

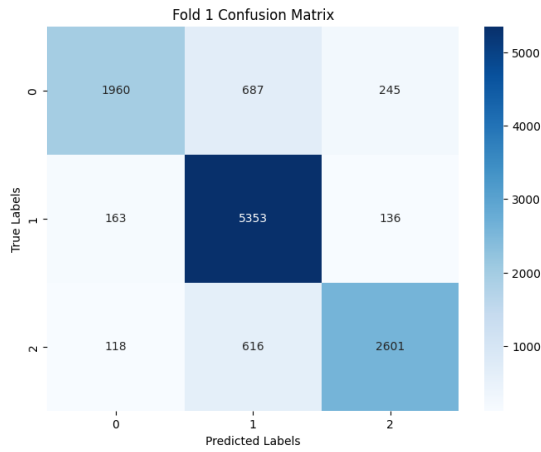


Fig. 8. Random forest (Drone &GEE) best fold confusion matrix

Figure 8 shows the confusion matrix of the first fold, which achieved the best validation accuracy across the folds at 83.46%. However, this value does not indicate good model performance, as there is a 4.69% difference between the test accuracy and the mean validation accuracy—a relatively large gap. This 4.69% gap suggests that the model has potential overfitting, as the training and validation accuracy are higher than the test accuracy, indicating that the model may have learned patterns excessively from the training and validation sets.

To summarize the experimental results, Figure 9 illustrates the performance of each model across different datasets.

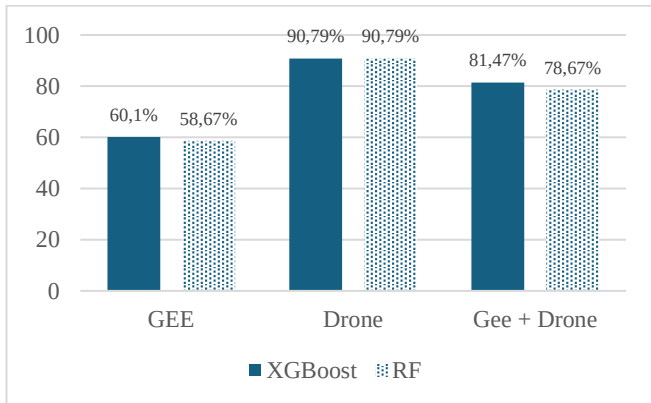


Fig. 9. Experiment results

IV. CONSLUTION

In this study, we proposed a machine learning-based image classification method for carbon stock measurement using XGBoost and Random Forest classifiers with a VGG16 feature extractor. These models were employed to classify carbon stock with the goal of identifying the best classifier and dataset combination. From the six experiments conducted, we observed that dataset quality is a crucial factor in classifying carbon stock using remote sensing methods, particularly with machine learning algorithms. The XGBoost model combined with the Drone dataset emerged as the best combination, achieving an accuracy of 90.79%. This model also showed no signs of overfitting, with only a 0.49% difference between the test accuracy and mean validation accuracy. XGBoost outperformed Random Forest by effectively handling intricate patterns in high-resolution drone data, leveraging its boosting mechanism to iteratively correct errors and capture complex

relationships, while regularization prevents overfitting and ensures stability, making it optimal for accurate and stable carbon stock classification. Based on the experiments conducted, the most optimal classifier performance, was achieved by a high-resolution dataset such as the drone dataset. However, if this is not feasible, a combination of high and low-resolution datasets can be used, albeit with a slight reduction in model performance. Whenever possible, it is recommended to avoid using low-resolution datasets to maintain better model performance. In addition, future research could explore the use of CNN or other state-of-the-art method for carbon stock classification to add an additional context for the comparison.

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