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A Convolutional Neural Network for Coastal Classification Based on ALOS and NOAA Satellite Data

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ABSTRACT Although coastal classification has been attended in recent years, it is still a complicated problem in quantitative geomorphological and hydrological sciences. Nowadays, the integration of deep learning in remote sensing and GIS analysis can quickly classify and detect different characteristics on both land and sea. Therefore, the authors proposed the use of a convolutional neural network (ConvNet) for coastal classification based on these technologies and geomorphic profile graphs. The primary input data is digital elevation/depth models obtained from ALOS and NOAA satellite. Eight hundred coastal samples representing eight types of coasts taken along the coastline in Vietnam were used for training and testing various ConvNets. As a result, three ConvNet models using three different optimizer functions were developed with the accuracies of about 98% and low values of the loss function. These models were used to classify 1029 in 1150 coasts (equal to 89%) in Vietnam. Nearly 11% of Vietnamese coasts could not be defined by three ConvNet models due to their complex geomorphic profile graphs, and require assessments of other natural components. The trained ConvNet models can potentially update new coastal types in different tropical countries towards coastal classification on national and global scales.

INDEX TERMS Geomorphology, coastline, digital elevation model, profile graphs, loss function, optimization.

I. INTRODUCTION

Since the early 1800s, coastal classification has been a complicated problem in geomorphological and hydrological sciences [1]–[3]. In modern scientific investigations, the analysis of land-sea boundary types is still discrete for decision-makers in the coastal classification and nomenclature [4], [5]. Coasts have been commonly classified based on one of the following sectors: (1) processes, (2) materials, (3) forms, (4) age or stage of development, and (5) environments [4], [6]–[8]. Depending on research scales, coast types can vary from global (worldwide coverage), continental, regional to local scales [9]–[11]. Therefore, it is necessary to have a better quantitative classification method that consists of assessments of terrain, wave energy, tidal range, sea-level stability, and material.

U.S. Geological Survey in the Coastal Classification Mapping Project[1] emphasized the essential roles of physical processes for coastal classification in the development of coastal landforms, especially with water and wind erosion, generation of sandy beaches, and barrier islands, and extreme climatic hazards. The natural coastal attributes can be observed, such as dune height (elevation) and continuity, beach width, and presence or absence of emergent sandbars [12]. Therefore, interpretation based on geomorphic features can be principle information for coastal classification [13], [14]. However, the former coastal classification systems based on geomorphic features were commonly developed based on local observation instead of quantitative

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[1] https://archive.usgs.gov/archive/sites/coastal.er.usgs.gov/coastal-classification/class.html

measurements [15]–[17]. It makes difficulties for upscaling these classifications for larger scales such as national or global scales. Most of the coast types were described on horizontal sides that cannot help to classify quantitatively these coast types in detail [11]. If the coasts are observed from vertical sides, it can provide quantitative information such as elevation, slope, and flow length for the coastal classification. Geomorphic profile graphs are commonly used to represent this information. The question raised here is how to classify coasts from various geomorphic profile graphs?

Nowadays, satellite and airborne remote sensors are used effectively to modelized coastal terrains, coastal land uses, and surface covers, such as National Oceanic and Atmospheric Administration (NOAA), Advanced Land Observation Satellite (ALOS), RADARSAT-1 and TerraSAR-X data [18]–[21]. Different advantages of satellite imagery to classify coasts were mentioned by Finkl (2014), such as timeliness, synoptic, and reduced costs. Especially, terrain observation from remote sensing images makes land-sea separation clearer [20], [22].

The integration of remote sensing, GIS into deep learning has become a potential method to quickly classify and detect different objects on both land and sea, especially with the use of convolutional neural networks (ConvNets) [23]–[25]. The ConvNets have been known as a unique structure of convolutional neural networks [26]. Although these networks were proposed by LeCun et al. (1998), they have been used more frequently since the 2010s [28]–[32]. The ConvNets analyze visual features, and one of the most popular applications of these networks is image classification [26], [33]. The main task of image classification is to interpret objects in an input image based on their spectral bands or attribute profiles. For ConvNet development, the model requires big data that consist of base images for training and testing processes. Once the model is completed, it can be used to classify new images [34], [35]. For coastal classification, the trained ConvNet model compares specific characteristics of the original input with the base coasts and quickly determine its type. For a computer, these characteristics can be shapes, boundaries, and curvatures [36]–[38]. With the use of these models, coast types can be potentially distinguished based on geomorphic profile graphs. The most crucial issue for training a ConvNet model is image data preparation. A large number of input image data for the training and testing process can make the ConvNet models more accurate, especially in the case with multi-class classification [33], [39].

Vietnam has about a 3260 km coastline with different coast types [40]. It helps to select various samples for training and testing a ConvNet model. The coasts in Vietnam has only been classified from expert experiences in some particular regions [6], [7], [16]. Therefore, coastal classification has not been mapped in Vietnam. Once the Vietnamese coasts are classified, the outcomes can become a useful tool for scientists in geomorphic zoning and managers in land-use planning. The following research questions - relevant to coastal classification – will make this study clearer:

- How many types of coasts can be identified in Vietnam?
- Is it feasible and effective to apply convolutional neural networks for coastal classification based on geomorphic features?
- How do coast types distribute in Vietnam?

In this study, four types of geomorphic profiles, including absolute elevation, relative elevation, slope, and flow length, were used as input variables for coastal classification. The geomorphic profiles of 800 coast samples were used to develop a ConvNet model for coastal classification. Afterward, the trained model was used to classify 1150 other coasts along the coastline in Vietnam. Before coming to the explanation of model development (from section 2.B to 2.E), the authors provided an overview of coastal classification systems and related characteristics of some coast types in Vietnam (section 2.A). Results related to coastal classification and model development will be compared with former studies in section 4.

II. MATERIAL AND METHODS

A. FORMER COASTAL CLASSIFICATION SYSTEMS IN VIETNAM

With a long coastline, natural and socio-economic characteristics of Vietnamese coasts are varied from Mong Cai city, Quang Ninh province (bordering China) in the North to Ha Tien, Kien Giang province (bordering Cambodia) in the South (Figure 1). The coastal zone in Vietnam is located in the tropical monsoon region with the northeast monsoon season from November to March and the southwest monsoon from May to September [40], [41]. Vietnam's coasts are divided by more than 380 rivers [42]. An estuary develops every 20 km along the coastline. One hundred twenty-five coastal districts with many natural ports, industrial centers, heritage sites, urban areas, and developed industries belong to 28 provinces, and cities annually suffer from 12-14 hurricanes [7], [43].

