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A study on the characteristics of applying oversampling algorithms to Fosberg Fire-Weather Index (FFWI) data

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Abstract. Oversampling algorithms are methods employed in the field of machine learning to address the constraints associated with data quantity. This study aimed to explore the variations in reliability as data volume is progressively increased through the use of oversampling algorithms. For this purpose, the synthetic minority oversampling technique (SMOTE) and the borderline synthetic minority oversampling technique (BSMOTE) are chosen. The data inputs, which included air temperature, humidity, and wind speed, are parameters used in the Fosberg Fire-Weather Index (FFWI). Starting with a base of 52 entries, new data sets are generated by incrementally increasing the data volume by 10% up to a total increase of 100%. This augmented data is then utilized to predict FFWI using a deep neural network. The coefficient of determination (R^2) is calculated for predictions made with both the original and the augmented datasets. Suggesting that increasing data volume by more than 50% of the original dataset quantity yields more reliable outcomes. This study introduces a methodology to alleviate the challenge of establishing a standard for data augmentation when employing oversampling algorithms, as well as a means to assess reliability.

Keywords: Borderline Synthetic Minority Oversampling TEchnique (BSMOTE); Deep neural network (DNN); Fosberg Fire Weather Index (FFWI); oversampling algorithm; Synthetic Minority Oversampling TEchnique (SMOTE)

1. Introduction

Machine learning algorithms, designed to predict and classify phenomena based on data characteristics, have found applications across a wide range of fields (Bang *et al.* 2023, Li *et al.* 2023a, Peng *et al.* 2023, Samadi *et al.* 2023, Abdi 2024, Al-Swaidani *et al.* 2024, Suh 2024). Enhancing the reliability of these algorithms requires a high learning rate, which in turn necessitates a dataset that accurately represents the features of interest (Li *et al.* 2023b, Zhu *et al.* 2023). However, achieving results that align with user objectives becomes challenging when the available data for the learning process is insufficient. To mitigate this issue, various data oversampling algorithms have been proposed. One of the initial methods, Random Oversampling (ROS), indiscriminately increases data volume. Yet, it has been observed that ROS can lead to overfitting and underfitting issues in machine learning applications (Kim and Yoon 2023, Park *et al.* 2023). To address these shortcomings, the Synthetic Minority Oversampling Technique (SMOTE) was developed. SMOTE identifies boundary points based on the proximity of neighbors and selectively amplifies data within these confines. This approach has been further refined by the Borderline SMOTE algorithm, which is specifically tailored for solving classification problems, ensuring smoother data amplification across the boundaries of different data groups. Although SMOTE and BSMOTE have been employed in various research areas to yield dependable outcomes, determining the optimal amount of data amplification remains a significant challenge. Consequently, this paper evaluates prediction reliability following incremental data amplification, based on the volume of raw data, with the goal of establishing a benchmark for efficiently scalable data volumes.

The global issue of wildfires is primarily characterized by the loss of human lives and property, but it encompasses a broader range of negative impacts caused by uncontrolled fires, affecting various environmental, social, and economic aspects (Gill *et al.* 2013). In United States, with a significant emphasis on safeguarding private residences, firefighting endeavors have led to a consistent increase in the expenditure on wildfire suppression by the US government, reaching approximately $3 billion annually in recent years (Burke *et al.* 2021). In Canada, in addition, the overall expenses associated with wildfire disasters are substantially greater when considering not only suppression

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costs but also recovery expenses, lost revenue, and additional impacts such as degradation of air and water quality (Tymstra *et al*. 2020). For this reason, various indices related to wildfire occurrence such as Canadian fire weather index (FWI) and Fosberg fire weather index (FFWI) are introduced for wildfire prediction. However, the applicability of those indices in South Korea has not been verified even though the meteorological and geomorphological aspects are dissimilar. Thus, this study utilized the wildfire dataset in South Korea to verify the wildfire indices regarding the machine learning algorithms.

The paper starts by introducing machine learning algorithms that can increase data volume and also explains the input and output variables comprising the FFWI database. Initially, it assesses reliability using the coefficient of determination, comparing prediction outcomes with actual values while focusing solely on the volume of raw data. In the discussion section, it presents the outcomes of amplifying data using the SMOTE and BSMOTE algorithms. Ultimately, after employing a deep neural network, the paper evaluates reliability via the coefficient of determination and identifies the minimum amplification ratio needed for effective data enhancement.

