ATCM: A Method for Land-Water Classification from Satellite Image Using MobileNetV2

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Abstract – **Land-water classification from satellite images plays a vital role in several applications such as urban planning, disaster response, and climate studies. Several methods have been proposed for land-water classification in the literature. However, they have several limitations such as higher computational power, and negligible use of preprocessing steps. Moreover, only a few methods accurately classify different types of landforms. To overcome these limitations, this paper proposes Aqua-Terra Classification using MobileNetV2 (ATCM) from low-resolution satellite images. Furthermore, the proposed ATCM method involves several preprocessing steps to increase the quality of the satellite images. Through an experiment, the accuracy of the ATCM method is compared with various CNN models. The ATCM method acquires 96.2% testing accuracy on the preprocessed satellite images.**

Keywords–Deep Learning, Satellite image, Land Classification, Water Classification, Pre-trained CNN

I. Introduction

Landform classification has become an integral tool for monitoring and observing the Earth's surface [1]. It involves identifying and classifying different landforms such as land areas or water bodies. It is an essential building block for various applications such as urban planning, catastrophe response, and climate studies.

Many methods are available in the literature to classify and segment different landforms from satellite images [1-6,8-11]. However, they face several limitations such as higher computations and the inability to work with low-resolution images. In some methods, multiple landforms are classified which results in lower performance. Furthermore, segmentation of the satellite images is performed in some methods which does not provide higher performance. However, to overcome these limitations, the proposed ATCM method includes working with MobileNetV2 model. The MobileNetV2 model is recognized as one of the most reliable because to its lightweight nature [2]. It greatly reduces the number of parameters and calculations when compared to standard models. With fewer parameters, MobileNetV2 shows higher accuracy than other models such as InceptionV3, ResNet50, and VGG16.

This paper addresses the above limitations by introducing a novel approach using a MobileNetV2 model which has not been widely used in previous studies to accurately classify land and water from satellite images. The performance of the ATCM is measured using vital evaluation metrics such as accuracy, precision, recall, and F1–score. MobileNetV2 demonstrates higher performance than other CNN models. Therefore, the paper will mainly focus on land-water classification from satellite images.

The rest of the paper is organized as follows: Section 2 discusses the previous research works conducted for land-water classification. Section 3 presents the proposed ATCM method, algorithm, and working of the ATCM method. Section 4 discusses the performance of the proposed ATMC method along with various graphs and the obtained results of the ATCM method. Section 5 presents the conclusion of the paper and an outlook on future scope.

II. Related Work

Several land-water classification methods have been proposed over the years and are available in the literature [3-5].

A model to present analytics of several classification models has been offered in [3]. It focuses on detecting land cover changes in Moroccan satellite images. It is evaluated on the Landsat dataset, which contains 6 classes: Water, Forest, Barren, Built-up, Sand, and Cropped. Dataset images are initially preprocessed to create noise-free images. Then the images are fed to different classification models and relevant features are extracted. Performance was evaluated before and after adding spectral indices, with the minimum distance classifier being the most effective. The primary restriction noted in this work was the low-resolution of satellite images.

AD-LinkNet method has been proposed to segment the satellite images accurately in [4]. Initially, three sets of satellite images are augmented. Then, the satellite images are fed to several models such as Deep Unet, LinkNet, D-LinkNet as well as AD-LinkNet. The IoU score and Growing Score were used as the performance metrics for this model which indicates fairly high segmentation accuracy. An AD-LinkNet method has been evaluated using the IoU score and growing score as they are more appropriate for multiple classes. However, the AD-LinkNet method does not include any pre-processing steps. Hence, the model misclassifies the land and water.

A model comprised of seven segmentation architectures has been proposed for land cover mapping using Sentinel-1 images in [5]. Firstly, the Sentinel-1 images are augmented and normalized. The augmented Sentinel-1 images are then loaded into numerous deep-learning models to accurately segment distinct groups. The overall performance of the model is evaluated using metrics such as the accuracy and kappa coefficient. However, the model does not includes testing on higher resolution satellite images.

From the literature study, it has been observed that existing methods have several limitations. 1) Requires high-resolution images, 2) High computations, 3) High memory requirement, 4) High misclassification rate. To overcome, these limitations we proposed the ATCM method. A detailed discussion of the ATCM method is presented in the next section.