Based on the difference of the natural characteristics in the continental strip and the shallow coastal wetlands, Vietnamese scientists divided the Vietnamese coast into ten main types [6], [44]. These sub-types can be checked in Table 1. These coast types can be grouped into some primary categories as following:

- **Tectonic and karst coasts:** distribute from Mong Cai city, Quang Ninh province to Do Son city, Hai Phong province in Vietnam. The dalmatian coasts as a primary type of shoreline were formed from the tectonic division of young mountainous ranges that are parallel with local geological faults. These coasts were submerged by the seawater during the last glacier periods. Whereas the karst coasts were generated from limestone sediments [45]. The karst coasts have hierarchical characteristics in Bai Tu Long and Ha Long bays [40]. Both coast types are sharply divided, generating about 3,000 islands and 5000 km^2 area of Northern bays in Vietnam [44].
- **Delta and alluvial coasts:** include the two largest estuaries are the Red River and Mekong River systems and

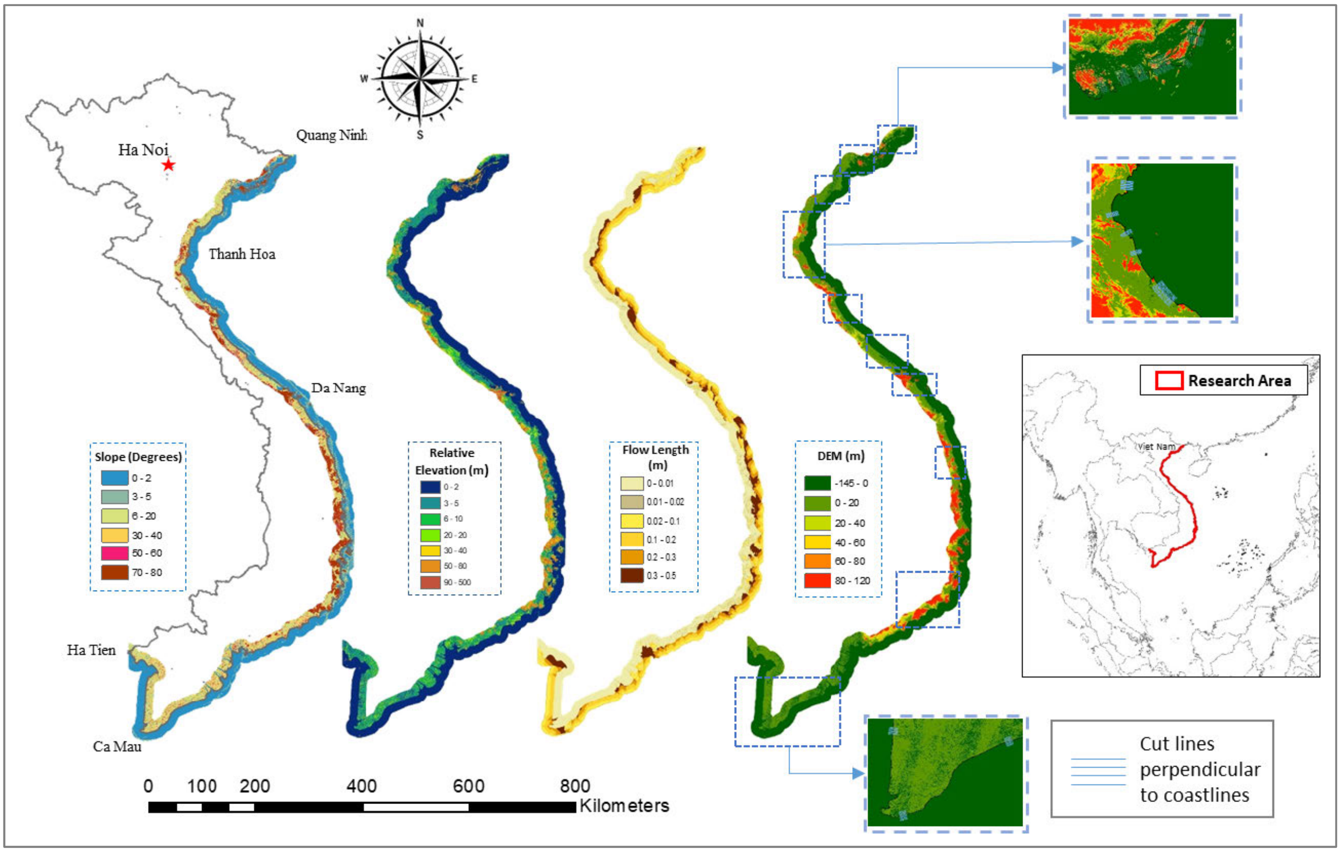

FIGURE 1. Geomorphic features (DEM, relative elevation, slope and flow length) in Vietnamese coasts.

various small rivers in the Middle part of Vietnam. Especially, mangrove ecosystems that are well grown in the delta coasts make suitable conditions for the accumulation process, resulting in seaward expansion. These coasts are commonly low (about 5-7m inland high) and slightly divided (every 20 km) by rivers [46], [47]. Notably, the coastal area of the Red River Delta has an average elevation of 0.5 - 1.3 m, whereas its levels can reach to 4-6m high. The offshore sector is the shallow seabed with 10m deep and 15-20km width. The terrain from a depth of 20-22m, the seabed is more distorted because of the development of ancient river valleys on the sea bottom [48]. The slight slope of coasts due to the effects of inflow water from the river causes significant obstacles for maritime transport [49].

- **Accumulative coasts:** were observed by Vietnamese scientists in coasts of Dai Lanh, Khanh Hoa province, and coasts from Ca Na, Ninh Thuan province to Vung Tau city, Ba Ria – Vung Tau province. This coast type has been slightly divided. The sediment is deposited from inflow and wave, generating stable terrains and long dunes. Wind erosion from the dunes is the main reason for the degradation in agricultural development. These dunes are commonly narrow with different levels of elevation, from 1.5-2m, 4-6m, 10-15m to 20-25m, sometimes up to 70-80m depending on the age of dunes [44]. The appearance of these dunes can make different sub-types of coasts that were explained in detail by [44], [50]
- **Abrasive coasts due to wave erosion:** were identified as steep and complicated coasts from Dai Lanh, Khanh Hoa province to Ca Na, Ninh Thuan province. The elevation of these coasts changes rapidly from more than 300-400m high in the mainland to zero-high in coastline [44]. The seabed on these coasts is the narrowest part of Vietnam. The average depth of the bay is 20-25m, sometimes down to 40-50m. The oldest red dunes observed on the elevation of 200m in Phan Thiet city are also assessed as abrasive coasts due to the effects of sea waves during the last century [6].