2. Background theory

2.1 Oversampling algorithm

The Synthetic Minority Oversampling Technique (SMOTE) is an oversampling algorithm designed to address disparities in data volumes across classes in classification problems (Chawla *et al*. 2002). Though initially developed for classification challenges, SMOTE has been extended to single data amplification issues, making it applicable not only to classification but also to prediction. SMOTE employs a distance coefficient based on the K-nearest neighbors (KNN) methodology, setting a range within which data amplification occurs. This process features random data amplification. Borderline SMOTE (BSMOTE) evolves from the SMOTE technique, aiming to improve the reliability of classification problems by increasing the number of distinguishable data points at each class's borderline (Han *et al*. 2005). BSMOTE is engineered to allow data amplification near borderlines, operating under the same principles as SMOTE. A distinctive aspect is its approach to deciding on data amplification at the borderline, which involves comparing the number of observations to the number of classes. Although numerous methods exist for data oversampling, this paper concentrates on two algorithms that have been extensively utilized in prior researches.

2.2 Fosberg Fire-Weather Index (FFWI)

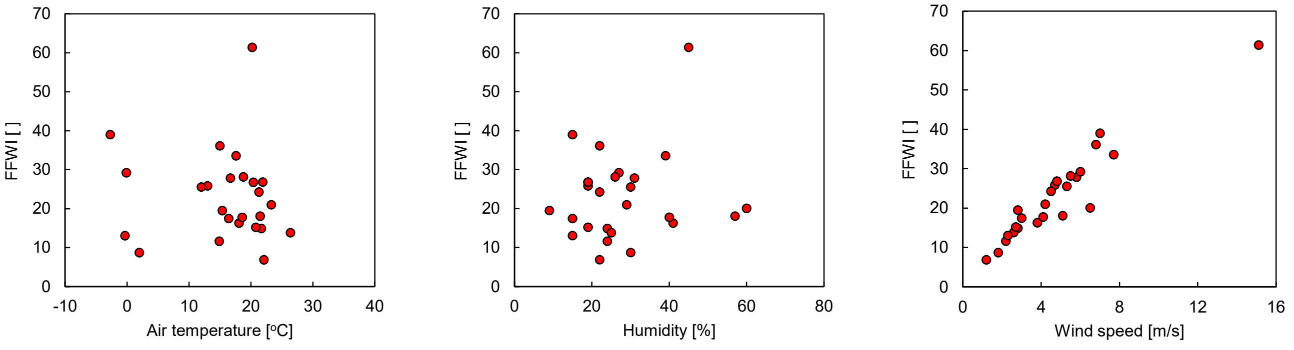
Among the various wildfire-related indices, The Fosberg fire weather index (FFWI) is a straightforward tool used to assess the potential impact of weather conditions on a wildland fire, taking into account factors including temperature, relative humidity, and wind speed. The FFWI serves as a non-linear filter of meteorological data, aimed at establishing a linear relationship between combined weather variables and wildfire behavior. This flame length formulation is essentially comprised of two components: a fuel moisture component and a rate of spread component. The rate of spread component is derived from Rothermel (1972), while the fuel moisture component is determined by the equilibrium moisture content as established by Simard (1968). The FFWI is calculated as follows

$$FFWI = \sqrt{1+WS^2}\,\frac{1-2a+1.5a^2-0.5a^3}{0.3002} \qquad (1)$$

where WS and a are wind speed and equilibrium moisture content normalized by 30.