III. THE PROPOSED AQUA-TERRA CLASSIFICATION USING MOBILENETV2

This section proposes the Aqua-Terra Classification using MobileNetV2 (ATCM) method. Fig. 1 shows the major steps of ATCM method. The complete workflow of ATCM method is demonstrated in Fig. 2. Table I outlines the notations used in the algorithm of the proposed ATCM method, and Table II describes the detailed pseudocode of the proposed ATCM method.

The satellite images used by the ATCM comprises of various collections of terrains [7]. Initially, the satellite images are rendered in a set I. Satellite images are assessed depending on the variety of terrains such as lakes, oceans, forests, and plains. Hence, in our proposed method, we classify major two classes of terrains: water and land. The ATCM method includes pre-processing, feature extraction, and classification which are discussed in the sub-sections below.

A. Pre-processing

The input to this step is the satellite images. It mainly consists of 3 operations: resize, denoise, and enhancement of the satellite images.

The dataset's satellite photos are initially distorted and have a low resolution. Hence, the satellite images are resized to 128 x 128 pixels to make the satellite images clearer. Furthermore, satellite images are also prone to atmospheric interference and varying illumination conditions. Hence, the GaussianBlur filter is used to remove the noise from the resized images. Subsequently, satellite images are enhanced using a Laplacian filter. All the pre-processed images are stored in the set I_i^P, as outlined in line no. 5 of the Algorithm.