Four main categories were mentioned by Vietnamese scientists were separated based on expert understandings about local geomorphic, geological, and hydrological characteristics. In this study, the authors only focused on the application of the geomorphic features for coastal classification. Other natural features were not added to ConvNet development. This issue will be discussed more in section 4.

B. DATA AND SAMPLE COLLECTION

To reclassify the coast types based on geomorphic features, digital elevation models (DEM) are the most crucial

TABLE 1. **Coastal classification in Vietnam and the distribution of these coast types adapted from Le and Le (2007) and Nguyen et al. (2010).**

Coast type	Distribution	Length
1. Tectonic and karst coasts		
Coast of tectonic dissection	From Vinh Thuc island (Quang Ninh province) to Ha Mai island (Quang Ninh province)	120km
Coral reef coast	Islands of Hoang Sa archipelago, Truong Sa archipelago (Khanh Hoa province), small islands of Trung Bo Coast region	
Tropical bio-chemical corrosive coast (Tropical karst coast))	Cat Ba, Lan Ha, Ha Long and Bai Tu Long islands areas (Quang Ninh province)	100km
Coast of abrasive bays	Bach Long Vi islands (Quang Ninh province) and Con Dao islands (Ba Ria - Vung Tau province)	
2. Delta and aluvial coasts		
Deltaic coast	From Do Son district (Hai Phong city), to Lach Truong estuary (Thanh Hoa province)	150km
	From Tieu estuary (Tien Giang province) to Rach Gia City (Kien Giang province)	670 km
Coast of alluvial flats	From Lach Truong estuary (Thanh Hoa province) to Hoi estuary (Nghe An province)	170 km
Coast of alluvial-marine flats	From Hoi estuary (Nghe An province) to Ron cape (Ha Tinh province)	130 km
Deltaic coast	From Do Son district (Hai Phong city), to Lach Truong estuary (Thanh Hoa province)	150km
3. Accumulative and abrasive coasts		
Coast of clayey and sandy tidal flats	From Mong Cai City (Quang Ninh Province) to Do Son (Hai Phong city)	350 km
	From Vung Tau city (Ba Ria - Vung Tau province) to Tieu estuary (Tien Giang province)	120 km
Coast of abrasive-accumulative bays	From Quy Nhon city (Binh Dinh province) to Vung Tau city (Ba Ria - Vung Tau province)	850 km
	From Hon Dat district (Kien Giang Province) to Mui Nai cape (Kien Giang Province)	250 km
Smoothed abrasive-accumulative coast	From Ron cape (Ha Tinh province) to Quy Nhon city (Binh Dinh province)	750 km

input data. Inland DEM were downloaded from the Google Earth Engine[2] with resolution of 30 meters obtained by the Panchromatic Remote-sensing Instrument for Stereo Mapping (PRISM) onboard the Advanced Land Observing Satellite (so-called as ALOS) [51]. Due to the DEM obtained from ALOS satellite can only show the height above sea level. The lowest value of the ALOS DEM is zero; therefore, the boundary between sea and land were clearly identified at the inland border of the value '0'. The DEM under the sea were downloaded from Global Relief Data obtained by NOAA National Centers for Environmental Information (NCEI), with the resolution of one arc-minute [52]. The DEM data needs to cover both inland and offshore areas in Vietnam (or 3260km of the coast). Therefore, both data were converted to the horizontal datum of WGS84/UTM – 48N and downscaled to raster of 30m resolution. Authors merged inland elevation ALOS

[2]https://earthengine.google.com

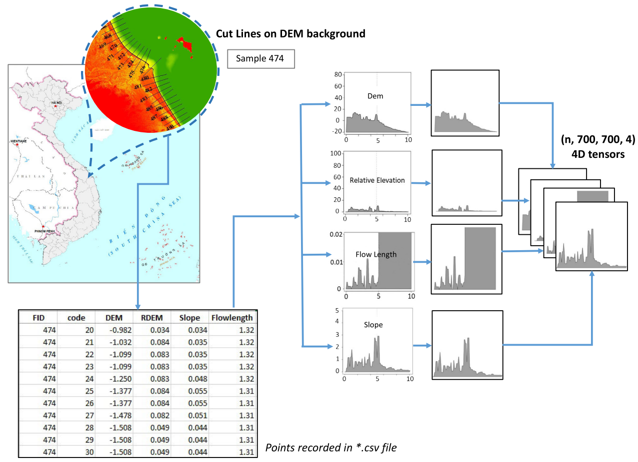

FIGURE 2. **Image preparation for coastal classification based on perpendicular lines to coastlines (so-called as "cut line"), example with cut line No.474. The "code" column shows the range of points valued from [1,101] corresponding to 101 points in the cut line No.474. "n" is the number of input cut lines to the ConvNets. In total, 800 cut-lines were generated for ConvNet development and 1150 cut-lines were created for Vietnamese coastal classification.**

data with the NOAA DEM through the sea-land boundary (or coastline) to generate a complete DEM from inland to offshore areas with the use of ArcGIS software.

In this study, four potential geomorphic features that will be used for coastal classification include absolute elevation, relative elevation, slope, and flow length. Whereas the absolute elevation of coasts was collected satellite data, the next three geomorphic features can be directly calculated from the DEM. While the relative elevation represents the differences between the highest and lowest elevation in a particular area, the slope represents the steepness or the degree of inclination of terrain surface relative to the horizontal surface [53]. The unit of the relative elevation in Vietnam fluctuate from 0 to 500m, and the slope fluctuates from 0 to 90 degrees (Figure 1 and 2). The feature "flow length" represents the most extended downslope length along the flow path, or the time of water concentration from each cell to a sink or outlet [54], [55]. All three geomorphic features were calculated based on the "spatial analysis" tool integrated into ArcGIS 10.5.

C. IMAGE PREPARATION BASED ON GEOMORPHIC PROFILE GRAPHS

In this study, coast types will be identified based on image classification. Therefore, four geomorphic features in coasts will be essential inputs for image preparation. In detail, to prepare input images for ConvNet development, three types of data need to be made, including (geomorphic) profile graphs, cut lines, and profile points. An input image contains four sub-graphs presenting four geomorphic profiles on a particular coast. To draw the profile graphs (Figure 2), the authors made cut lines perpendicular to coastlines with about 400m equally apart and 10km in length (5km inland and 5km offshore). These cut lines were converted to 101 points with 50 inland points, 50 offshore points, and one point located on the coastline. Geomorphic values from corresponding raster maps were assigned to the points; therefore, four types of geomorphic profile graphs were generated from each cut line. The connection between points in a cut line containing geomorphic features from land to sea will make geomorphic profile graphs.