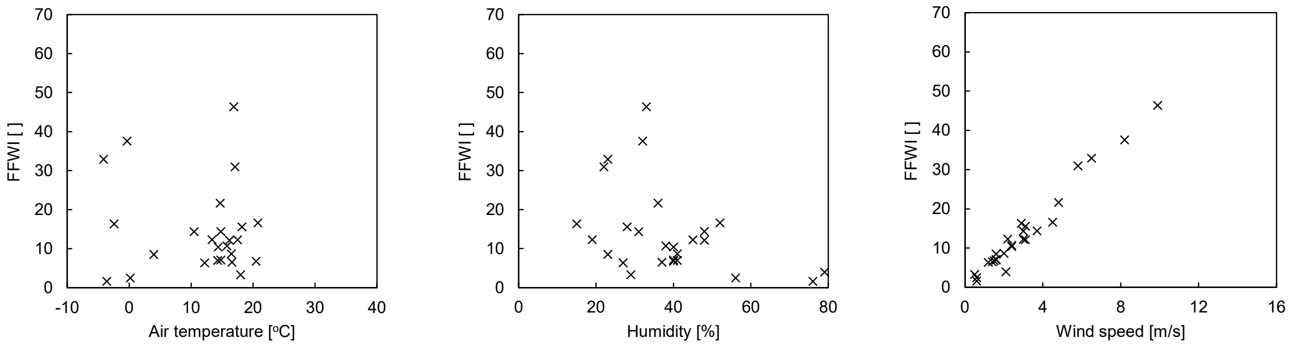
3. Database

The dataset is composed of air temperature, humidity, and wind speed in South Korea, which are the influencing factors of FFWI. Note that three influencing factors are obtained from Korea Meteorological Administration (KMA). The wildfire occurrence data at 26 cases in last decade are collected, and the non-occurred wildfire cases are acquired at 3 hours before each wildfire occurrence. The relationships between FFWI with influencing factors at wildfire occurrence and non-occurrence are presented in Figs. 1 and 2. The relationship of FFWI and air temperature



(a) (b) (c)

Fig. 1 Relationships between FFWI with influencing factors at wildfire occurrence: (a) air temperature; (b) humidity; (c) wind speed



(a) (b) (c)

Fig. 2 Relationships between FFWI with influencing factors at wildfire non-occurrence: (a) air temperature; (b) humidity; (c) wind speed

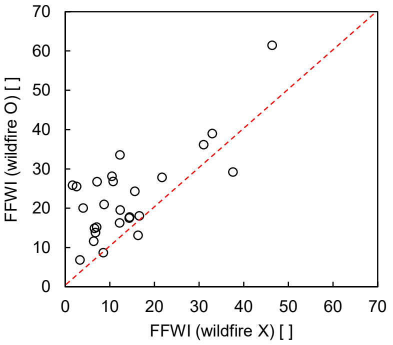


Fig. 3 Correlation between calculated FFWI at wildfire occurrence and non-occurrence

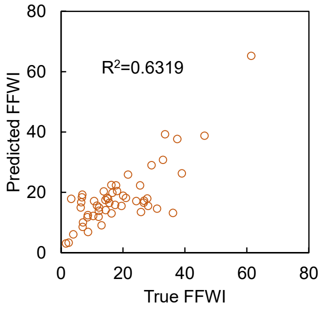


Fig. 4 Relationship between true and predicted FFWIs. The deep neural network (DNN) was applied to obtain the predicted FFWI

shows randomly scattered trend as shown in Figs. 1(a) and 2(a). Meanwhile, the relationship of FFWI and humidity in Fig. 1(b) presents scattered trend as well, but Fig. 2(b) shows inversely proportional relationship due to the fact that low humidity increases the wildfire occurrence. In particular, the FFWI and wind speed shows linear proportional relationship even the wildfire occurs or non-occurs. Thus, the wind speed can be regarded as the most significant influencing factor on FFWI in South Korea. In addition, most of FFWIs at wildfire occurrence are greater than those at non-occurred wildfire as shown in Fig. 3 that verifies the reliability of dataset used in this study.

4. Result

The Deep Neural Network (DNN) algorithm functions by deducing the relationship between input and output data, subsequently predicting output values for new input data. In this study, the input data was identified as three factors that constitute the FFWI, with the FFWI itself being the output variable. The algorithm processes the three input variables through hidden layers containing 100, 500, and 100 nodes, respectively, ultimately outputting through a single node. To define the relationship between input and output values at each layer, the activation function selected was ReLU, aimed at reducing the vanishing effect. The optimization method used is the Adam optimizer, with a learning rate of 0.0001. The DNN was trained over 200 iterations, using the Mean Squared Error (MSE) method for the cost function. This setup allowed for the observation of the convergence interval across epochs.

The results of the DNN, obtained with the specified hyperparameters, are depicted in Fig. 4 alongside the physically computed true values. To visually assess the correlation between the two sets of FFWI values, a 1:1 line was plotted diagonally. It's noticeable that the bulk of the FFWI values are clustered below approximately 30, suggesting that a significant number of predictions fell within the 1-30 range. Conversely, the frequency of data points with FFWI values over 40 is comparatively low. In the segment where FFWI values range from 1-30, the predicted FFWI values were found to either under or overestimate, displaying no consistent pattern when juxtaposed with the actual values. Consequently, the coefficient of determination was calculated to be 0.6319, illustrating that the predicted FFWI values have low reliability.

