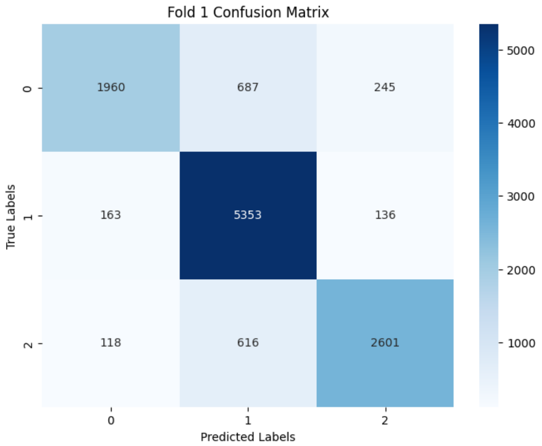

Fig. 8. Random forest (Drone &GEE) best fold confusion matrix

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.

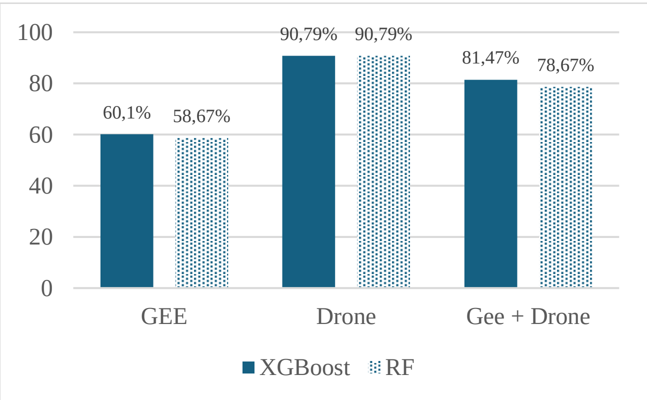

Fig. 9. Experiment results

IV. CONSLUSION

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.

REFERENCES

[1] S. H. M. Satrio Jati Kinantyo Widhi, "ESTIMASI STOK KARBON HUTAN DENGAN MEMANFAATKAN CITRA LANDSAT 8 DI TAMAN NASIONAL TESSO NILO, RIAU," *Jurnal Bumi Indonesia*.

[2] M. Mulyoto, "ESTIMASI KANDUNGAN BIOMASSA DAN KARBON PADA KOMUNITAS MANGROVE DI KOTA TARAKAN, KALIMANTAN UTARA," *Jurnal Perikanan dan Kelautan*, vol. 11, no. 1, p. 60, Jun. 2021, doi: 10.33512/jpk.v11i1.11279.

[3] A. Crimmins *et al.*, "The Impacts of Climate Change on Human Health in the United States: A Scientific Assessment," Washington, DC, 2016. doi: 10.7930/J0R49NQX.

[4] R. T. Conant, S. M. Ogle, E. A. Paul, and K. Paustian, "Measuring and monitoring soil organic carbon stocks in agricultural lands for climate mitigation," *Front Ecol Environ*, vol. 9, no. 3, pp. 169–173, Apr. 2011, doi: 10.1890/090153.

[5] J. Ahirwal, A. Nath, B. Brahma, S. Deb, U. K. Sahoo, and A. J. Nath, "Patterns and driving factors of biomass carbon and soil organic carbon stock in the Indian Himalayan region," *Science of The Total Environment*, vol. 770, p. 145292, May 2021, doi: 10.1016/j.scitotenv.2021.145292.

[6] B. Liu, W. Bu, and R. Zang, "Improved allometric models to estimate the aboveground biomass of younger secondary tropical forests," *Glob Ecol Conserv*, vol. 41, p. e02359, Jan. 2023, doi: 10.1016/j.gecco.2022.e02359.

[7] H. Zhang, L. Wan, and Y. Li, "Prediction of Soil Organic Carbon Content Using Sentinel-1/2 and Machine Learning Algorithms in Swamp Wetlands in Northeast China," *IEEE J Sel Top Appl Earth Obs Remote Sens*, vol. 16, pp. 5219–5230, 2023, doi: 10.1109/JSTARS.2023.3281732.

[8] L. Tian *et al.*, "Review of Remote Sensing-Based Methods for Forest Aboveground Biomass Estimation: Progress, Challenges, and Prospects," *Forests*, vol. 14, no. 6, p. 1086, May 2023, doi: 10.3390/f14061086.

