1. INTRODUCTION

Forests are an important aspect in mitigating the impacts of climate change because they act as carbon sinks, absorbing and storing carbon dioxide from the atmosphere [1], [2], [3]. Monitoring, reporting, and policy-making efforts to lower greenhouse gas emissions depend on accurate assessments of carbon stocks [4], [5]. The manual tree measurements used in traditional carbon stock calculation methods are expensive, time consuming, and have a restricted geographic coverage [5], [6]. According to recent estimates, between 1988 and 2014, Russian woods stored about 354 teragrams (Tg) of carbon annually. This number, which is noticeably 47% greater than what was previously recorded in national inventories, shows how much carbon these forests can store because of their higher biomass density and larger forest area.

The combination of Unmanned Aerial Vehicles (UAVs) and Google Earth Engine (GEE) has emerged as a promising remote sensing technology advancement that could help overcome the drawbacks of traditional approaches. A supplementary dataset for tracking vegetation dynamics is made possible by GEE's broad, global-scale coverage and UAVs' high-resolution, localized observations [7], [8]. Higher spatial resolution carbon stock estimations can be obtained by researchers by utilizing both approaches, particularly in remote or intricate forest environments [9], [10]. For instance, merging GEE and UAV data enables the integration of large-scale geographical patterns with fine-grained vegetation data, which is crucial for precise and scalable carbon monitoring [11], [12], [13]. Studies have demonstrated that GEE and UAVs have different color and texture extraction characteristics. GEE often uses conventional methods to isolate and transform raw data into a set of measurable attributes that can be used for further analysis, a process known as feature extraction techniques that may not be able to capture the same level of detail in texture analysis, where UAV-based uses advanced algorithms to improve classification accuracy [14], [15]. Therefore, combining the different properties of these two data will be a contribution that can support similar research in the future.

Convolutional Neural Networks (CNN), in particular, are deep learning models that have proven to be efficient tools for evaluating data from GEE and UAVs. CNNs excel at extracting hierarchical spatial properties, which describe CNNs' capacity to identify patterns at various granularities, including edges, forms, and intricate structures in pictures and makes them ideal for tasks involving images, such as classification and segmentation [16]. Previous research has demonstrated the ability of CNNs in biomass estimation, with a good R2 value of 0.943 [8].

CNN models outperformed conventional machine learning techniques in previous studies on individual tree biomass estimation in natural secondary forests using WorldView-3 images and aerial laser scanning (ALS) data, with RMSE values ranging from 7.47 kg to 36.83 kg and R2 values between 0.68 and 0.85 [17]. Precision forestry and carbon management techniques were advanced by the combination of ALS with high resolution photography, which increased classification accuracy and gave comprehensive spatial AGB distribution. The integration of spectral and texture information, the requirement for sizable labelled datasets, and the dangers of overfitting persist despite CNNs' ability to detect spatial patterns [16].. In order to improve CNN's scalability and generalization across various forest types, settings, and regions in carbon stock estimation, these problems must be resolved.

For non-spatial data analysis, Multilayer Perceptrons (MLP) have been employed extensively in addition to CNNs. Although MLP works well with numerical and categorical data, it is not as useful for tasks like carbon stock estimation because it cannot capture the spatial hierarchy of image data. Nonetheless, a hybrid strategy that combines MLPs for examining supplementary spectral or textural characteristics with CNNs for extracting spatial features may have a great deal of promise for increasing prediction accuracy [18], [19].

In the calculation of carbon stocks based on remote sensing, feature extraction is essential. Green Chromatic Coordinates (GCC), Color Vegetation Index (CVI), and Excess Green Index (ExG) are a few examples of vegetation indicators that offer useful spectral data about biomass and vegetation health. In a similar vein, texture attributes such as homogeneity, contrast, and entropy provide information on structural complexity and spatial patterns, both of which are connected to carbon storage capability [20], [21]. Although previous studies have demonstrated that each of these traits can increase prediction accuracy on its own, little is known about how to integrate and use them with CNNs [22], [23].

This study fills a major gap in current approaches by evaluating the integration of color and texture information with CNNs for carbon stock classification. It does this by investigating the best way to combine spectral and spatial characteristics to increase classification accuracy. In contrast to earlier research that concentrated on texture features like homogeneity, contrast, and entropy or spectral indices like ExG, CVI, and GCC independently, this study employs CNN architecture to capture the structural complexity and spectral richness of vegetation by integrating these features into a single, unique framework. Furthermore, this study aims to determine the most effective method for classifying carbon stocks by methodically comparing the performance of several feature combinations, including color-based, texture-based, and mixed features. This research is a new addition to the field of remote sensing-based carbon stock estimation, as it contributes to the development of an integrated approach that combines spectral and textural features for carbon stock classification, identifies the most effective classification method by comparing feature combinations, and proposes a scalable framework that combines UAV and GEE data for applications in various forest ecosystems. As far as the authors are concerned, in order to classify carbon stocks, the majority of previous research either only looks at textural features or spectral indices, without merging the two in a cohesive manner. By connecting local high-resolution observations with global-scale data, the complementing datasets from UAVs and GEE enhance this research and provide a precise and scalable approach that can be tailored to different forest ecosystems. In addition to increasing the precision of carbon stock monitoring, this novel framework is anticipated to be a significant step in the development of dependable and scalable approaches to tackle climate change issues and guide conservation policies.