Related to the design of the profile graphs, the scale of the x- and y-axis was fixed. In all profile graphs, the x-axis represents the distance from the land (left side) to the sea (right side). It starts at 5km inland points and ends at 5km offshore points from the coastline. The reference of the y-axis is different between geomorphic features. For the elevation profile graph, the range of values was fixed from '-20' to '80' to fully observe the fluctuation between inland and offshore elevation. The ranges of flow-length, relative elevation, and slope values were fixed from '0' to '0.02', '0' to '100', and '0' to '5', respectively. To make the profile graphs simplest as possible for the model development explained in section 2.D, all labels on the graphs were eliminated. The final graphs inputted for the model development only contain the shapes of the geomorphic features (Figure 2).

Based on field trips in 2017, 2018, and 2019 along the coastline in Vietnam, authors identified eight coast types that can be separated based on local geomorphic features. The characteristics of these coast types will be mentioned in the result section. Additionally, coastline parts specified for eight coast types were selected. Among these parts, 100 cut line samples are built for each coast type with about 400m equally apart and 10km in length. The location and distance of cut-line samples are explained in Table 2. Terrains fully affected by the inland runoffs (or estuaries) were eliminated in the analysis and sampling. Accordingly, 2400 profile sub-graphs were generated from 800 cut line samples. To optimize input data for ConvNet development, all profile sub-graphs were simplified to grey-scale images, instead of using Red-Green-Blue (RGB) images. Four geomorphic profile graphs in a cut line were stacked together as four bands of one image. Therefore, we call the combination of four profile graphs in one cut line as an image from here. Lastly, the number of the input images for training and testing models is 800 ('n' in Figure 2). The dimension of the images is fixed at 700×700 pixels. It is the perfect size to observe the fluctuation of four geomorphic features in the images. During the training and testing processes, the smaller sizes made the image blurrier, whereas the larger sizes reduce the performance of trained ConvNet models.

D. CONVOLUTIONAL NEURAL NETWORKS ARCHITECTURE FOR COASTAL CLASSIFICATION

Convolutional Neural Networks (ConvNet) exploit the information containing in pictures [56]. Unlike a regular Neural Network, the layers of a ConvNet as a sequence of layers contain neurons organized in 3 dimensions: width, length and depth. The depth dimension of a picture can be the number of bands or number of input variables. For instance, the depth dimension of input images in this study is an input volume of activations or the number of geomorphic features; therefore, the volume has dimensions 700x700x4

TABLE 2. Coastal classification in Vietnam and the distribution of these coast types adapted from Le and Le (2007) and Nguyen et al. (2010).

	Distribution	No. cut lines	No. points	Length of coastline (km)
1	Mong Cai - Cam Ha district, Quang Ninh province	76	7676	35
	Van Don district, Quang Ninh province	24	2424	10
	Total	**100**	**10100**	**45**
2	Van Don district, Quang Ninh provice	59	5959	25
	Ha Long natural heritage area, Quang Ninh province	31	3131	12.2
	Cat Hai district, Quang Ninh province	10	1010	4
	Total	**100**	**10100**	**41.2**
3	Hai Hau district, Nam Dinh province	40	4040	15.6
	Vinh Chau district, Soc Trang province	20	2020	8.2
	Ngoc Hien district, Ca Mau province	20	2020	7.6
	U Minh district, Ca Mau province	20	2020	7.8
	Total	**100**	**10100**	**39.2**
4	Quynh Luu district, Nghe An province	20	2020	7.6
	Dien Chau district, Nghe An province	10	1010	3.6
	Cua Lo district, Nghe An province	10	1010	3.6
	Nghi Xuan district, Ha Tinh province	10	1010	3.6
	Thach Ha district, Ha Tinh province	25	2525	9.6
	Cam Xuyen district, Ha Tinh province	25	2525	9.6
	Total	**100**	**10100**	**37,6**
5	Gio Linh district, Quang Tri province - Phong Dien district, Thua Thien Hue province	90	9090	36
	Dien Bien district, Quang Nam province	10	1010	3.6
	Total	100	10100	39.6
6	Duy Xuyen - Nui Thanh district, Quang Nam province	100	10100	39.7
	Total	**100**	**10100**	**39.7**
7	Quang Dien district, Thua Thien Hue province	24	2424	11.2
	Phu Vang district, Thua Thien Hue province	19	1919	7.2
	Phu Loc district, Thua Thien Hue province	12	1212	4.4
	Phu My district, Binh Dinh province	10	1010	3.6
	Phu My – Phu Cat district, Binh Dinh province	12	1212	4.4
	Tuy An district, Phu Yen province	7	707	2.4
	Cam Lam district, Khanh Hoa province	16	1616	6
	Total	**100**	**10100**	**39.2**
8	Thuan Nam district, Ninh Thuan province	20	2020	9.0
	Bac Binh – Phan Thiet district, Binh Thuan province	60	6060	27.3
	Phan Thiet district, Binh Thuan province	20	2020	7.6
	Total	100	10100	43.9

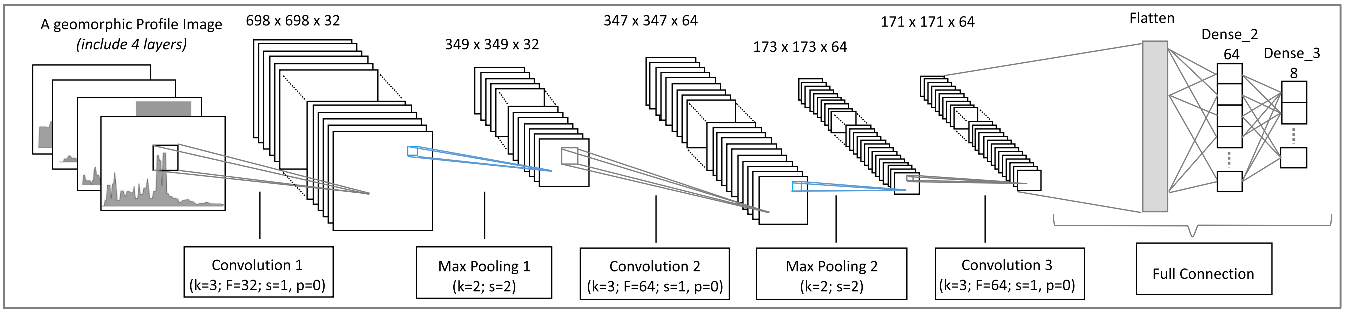

FIGURE 3. **The architecture of a convolutional neural network for coastal classification, where 'k' is size of a kernel in a convolutional layer; 'F' is number of kernels in a convolutional layer; 's' is stride or the distance between two continuous kernel; and 'p' is padding amount or width of padded border.**

(width, height, depth respectively). The neurons in a layer will work with small parts of pictures, instead of working with entire pictures at once [34], [36]. At last, the size of the full images has to be reduced to a single vector that is represented in the last layer with the dimension of $1\times1\times8$ (Figure 3).