[9] Y. Ibrahim, U. Y. Bagaye, and A. I. Muhammad, "Machine Learning-Based Forest Type Mapping from Multi-Temporal Remote Sensing Data: Performance and Comparative Analysis," in *ECRS 2023*, Basel Switzerland: MDPI, Dec. 2023, p. 9. doi: 10.3390/ECRS2023-15848.

[10] F. Cheng, G. Ou, M. Wang, and C. Liu, "Remote Sensing Estimation of Forest Carbon Stock Based on Machine Learning Algorithms," *Forests*, vol. 15, no. 4, p. 681, Apr. 2024, doi: 10.3390/f15040681.

[11] J. Lei *et al.*, "Prediction of soil organic carbon stock combining Sentinel-1 and Sentinel-2 images in the Zoige Plateau, the northeastern Qinghai-Tibet Plateau," *Ecol Process*, vol. 13, no. 1, p. 32, May 2024, doi: 10.1186/s13717-024-00515-7.

[12] N. Gorelick, M. Hancher, M. Dixon, S. Ilyushchenko, D. Thau, and R. Moore, "Google Earth Engine: Planetary-scale geospatial analysis for everyone," *Remote Sens Environ*, vol. 202, pp. 18–27, Dec. 2017, doi: 10.1016/j.rse.2017.06.031.

[13] K. Anderson and K. J. Gaston, "Lightweight unmanned aerial vehicles will revolutionize spatial ecology," *Front Ecol Environ*, vol. 11, no. 3, pp. 138–146, Apr. 2013, doi: 10.1890/120150.

[14] M. Chen, Q. Liu, S. Chen, Y. Liu, C.-H. Zhang, and R. Liu, "XGBoost-Based Algorithm Interpretation and Application on Post-Fault Transient Stability Status Prediction of Power System,"

IEEE Access, vol. 7, pp. 13149–13158, 2019, doi: 10.1109/ACCESS.2019.2893448.

[15] W. Mao, G. Feng, Z. Wu, W. Huang, and T. T. Toe, “Image Classification of Alzheimer’s Disease Based on ViT-Random Forest Model,” in *2023 9th International Conference on Computer and Communications (ICCC)*, IEEE, Dec. 2023, pp. 1916–1922. doi: 10.1109/ICCC59590.2023.10507644.

[16] B. Kumar, O. Dikshit, A. Gupta, and M. K. Singh, “Feature extraction for hyperspectral image classification: a review,” *Int J Remote Sens*, vol. 41, no. 16, pp. 6248–6287, Aug. 2020, doi: 10.1080/01431161.2020.1736732.

[17] W. Zhao and S. Du, “Spectral–Spatial Feature Extraction for Hyperspectral Image Classification: A Dimension Reduction and Deep Learning Approach,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 54, no. 8, pp. 4544–4554, Aug. 2016, doi: 10.1109/TGRS.2016.2543748.

[18] S. Tammina, “Transfer learning using VGG-16 with Deep Convolutional Neural Network for Classifying Images,” *International Journal of Scientific and Research Publications (IJSRP)*, vol. 9, no. 10, p. p9420, Oct. 2019, doi: 10.29322/IJSRP.9.10.2019.p9420.

[19] A. B. Omotoso and A. O. Omotayo, “The interplay between agriculture, greenhouse gases, and climate change in Sub-Saharan Africa,” *Reg Environ Change*, vol. 24, no. 1, p. 1, Mar. 2024, doi: 10.1007/s10113-023-02159-3.

[20] “Pengukuran dan penghitungan cadangan karbon-Pengukuran lapangan untuk penaksiran cadangan karbon berbasis lahan.” Accessed: Dec. 12, 2024. [Online]. Available: www.bsn.go.id

[21] BAPPENAS, “Rancangan Strategi Nasional REDD+ Versi 18 November 2010,” 2010

[22] N. Memon, S. B. Patel, and D. P. Patel, “Comparative Analysis of Artificial Neural Network and XGBoost Algorithm for PolSAR Image Classification,” in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, Springer, 2019, pp. 452–460. doi: 10.1007/978-3-030-34869-4_49.

[23] Z. Shao, M. N. Ahmad, and A. Javed, “Comparison of Random Forest and XGBoost Classifiers Using Integrated Optical and SAR Features for Mapping Urban Impervious Surface,” *Remote Sens (Basel)*, vol. 16, no. 4, Feb. 2024, doi: 10.3390/rs16040665.