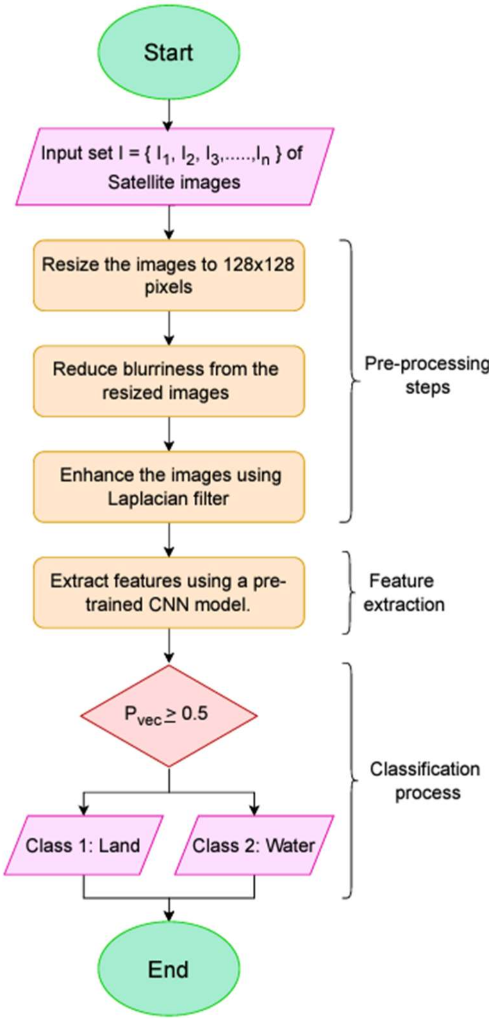


Fig. 2. Flowchart of the proposed ATCM method

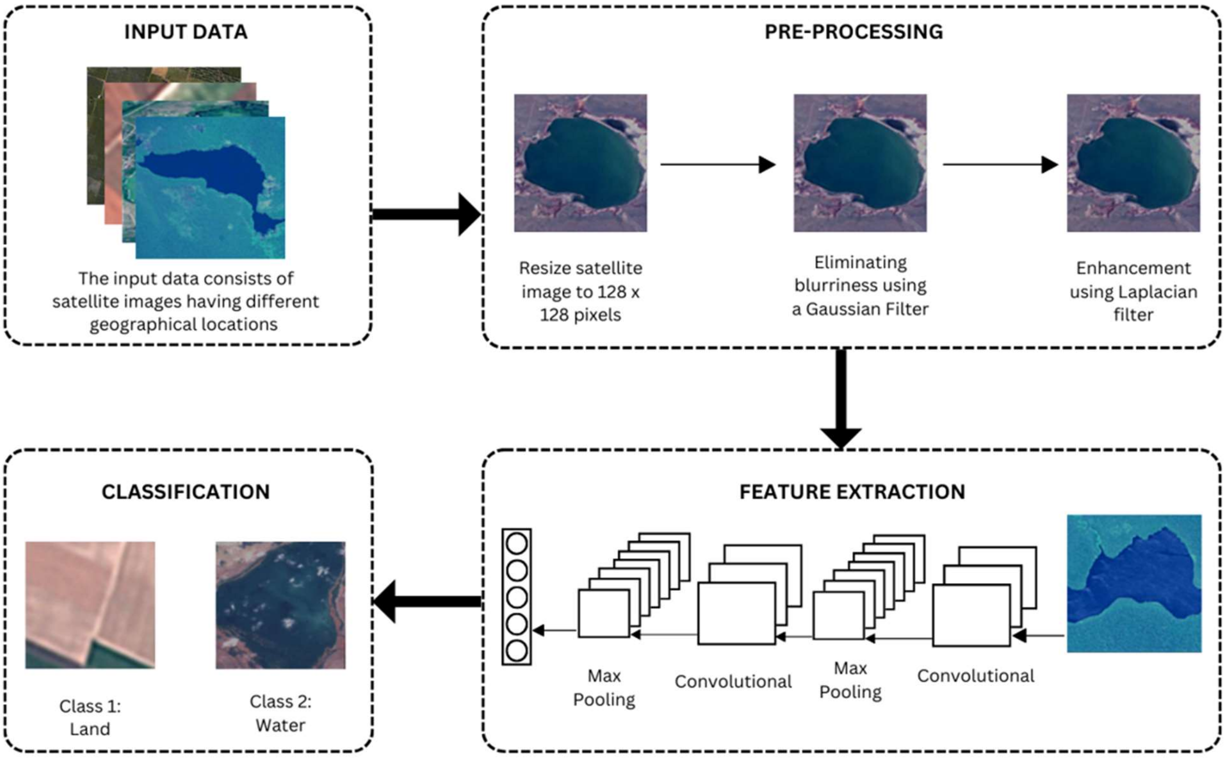


Fig.1. Major steps of the proposed ATCM method

TABLE I: THE LIST OF NOTATIONS

Notation	Description
n	Number of images in the dataset
I	A set of satellite images
I^R	A resized image
I^D	A denoised image
I^S	A enhanced image
I^P	A set of pre-processed images
F_{map}	A feature vector
P_{vec}	A probability vector
FC	A fully – connected layer

Algorithm: Pseudo-code of the ATCM method

Input: Image set I = { I_1, I_2, I_3, ……. , I_n }of satellite images

Output: One of the two landforms classes C_1 and C_2, where C_1 : Land and C_2 : Water

BEGIN

1. $I^P = \Phi$
2. For each $I_i \in I$
3. I_i^R = Resize(I_i) *// Resize the image Ii to a standard size*
4. I^D = Gaussian_Blur(I_i^R) *//Apply GaussianBlur on the resized image to reduce noise*
5. I^S = Laplacian_Filter2D(I^D) *//Apply Laplacian filter to the resized image to enhance images*
6. $I^P = I^P \cup I_i^D \cup I_i^S$ *//Final set of pre-processed images*
7. End For
8. For each $I_i^P \in I^P$
9. F_{map} = Extract features from I_i^P using pre-trained MobileNetv2 model
10. P_{vec} = Feed F_{map} to FC model to calculate probability of class
11. Display corresponding class based on the higher probability from P_{vec}
12. End For

END

B. Feature extraction

MobileNetV2 model is used as a feature extractor in our proposed ATCM as it gave us lower computational complexity on the classification of the satellite images. The pre-processed satellite images of set I_i^P are fed to the MobileNetV2 model. The model is further trained using the Adam optimizer as they showcased better performance for the binary classification. A learning rate scheduler is added to the training process to ensure more consistent convergence. If the validation loss remains static, the scheduler reduces the learning rate. As the satellite images go through the training process, the convolutional layers of the MobileNetV2 model identify the patterns and classify them as land or water. Furthermore, the ReLU activation function is used with MobileNetV2 using (1).

$$f(x) = \max(0, x) \tag{1}$$

where x is the input vector.

The ReLU activation function was utilized in the ATCM method to deal with non-linearity and to optimize model training. It generates a feature map which is stored in an F_{map} vector.

C. Classification

The last step consists of classifying the input satellite images based on the extracted features F_{map}. The $F_{map}$is the input to the FC model. The FC model is responsible for understanding the extracted features and making the final classification. The class with the highest probability is then allocated to the satellite image to complete the classification after a threshold is applied to the probability vector P_{vec}. The output is produced and the satellite image is categorized as either land or water based on P_{vec} .