In Figure 3, every layer of the ConvNet converts one volume of activations to new states through a chosen function. During the ConvNet architecture development for coastal classification, 800 profile images built-in section 2.C were separated into two groups with 75% of data (or 600 images) for the training process and 25% of data (or 200 images) for the testing process. The ratio of coast types in the training and testing data is equal. Three main types of layers commonly used to build ConvNet architectures include Convolutional Layer (CONV), Pooling Layer (POOL), and Fully-Connected (FC) Layer. These layer types were stacked to form a full ConvNet architecture as following:

- INPUT layer keeps the raw pixel values of all images ($700\times700\times4$); in this case the dimension of an image has a width of 700-pixel, the height of 700-pixel, and four geomorphic feature channels (DEM, RDEM, slope, and flow-length).
- CONV layers compute the output of neurons through a set of filters. Dong et al. (2019) suggested that the weight and length of the filters are smaller than those of the input images. The filter is slid across the input width and length, connect to small local regions of input images. New pixel values will be calculated from the input based on activation functions chosen for the filters (explained more in section 2.E). In this study, the authors chose three CONV layers for the ConvNet development, as suggested by Feng et al. (2019). To reduce the training and validation time, 32 filters for the first CONV layer and 64 filters for the next two CONV layers were chosen with the size of 3x3, respectively as width and length.
- POOL layer downscales operation to the spatial matrices of 2×2, respectively as width and height. This layer also uses specific activation functions for the downscaling process that will be explained in section 2.E.
- FC layer transforms simplified outputs from the POOL layer to the class scores as the volume of size $[1\times1\times8]$. Each of the eight numbers is represented as a class score in eight coast types. In this layer, some spatial matrices calculated in the POOL layer will as assigned to a class score based on training output data. The assignment process will be recorded in the trained ConvNets.

TABLE 3. **Mathematical structure of the developed ConvNet for coastal classification.**

Layers	Output Shape	No. parameters
Conv2D - 1	(None, 698, 698, 32)	1,184
MaxPooling2D - 1	(None, 349, 349, 32)	0
Conv2D - 2	(None, 347, 347, 64)	18,496
MaxPooling2D - 2	(None, 173, 173, 64)	0
Conv2D - 3	(None, 171, 171, 64)	36,928
Flatten	(None, 1,871,424)	0
Dense – 1	(None, 64)	119,771,200
Dense - 2	(None, 8)	520
Total parameters		**119,828,328**
Trainable parameters		**119,828,328**

Table 3 shows the image processing procedure with eight layers according to the ConvNet architecture. The output of the previous layer is the input data of the subsequent layer. Five layers Conv2D-1, Conv2D-2, Conv2D-3, MaxPooling2D-1 and MaxPooling2D-2 consist of the matrixing and normalizing functions of the Pooling matrix, expressed as a 3-dimensional matrix. The size of the output shape in the Conv2D layer is calculated as follow:

$$(H*W*F)_{layer} = \frac{H_1 - H_2 + 2*P}{S+1} * \frac{W_1 - W_2 + 2*P}{S+1} * F \tag{1}$$

where H1 * W1 * D correspond to height, width and depth of inputs and H2 * W2 * D correspond to height, width and depth of filters. Filters always has the depth equal to the depth of inputs; 'S' is the value of stride; 'P' is the number of padding and 'F' is the number of filters. The Figure 3 shows the particular values of stride and padding for each layer.

The number of parameters of the Conv2D layers is calculated as following:

$$N_{parameter} = (H * W * D + 1) * F \tag{2}$$

where 'H' is height, 'W' is width, 'D' is depth and 'F' is number of filters. Each filter has one parameter to store the bias value. For example, the Conv2D-1 has $(3 \times 3 \times 4 + 1) * 32 = 1184$ parameter.

Three layers Flatten, Dense 1 and Dense 2 transform outputs from the first five layers to a vector form. Similar with the Conv2D layers, each node in a vector of the Dense layers also has one parameter that holds the bias value. The number of parameters in the Dense layer is calculated as following:

$$N_{parameter} = N_{output} * (N_{input} + 1) \tag{3}$$

where N_{input} is the number of nodes in the input vector, N_{output} is the number of nodes in the output vector. For example, the Dense-2 has $8 * (64 + 1) = 520$ parameter. The outcome of the final layer is a vector with eight values, corresponding to 8 coast types. Based on nine layers (1xINPUT, 3xCONV, 2xPOOL, and 3xFC layers), the trained ConvNets transformed the original pixel values in 800 geomorphic profile images to the final class scores. Only three CONV and two POOL layers contain parameters due to they used respective activation and optimizer functions for the training process. The detail of these functions will be presented in section 2.E. Based on alternative options to choose activation and optimizer functions, the parameters in the CONV, POOL and FC layers will be trained. During the ConvNets development, the accuracy of both training and testing data was checked to avoid overfitting and underfitting errors [57]. The best ConvNet requires the output class scores from the trained ConvNet consistent with the labels assigned in the training and testing image data.

E. ALTERNATIVE OPTIONS TO DEVELOP THE CONVNETS

According to the architecture of the ConvNets for coastal classification, three types of functions can be chosen to develop the ConvNets. They include activation function, loss function, and optimizer method. These types of functions will help to identify optimal parameters for filters contained in hidden layers. The selection of function and method depends on the type of input data and output labels, and the accuracy/loss of trained models. This information will be explained in this section.