5. Discussion

5.1 Oversampling algorithm

Fig. 4 indicates that the reliability of the DNN results is low. To enhance this, common approaches include hyperparameter tuning and increasing the data volume to incorporate diverse features. The objective of this research is to examine the impact on reliability with an increase in data volume; therefore, the emphasis was on data augmentation. The methods employed for data augmentation were the Synthetic Minority Oversampling Technique (SMOTE) and the Borderline Synthetic Minority Oversampling Technique (BSMOTE), as discussed in the background theory section. Data amplification is applied to attributes for which it is challenging to secure large quantities, aiming to enhance the reliability of predictions. However, deciding on an appropriate data volume is problematic because the amount of data needed to comprehend a phenomenon depends on the data and physical quantities obtained. Previous studies using amplification algorithms have expanded the data volume by factors, such as doubling or tripling the raw data count (Lee *et al*. 2022, Min *et al*. 2023). Yet, the reliability of the prediction outcomes has consistently been satisfactory, even with data quantities doubled at a minimum, leading to the evident conclusion that the mere application of an oversampling algorithm tends to produce favorable outcomes. Consequently, it is challenging to propose clear and detailed guidelines for increasing data volumes. In this study, to determine a more precise criterion for data expansion, the data volume was increased by 10% relative to the raw data count, up to a 100% increase, effectively doubling the data volume. The augmented data volumes are depicted in Fig. 5, with equal amplification for both the SMOTE and BSMOTE algorithms. Specifically, starting with 52 raw data points, an increase of 5 points was added for each 10% increment. Thus, data volumes were achieved at 57, 62, 67, 72, 77, 82, 87, 92, 97, and 102 points for increments from 10% to 100%. Moreover, the k-nearest neighbors (KNN) value was set to 5 for the application of the SMOTE and BSMOTE algorithms.

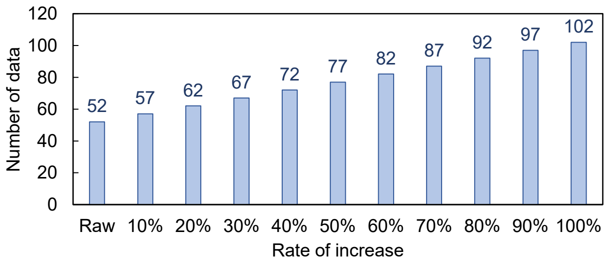


Fig. 5 Raised number of data through oversampling algorithms

5.2 Cost function

The datasets newly created with SMOTE and BSMOTE were utilized for FFWI prediction, applying the DNN algorithm. In this application, the hyperparameters were set identically to those used in predicting FFWI with raw data. Although adjusting hyperparameters might improve reliability to suit the characteristics of each data volume, this study focused solely on assessing the impact of data volume, setting aside the effects of hyperparameters. Thus, the hyperparameters were retained at their initial settings. Fig. 6 illustrates the cost function over epochs when applying the DNN algorithm to the enhanced data. The data amplified with SMOTE shows a lower cost function in both training and testing phases compared to raw data. Within the converging range, the cost function for raw data exceeds 100, whereas all amplified datasets display values below 100, indirectly indicating a gradual increase in reliability with the number of computations. Furthermore, in the training phase, data volumes increased by 10%, 50%, and 100% exhibit a cost function approaching zero from epoch 50, signifying efficient learning. The testing phase shows a similar pattern, yet the cost function values are significantly