IV. RESULTS AND DISCUSSION

In this section, we present the evaluation of the entire ATCM method along with details of the dataset, evaluation metrics, and the obtained results. An experiment is conducted to compare different pre-trained CNN models with each other, and selecting the higher performing model. For the experiment, the dataset is divided into 80% training and 20% testing ratio. Furthermore, a set of hyper-parameters are also defined. The hyper-parameters affect the performance of the deep learning models as discussed in [12-14]. The learning rate was set to 0.001 to increase the learning. A training batch of 32 was used to speed up the training.

The performance of the ATCM method was measured with the help of several metrics such as accuracy, precision, recall, and F1–score. The equations for the evaluation metrics are defined in (2), (3), (4), and (5) respectively. The ATCM method requires True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) to analyse the metrics. TP refers to the land areas correctly classified as Land by the ATCM. This implies that the ATCM successfully detects locations in satellite images that belong to the land class. TN refers to water bodies accurately classified as Water by the ATCM. This suggests that the ATCM = effectively identified and classified water zones without mistaking them for land. FP occurs when the ATCM inaccurately classifies water as land. This indicates that the ATCM has incorrectly recognized a water region as a land area, leading to probable misinterpretations and faults in geographical data analysis. FN occurs when the ATCM incorrectly classifies land as water. This shows the ATCM failed to accurately identify a land region and classified it as water. Using these metrics, we may evaluate the ATCM method's ability to accurately distinguish between land and water areas. A strong model would strive to maximize True Positives and True Negatives while reducing False Positives and False Negatives.

The accuracy metric is used to find the overall performance of the proposed ATCM method. The accuracy measures the quality of the ATCM method by calculating the proportion of correct classes such as Land and Water among all classes. Precision is defined as the proportion of correctly classified land areas among all instances classified as land as well as the proportion of correctly classified water bodies among all instances classified as water. In contrast, recall is the proportion of correctly classified land areas among all the land instances. F1-score is the harmonic mean of precision and recall. The results of the proposed ATCM method are represented in Table II.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (3)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (4)$$

$$F1-\text{score} = 2 * \frac{\text{Precision}*\text{Recall}}{\text{Precision}+\text{Recall}} \quad (5)$$

The plots of the accuracy and loss of various pre-trained CNN models as well as the proposed ATCM method are presented in Fig 3.

A. Comparison of pre-trained CNN models

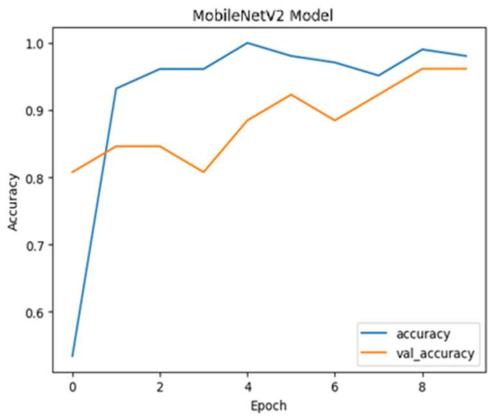
Table II represents the comparison between various pre-trained CNN models by evaluating different evaluation metrics of the pre-trained CNN models.

TABLE II: RESULTS OF THE COMPARISON OF PRE-TRAINED CNN MODELS

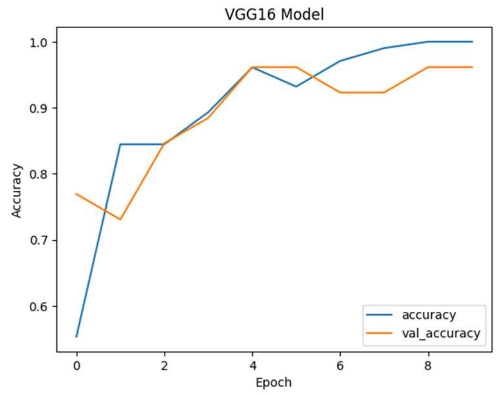
Models Used	**Evaluation Metrics**			
	Accuracy	**F1-Score**	**Precision**	**Recall**
MobileNetV2	96.2%	0.97	0.94	1.0
VGG16	96.1%	0.96	0.92	1.0
ResNet50	69.34%	0.79	0.66	0.92
InceptionV3	92.30%	0.91	0.84	0.93