1) ACTIVATION FUNCTIONS

In the CONV layer, an activation function needs to be chosen to optimize the convergence speed of the ConvNets. Due to the differentiation of four geomorphic features between eight coastal types, Binary Step Function or Linear Activation Function were not chosen. The best option will be one in five non-linear activation functions that include TanH/Hyperbolic Tangent, ReLU (or Rectified Linear Unit), leaky ReLU, Parametric ReLU and Swish types [58], [59]. The ReLU function using max (0, x) - thresholding at zero - can keep the size of the images ($64 \times 3 \times 3$) and allows the ConvNet models to converge very quickly. These advantages are not optimized in other functions. Especially, this function also allows backpropagation in the training process [60]. Additionally, in five trained ConvNet models using five non-linear activation functions, the authors realized that the performance of the ConvNet using the ReLU function provides better results than those using other functions. Therefore, the ReLU function was chosen for four ConvNet layers.

Two activation functions that can be chosen for the POOL layer include Sigmoid/Logistic and Softmax [61]. The Sigmoid/Logistic function provide uncertainties related to vanishing gradient problems if the maximum and minimum values of input data are too high. Whereas, the Softmax function is commonly used to normalize the outputs to classes between 0 and 1 and provide prediction probability in a specific type [62]. Additionally, the performance of the Softmax function seems to be faster than those of the Sigmoid/Logistic function. Therefore, the Softmax function was chosen for the POOL layer.

2) LOSS FUNCTIONS

To reduce the gap between the predicted and actual outputs, the trained ConvNet need to have a minimized Cost function(C) or Loss function as convex functions based on identifying optimized value for weights [57]. Once the weights of the trained networks can minimize the loss function, they can make a better prediction for new input data. It was explained in detail by [63]. The loss function is dependent on weights, input images, and output labels. The average loss value is computed with the use of entire training image data and represented by the following function:

$$\mathcal{J} = \frac{1}{n} \sum\nolimits_{x=1}^{n} \mathcal{L}^{(x)} \tag{4}$$

with 'n' is the training data size set, and $\mathcal{L}^{(x)}$ is the loss of a single training image for the training process.

The loss function (e.g. regression, binary classification and Multi-Class Classification Loss Functions) will be chosen depending on the type of training ConvNets [64]. In this study, eight types of coasts need to be classified; therefore, authors chose one in three kinds of Multi-Class Classification Loss Functions that include:

- Multi-Class Cross-Entropy Loss: is the standard method to calculate the loss function in the case of the target values in the set [0, 1, 2, ..., n] [65], [66]. Each unique integer value in this study is represented for a coast type. Mathematically, this method uses the framework of maximum likelihood to calculate the loss. This method calculates a score representing the average probability gaps between the actual and predicted outputs for all coast types. The last score has to be minimized till 0 as the perfect cross-entropy value. This method can be specified in the Keras coded in python with a "categorical_crossentropy" function when compiling the model [67]. The performance of the Multi-Class

Cross-Entropy Loss seems to be reduced, especially in the encoding process, if the network works with a large number of labels and requires a significant memory.

- Sparse Multi-class Cross-Entropy Loss: has been developed to improve the performance of Multi-class Cross-Entropy Loss function to classify a large number of labels during the training process. It performs the same cross-entropy calculation of error as the Multi-Class Cross-Entropy Loss function, but this method does not require the encoded target variables during the training process. This method was developed in the Keras by using "sparse_categorical_crossentropy" function when compiling the model 67].
- Kullback Leibler Divergence Loss: has been designed to measure the differences between the probability distribution of the outcomes and a baseline distribution. If the difference of 0 shows that the distributions are fitted. Although this method seems to be very similar to the cross-entropy methods, it calculates the amount of lost information in the case of the predicted probability distribution approximating with the desired target probability distribution. [68], [69] suggested the Kullback Leibler Divergence Loss function is more useful for complex tasks than simple multi-class classification. This method has been developed in the Keras in python by using "kullback_leibler_divergence" function when compiling the model [67].

3) OPTIMIZER FUNCTIONS

Deep learning neural network optimization based on a stochastic gradient descent algorithm is commonly used to reduce the cost functions. In other words, this method increases the accuracy of trained neural networks by updating weights in the negative gradient direction to minimize the loss. During the optimization process, the error of the trained models (or the loss function) must be calculated repeatedly. When all data is passed forward and backward through the ConvNet model only once, it completes one epoch [70]. After one epoch, the weights were updated to decrease the loss value for the next evaluation. In this process, six optimization algorithms were sequent changed during the ConvNet development, including Nesterov accelerated gradient (NAG), Adagrad (Adaptive Gradient Algorithm), Adadelta, RMSProp (Root Mean Square Propagation), Adam (Adaptive Moment Estimation) and Nadam (Nesterov-accelerated Adaptive Moment Estimation). The description of these optimization algorithms was explained in detail in Table 4. The best optimizer method will provide the highest accuracy and lowest loss function values.

TABLE 4. The optimization algorithms to calculate parameters in the ConvNets in coastal classification, adapted from [67], [70]–[73].

Formula	Optimizer method	Algorithms
5	Adagrad	$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{G_t + \epsilon}} g_t$
6	Adadelta	$\Delta\theta = -\frac{RMS[\Delta\theta]_{t-1}}{RMS[g]_t} g_t$ and $\theta_{t+1} = \theta_t + \Delta\theta_t$
7	RMSprop	$E[g^2]_t = 0.9E[g^2]_{t-1} + 0.1g_t^2$ and $\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{E[g]^2{}_t + \epsilon}} g_t$
8	Adam	$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t} + \epsilon} \hat{m}_t$
9	Adamax	$\theta_{t+1} = \theta_t - \frac{\eta}{u_t} \hat{m}_t$
10	Nadam	$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t} + \epsilon} (\beta_1 \hat{m}_t + \frac{(1-\beta_1) g_t}{1-\beta_1^t})$

where θ is parameter value; η is the learning rates; t is time step; $\epsilon = 10^{-8}$; g_t is the gradient; E[g] — moving average of squared gradients; m, v are estimates of first and second moments; u_t - the max operation; β - moving average parameter (good default value — 0.9).

F. CONVOLUTIONAL NEURAL NETWORKS FOR COAST RECOGNITION

Once the best ConvNet for the coastal classification was developed, its most important function is to classify new coasts. In this study, the authors focused on coast types along the Vietnamese coastline. Therefore, 4600 profile sub-graphs corresponding to 1150 new cut lines along 3260 km in length of the coastline in Vietnam were made. The new cut lines were spaced at 2km intervals and 10km in length. Therefore, these cut-lines are different with 800 cut-lines made in the particular regions. The images were also prepared as explained in section 2C. Once these new images were inputted to the trained ConvNet, the model accessed the parameters trained for eight layers to transform original images to specific spatial matrices, and then interpret the final class scores for each image. In the FC layer, the name of coast types will be assigned to class scores. The outcomes of the trained ConvNet will be assessed and compared with former coastal classification systems in Vietnam that were explained in section B.