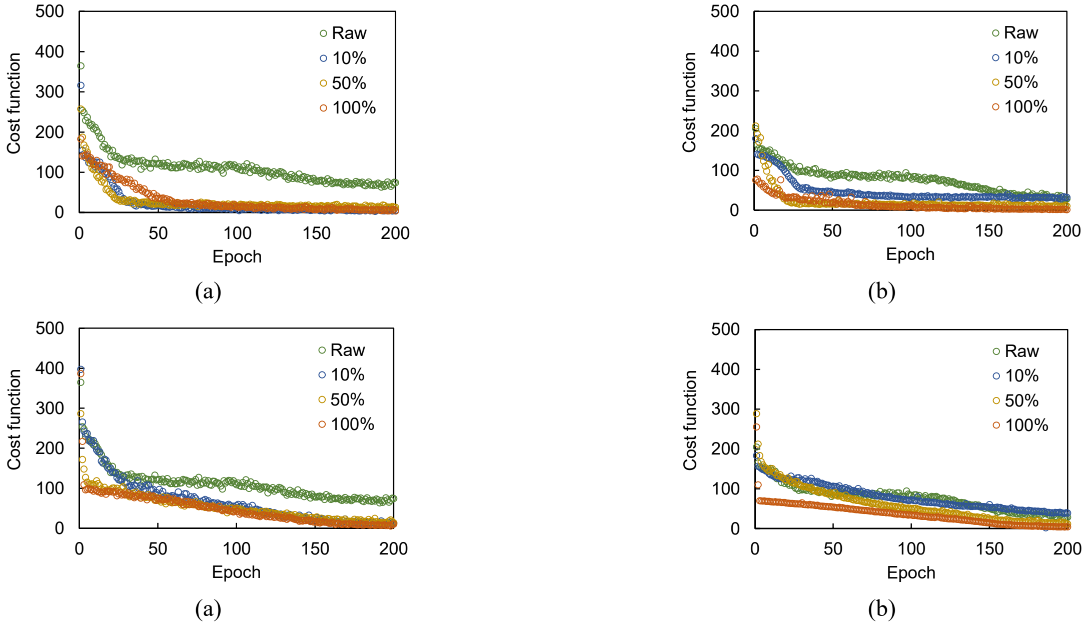
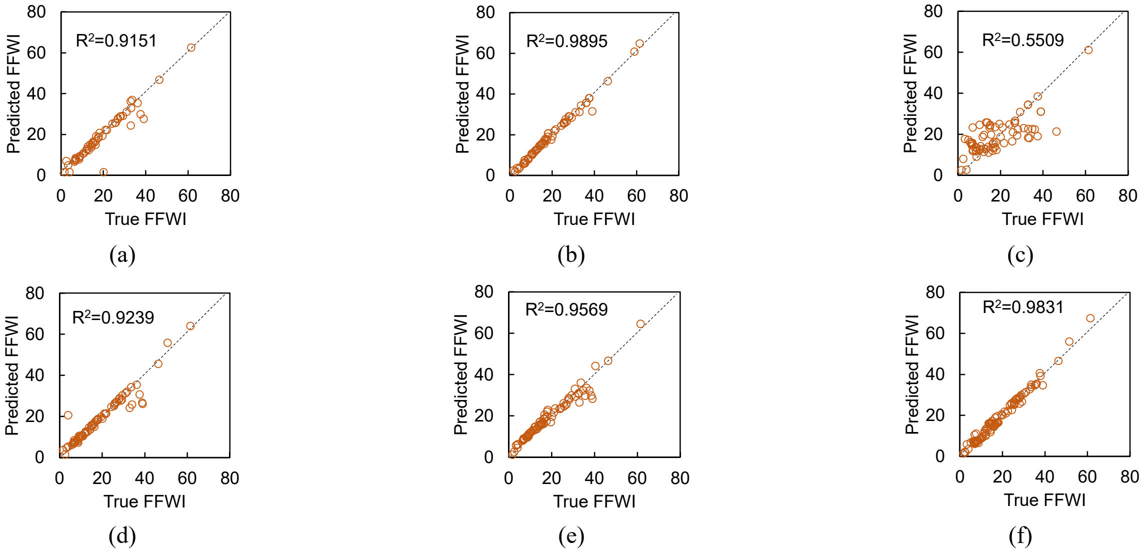


Fig. 6 Cost function according to each epoch: (a) synthetic minority oversampling technique (SMOTE); (b) borderline synthetic minority oversampling technique

lower when data volumes are increased by 50% and 100% versus a 10% increase. With data enhanced using BSMOTE, the cost function values decrease below 100 in the training phase, presenting relatively lower figures compared to those derived from raw data. However, the testing phase diverges from the training experience, displaying final cost function values nearly identical to those of raw data. Notably, data volumes increased by 10% demonstrate minimal variance from the cost function of raw data. Despite the 10% data volume increase, the elevated cost function in the testing phase suggests a relatively lower reliability for FFWI predictions.