As shown in Table II, MobileNetV2 model has the highest performance among other pre-trained CNN models and thus, the ATCM method is evaluated using the MobileNetV2 model. MobileNetV2 obtained the highest accuracy of 96.2% among other pre-trained models which indicates strong classification of the satellite images. The ATCM has an F1-score of 0.97, indicating an excellent balance between precision and recall, making it highly reliable in predicting both classes, with no notable bias toward False Positives or False Negatives. The ATCM's precision of 0.94 indicates that the method correctly anticipates a region as land 94% of the time. This high precision is critical for limiting the misinterpretation of water bodies as land, which could otherwise lead to severe inaccuracies. More importantly, the ATCM method has a perfect recall of 1.0, which means it correctly identifies all water bodies in the dataset without missing any. This perfect recall is especially useful in applications where it is critical to detect every single instance. Overall, the exceptional performance metrics of the ATCM — high accuracy, balanced F1-score, good precision, and flawless recall—showcases its resilience and reliability in land-water classification tasks.

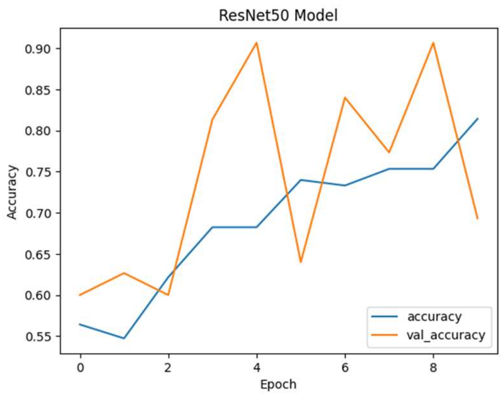
Fig. 7 illustrates a graphical representation of the comparison of various pre-trained CNN models to the proposed the ATCM method. It demonstrates the superiority of the ATCM method over several pre-trained CNN models.



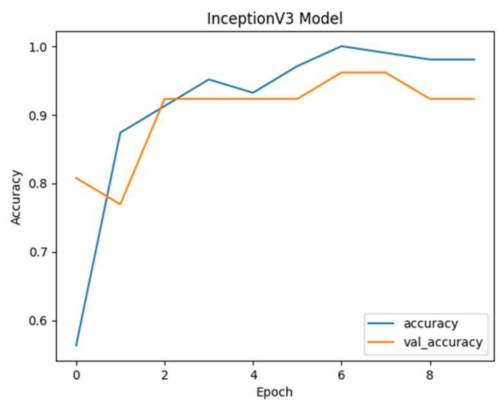
(a)



(b)



(c)



(d)

Fig. 3. Accuracy plot of different pre-trained CNN models such as (a) MobileNetV2, (b) VGG16, (c) ResNet50, and (d) InceptionV3 model

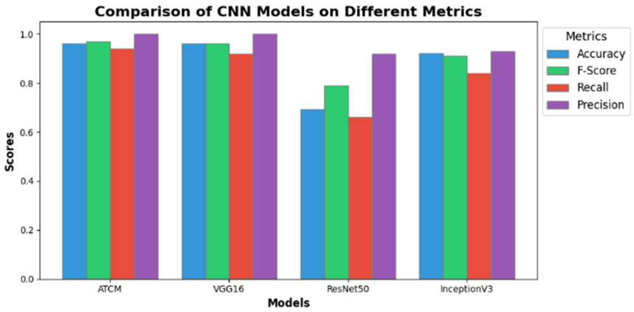


Fig. 7. Performance comparison of the ATCM method with other models

V. CONCLUSION

This paper presents a novel method for land-water classification from satellite images using MobileNetV2 model. The efficiency of the proposed method has been evaluated using the EuroSAT dataset, which consists of satellite photos with diverse landforms. The results obtained illustrates that the ATCM method outclasses various pre-trained CNN models. Through the results, it is observed that the ATCM method showcases accuracy, f1-score, precision, and recall of 96.2%, 0.97, 0.94, and 1.0 respectively. This work can be expanded in the future by gathering real-time satellite images for training and testing. Moreover, the proposed method can be enhanced to handle multispectral and hyperspectral satellite images that provide richer set of satellite images to improve the classification analysis.

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