III. RESULTS

A. GEOMORPHIC PROFILES OF COAST TYPES IN VIETNAM

Figure 4 depicts the top surfaces of 8x100x101 elevation profile points from the continent to the sea (from left to right), perpendicular to the coastline in Vietnam. The profile point graphs of relative elevation, slope, and flow length characteristics were shown in Figure 7, 8, and 9. According to the geomorphic profiles of coastal surfaces, eight types of coasts in Vietnam can be separated into four groups. The first group includes tectonic and karst coasts. These strongly fragmented coasts distribute along rocky coastlines, resulting in complicated bays and offshore islands. Primarily, the tectonic coasts consist of one or a few abrasive mountains parallel to the coastlines. Both coast types in this group have a steep slope of more than 25 degrees and are strongly partitioned by rivers and streams along the coastlines. The difference between the two types of coasts in group 1 relates to the distribution of mountains along the coastlines and the difference in height

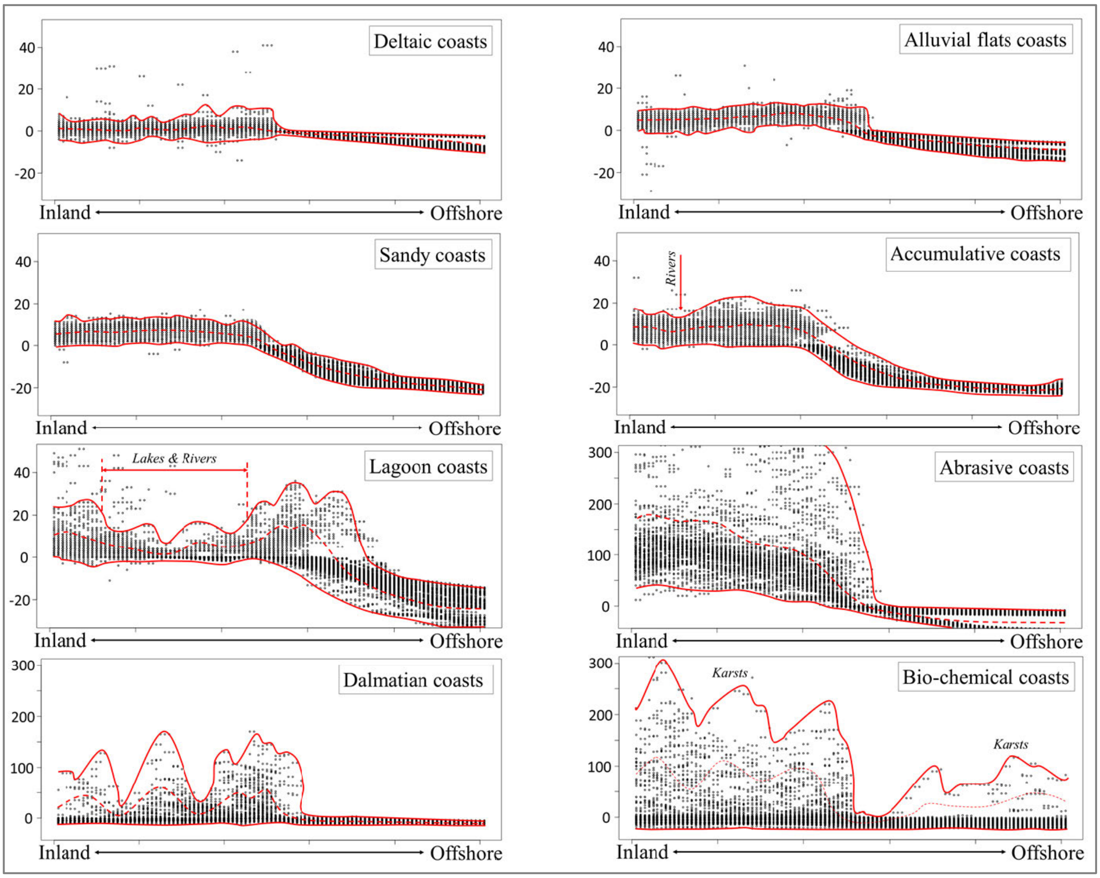

FIGURE 4. Surfaces of elevation points from the continent to the sea (from left to right), perpendicular to the coastline in Vietnam. Each sub-figure contains 10100 points of a respective coast type (linked to Table 2). The red lines show boundary of elevation point surfaces, whereas the red dot-lines show the average fluctuation of elevation surfaces.

per one hectare. The difference in height per hectare in the karst coasts reaches from 50 to 300m, whereas the difference in the tectonic coasts only reaches from 25 to 170m. Additionally, the karst coasts contain offshore limestone islands with the elevation of from 50 to 100m.

The second group includes delta coasts and coasts of alluvial flats. These coasts are often formed in a transitional zone between river and maritime environments. According to the geomorphic profile graphs (Figure 4), the inland elevation fluctuates from 0-15m, whereas the offshore elevation gradually declined from the coastline to the sea. The slope of the offshore part of alluvial coasts seems to be steeper than the delta coasts. Notably, the foredunes formed along the coastline at the elevation from 5 to 7m is a difference between coasts of alluvial flats and delta coasts.

The third group includes sandy coasts, accumulative coasts, and coastal lagoon formed by wave and tide activities. In general, the coasts in this group consist of lagoons, rivers, and dunes parallel the coastlines, in which the average elevation of dunes is from 7 to 15m. The inland part of the sandy coasts contains flat and stable dunes, whereas the inland part of the accumulative coasts and coastal lagoon contain rivers and lakes. The fourth group only has an abrasive coast type due to wave activities. The erosion process caused by waves prevails and makes cliffs along the coastlines. The inland elevation fluctuates from 100 to over 300m with the slope of more than 30 degrees.

