, with and without SMOTE. LSTM has been utilized in several dyslexia determination studies [40] and can also be employed in combination of several data forms such as electroencephalograph (EEG) [41] and handwriting images [42]. However, the issue causing suboptimal data processing using LSTM often arises from data imbalance, leading to the random appearance of hyperparameters. Previous studies have employed a modified model, bidirectional long-short term memory (BLSTM), termed robust BLSTM (RBLSTM), which enhances dyslexia prediction accuracy compared to LSTM [40]. Unlike RBLSTM, which employs the red fox optimization algorithm by integrating both local and global search, we focus on minority data sampling using SMOTE to overcome data class inequality and optimize system performance [25].

The results we obtained show that employing SMOTE to synthesize minority data in the dataset can improve accuracy across nearly all models used (RNN, LSTM, and GRU). Similar findings have also been reported that the use of SMOTE is slightly more effective in improving the performance of several dyslexia forecasting algorithms compared to the adaptive synthetic sampling approach (ADASYN) oversampling method for addressing data imbalance [43]. However, it is possible that the use of ADASYN and Borderline as oversampling methods also influences the accuracy of simulation results on ensemble classifiers such as XGBoost (XGB) and single classifiers such as SVM, logistic regression (LR), and decision tree (DT) [44]. However, oversampling methods used in this study or other studies can be applied to overcome the imbalance of the dataset. In this study, it is confirmed that applying SMOTE optimizes the accuracy of dyslexia forecasting using RNN, LSTM, and GRU.

4. CONCLUSION

Dyslexia is a learning difficulty in children and has become a problem that needs serious attention. To diagnose dyslexia, psychiatrists will usually assess people suspected of having dyslexia. At this time, academic tests are the easiest thing to do to predict and recognize dyslexia. Then the results of this test will be analyzed by experts in their fields and become the basis for determining whether a person has dyslexia. However, if the test results are analyzed manually, it will take a long time, and the prediction/diagnosis results may need more accuracy. Therefore, we are trying to build a system that can accurately predict the likelihood of a child having dyslexia. The prediction process uses several algorithms such as RNN, LSTM, and GRU. In addition, we also added the SMOTE method to overcome the data imbalance problem in the dyslexia dataset. The result is an increase in accuracy when SMOTE is applied compared to without SMOTE in the dyslexia forecasting process using RNN, LSTM, and GRU. It proves that dyslexia data imbalance can affect prediction accuracy and the application of SMOTE to dyslexia datasets can improve the accuracy of the forecasting algorithm. In addition, using more dyslexic data in future studies is very important to increase the accuracy of the prediction results.

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