5.3 Prediction

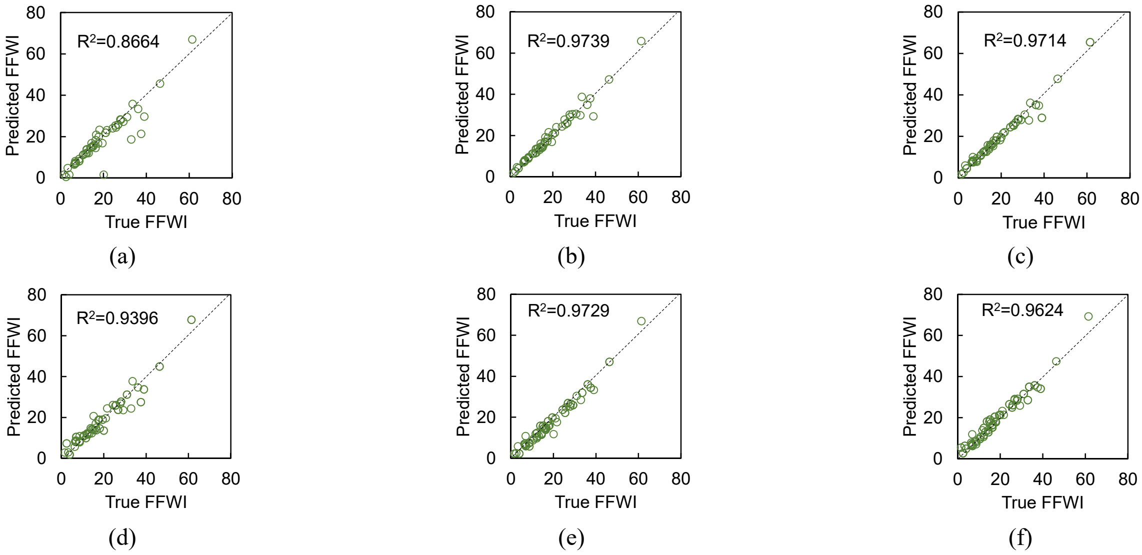
The DNN algorithm was applied to datasets amplified with SMOTE and BSMOTE, with the outcomes illustrated in Figs. 7 and 8, respectively. These figures combine the results from both the training and testing processes, showcasing the average coefficient of determination. The figures summarize findings from datasets that were amplified by 10%, 30%, 40%, 50%, 70%, and 100% relative to the volume of raw data. Fig. 7 reveals that a mere 10% increase in data volume with the SMOTE algorithm significantly boosts the coefficient of determination to nearly 0.9. Moreover, a 30% data amplification results in



(a) (b) (c)

(d) (e) (f)

Fig. 7 Distributions of predicted FFWI with various number of input variables oversampled by synthetic minority oversampling technique (SMOTE) where the number of data has increased by (a) 10%; (b) 30%; (c) 40%; (d) 50%; (e) 70%; (f) 100% based on the original data count



(a) (b) (c)

(d) (e) (f)

Fig. 8 Distributions of predicted FFWI with various number of input variables oversampled by borderline synthetic minority oversampling technique (BSMOTE) where the number of data has increased by (a) 10%; (b) 30%; (c) 40%; (d) 50%; (e) 70%; (f) 100% based on the original data count

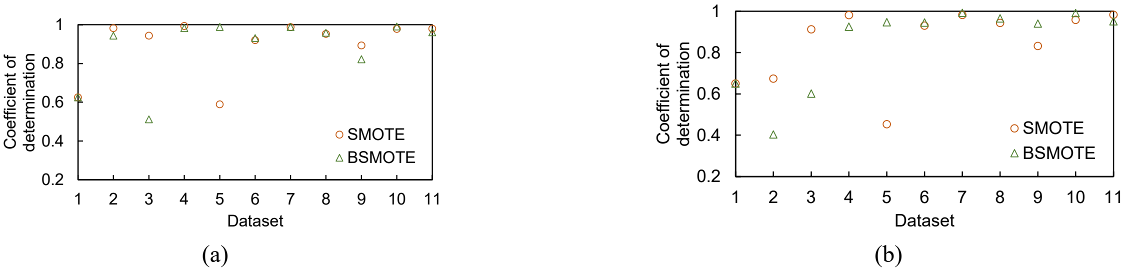


Fig. 9 Comparison of performance with coefficient of determination: (a) train process; (b) test process. In the x-axis, 1 represents the count of raw data, while from 2 to 11, it indicates the data quantity incrementally increasing from 10% to 100%, based on the raw data

