testing subsets using a $9:1$. ratio. Subsequently, the classes within both the training and testing data are separated into two sets: x, which includes the classes that the model will learn to classify, and y, which represents the target classes. The model is trained and tested using the same prepared data as the BK method, with a reweighting mechanism applied to each misclassified sample during each iteration. This approach boosted the base classifier by ensuring the model focuses more on learning from the misclassified samples in each iteration. The results of these experiments are presented in Table II.

TABLE II
CONFUSION MATRIX FOR THE BN METHOD

		Predicted Values		
		Normal	***Short***	***Very Short***
Actual Values	***Normal***	14899	0	0
	Short	3753	9832	0
	Very Short	2209	0	76

E. Accuracy Comparison

The methods that are used to classify the stunting dataset perform differently. Here are the classification results between BK and BN.

TABLE III
ACCURACY AND F-1 SCORE FOR COMPARISON

Method	**Accuracy**	**F-1 Score Macro Avg**
BK	98.62%	97.44%
BN	80.62%	57.91%

Table III demonstrates that although the accuracy of the BN method is not as high as that of the BK method, the classification performance of the BN method surpasses that reported in previous research[7], achieving an accuracy exceeding 80%. Furthermore, the F-1 score macro average of the BK method is nearly identical to that of the BK method in previous research, despite the preprocessing results in this study being significantly more imbalanced compared to those in earlier work[2]. These findings indicate that the boosting technique has effectively enhanced both the KNN and Naïve Bayes methods, despite the unsatisfactory results of the preprocessing step.

IV. CONCLUSION

This research demonstrates that the BK and BN methods yield different results. As shown in Table III, the accuracy of the BN method is lower than that of the BK method. However, the BN method exhibits a significant improvement in their accuracy compared to previous studies, indicating enhanced performance overall. Table III further illustrates the comparison between the BK and BN models. The BK model, which employs AdaBoost to enhance KNN as the base classifier, achieves an accuracy of 98.62% and an F-1 score of 97.44%. Meanwhile, the BN model, which uses AdaBoost to boost Naïve Bayes as the base classifier, achieves an accuracy of 80.62% and an F-1 score of 57.91%. Therefore, the BK and BN have succeeded in boosting the performance of the original KNN and Naïve Bayes method. Future work should focus on further balancing the training and testing data prior to implementing the BN method, as this is expected to enhance both the F-1 score and the accuracy of the model. Additionally, this research concludes that the BK method is superior for classifying stunting data among toddlers.

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