a coefficient of determination of 0.9895, indicating a notable boost in reliability as it nears 1. However, increasing the data volume by 40%, which equates to 72 data points, leads to a reduced coefficient of determination and increased variability in the predicted FFWI. With further increases in data volume, the coefficient of determination again exhibits an upward trend. This suggests that while the amplified data functions on a KNN basis, its performance reliability hinges on the efficient amplification of the three physical variables. Thus, even with a 40% increase in data volume, if the three input variables fail to accurately represent the characteristics of the raw data, the reliability diminishes. Fig. 8 displays the outcomes for datasets amplified with the BSMOTE technique, showing a coefficient of determination of 0.8664 with a 10% increase in data volume. Mirroring the SMOTE findings, adding just 10% more data significantly improves the coefficient of determination beyond that of the raw data. Furthermore, as data volume increases, the coefficient of determination generally stays above 0.9, validating that data amplification effectively enhances reliability.

To assess reliability in relation to data volume, the coefficient of determination for both raw data and data amplified from 10% to 100% was compiled in Fig. 9. Contrasting with Figs. 7 and 8, Fig. 9 differentiates between the training and testing phases, depicting their detailed behaviors in parts (a) and (b), respectively. Throughout the training phase, the coefficient of determination is generally higher than in the testing phase, with SMOTE and BSMOTE demonstrating significantly elevated values of 0.9821 and 0.9433, respectively, in comparison to the raw data's 0.625. However, the testing phase presents coefficients of determination for SMOTE and BSMOTE at 0.6739 and 0.4038, respectively, indicating similar or reduced reliability compared to the raw data outcomes. This is in stark contrast to the higher coefficients of determination observed when amalgamating the training and testing processes in Figs. 7 and 8, underscoring the necessity for distinct analyses of the training and testing phases as illustrated in Fig. 9. During the training phase, SMOTE and BSMOTE showcased reduced reliability with coefficients of determination at 0.5893 and 0.5118, respectively, when data volume was increased by 40% and 20%. In the testing phase, SMOTE exhibited low coefficients of determination of 0.6739 and 0.4534 at 10% and 40% amplification rates, respectively. Furthermore, BSMOTE revealed coefficients of determination of 0.4038 and 0.6014 at 10% and 20% amplification rates, highlighting inadequate reliability. In other intervals, the coefficient of determination generally surpasses 0.9, implying enhanced reliability beyond the results from raw data. Nevertheless, an examination of the testing phase outcomes for both SMOTE and BSMOTE algorithms exposes diminished reliability in two particular intervals, corresponding to amplification rates below 50%. The absence of sufficient data to accurately mirror physical attributes, even after amplification, inevitably leads to lower reliability. This study's findings suggest that an amplification rate of at least 50% relative to raw data volume is essential for ensuring dependable outcomes. Although the proposed benchmark is derived from the characteristics of the input variables utilized in this study and may be difficult to standardize, the recommended methodology is anticipated to facilitate improved reliability in the selection of amplification algorithms for future research.

6. Conclusions

In this paper, we examined how changes in data volume affect reliability using the Synthetic Minority Oversampling Technique (SMOTE) and the Borderline Synthetic Minority Oversampling Technique (BSMOTE). The study's principal conclusions are as follows:

- The input variables were air temperature, humidity, and wind speed, with the Fosberg Fire-Weather Index (FFWI) chosen as the output variable. The FFWI was calculated based on a physical relationship formula among these input variables.
- The initial dataset comprised 52 raw data points. Data volume was incrementally increased by 10% across a range from 10% to 100%, relative to the number of raw data points. Thus, the dataset amplified to 100% included a total of 102 data points. It was observed that the reliability of FFWI predictions, made using a deep neural network, improved when the data amplification rate exceeded 50%.
- The research indicates that a data amplification rate of at least 50%, relative to the raw data volume, is necessary. While the findings are influenced by the specific input variables used, providing a standardized numerical guideline is challenging.

Nevertheless, the methodology and outcomes of this study may serve as valuable references for enhancing prediction reliability with amplification algorithms.

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