B. CONVNET MODEL PERFORMANCE

Six ConvNet methods used for model optimization include Adadelta, RMSprop, Nadam, Adamax, Adagrad, and Adam functions to calculate the optimal values for filter parameters. According to Figure 5, the efficiency in 10 epochs of six trained models was explained through two indicators: loss function and accuracy. Each indicator is measured by both testing and training data. Whereas the loss function values are focused from 0 to 5, the efficiency is measured in the range from 0 to 1 (corresponding for accuracy from 0% to 100%). Six models can be divided into two groups. The first group includes trained ConvNet models using the Adadelta, RMSprop, and Nadam optimizer methods. The trained model using the Adadelta method is underfitted with poor accuracy over ten epochs. The trained model using the RMSprop method has fluctuated significantly in 10 epochs. Although the accuracy of this model reaches the highest value in the 9th loop, it was reduced in the 10th epoch,

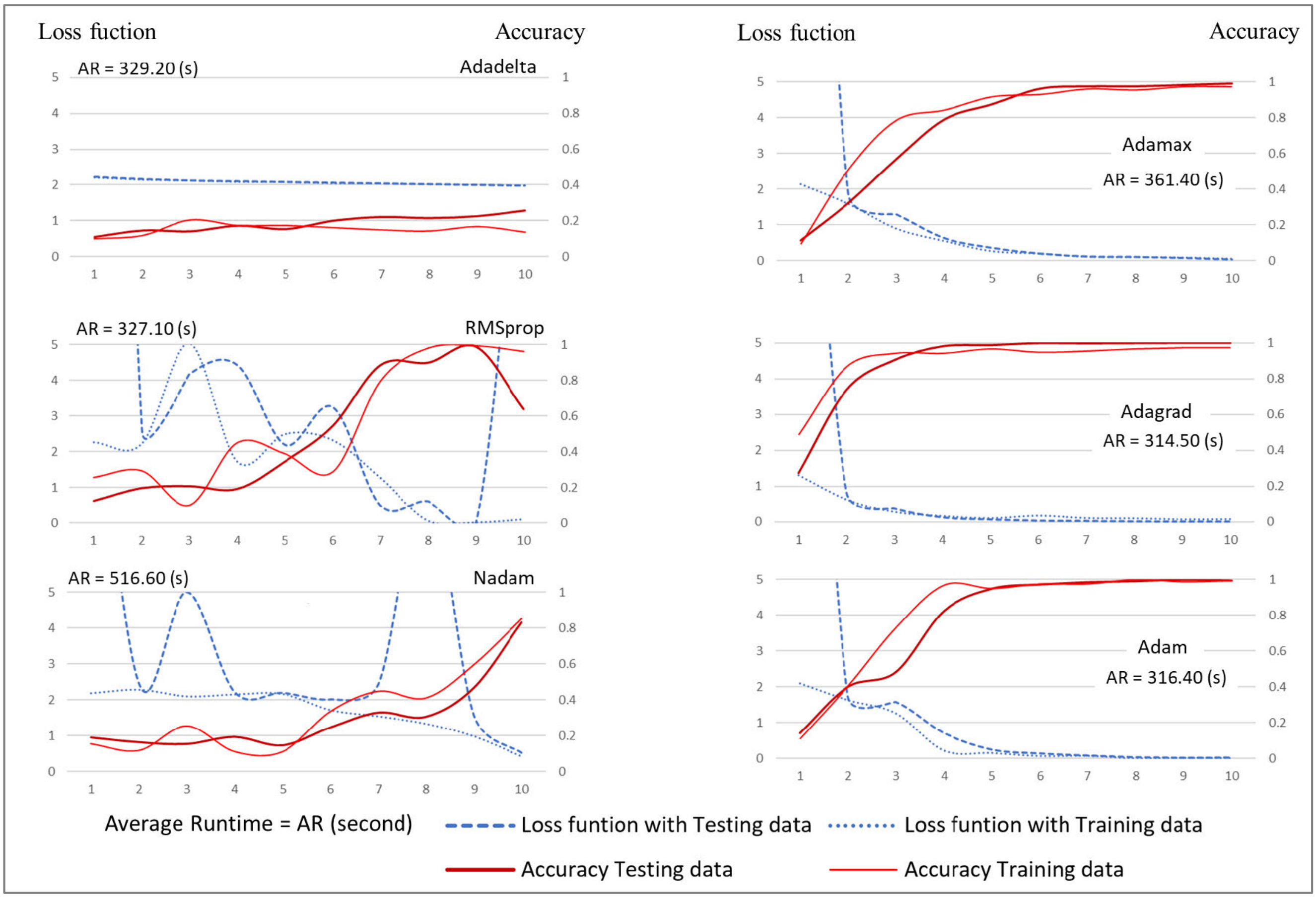

FIGURE 5. **The loss function and accuracy values of six models using six optimization methods.**

resulting in overfitting. In three trained models of the first group, the trained model using the Nadam method has a linear trend during the optimization process. The accuracy of this model gradually increases from the 1st to 10th loop for both training and testing data. However, the highest efficiency achieved from this model is only about 0.8 (or 80%). Therefore, this model was not chosen as the most optimal model.

The second group consists of three trained models using the Adamax, Adagrad, and Adam methods. They are highly accurate models. The accuracy of these models reached more than 0.9 from 4th to 6th epochs, which is equivalent to about 98% accuracy. The loss function values reduced to near zero since the sixth epoch. It is easy to assess that all three trained models in group 2 can be used for coastal classification in six models.

C. COAST INTERPRETATION IN VIETNAM

Figure 6 shows the analysis of 1150 coastal cut-lines in Vietnam. As a result, 888 lines (accounting for 77% in total) were interpreted similarly from three models using Adam, Adamax, and Adagrad optimizer methods. In the rest, 124 lines (corresponding to 11%) were classified differently from only two models; and 53 lines (corresponding to 5%) were classified separately between three models. After checking results in 262 lines, the coasts in Vietnam were divided into 20 parts, as shown in Figure 6. Eight coast parts are homogeneous, with the similarity of coast types higher than 90%.

Additionally, the results show that the ConvNet models using Adam and Adamax optimizer methods can classify well about 89% of Vietnamese coasts. The model using the Adagrad method can classify about 87% of Vietnamese coasts. About 11% of the coasts provide complicated geomorphic profile graphs, leading to difficulties to interpreting the best coast types for them. This issue will be discussed in section 4.B.

IV. DISCUSSION

A. COMPARISON WITH FORMAL COASTAL CLASSIFICATION SYSTEMS

The results are mostly in harmony with Vietnamese coastal classification systems of Dang (2019), Le et al. (2007) and Nguyen et al. (2010), especially in coasts from Mong Cai, Quang Ninh province to Do Son, Hai Phong province; and coasts in Red and Me Kong river deltas. The new coastal classification from this study is more precise in abrasive coasts in bed-rock edges, compared to the former coastal classification systems of Le (2007) and Nguyen et al. (2010).

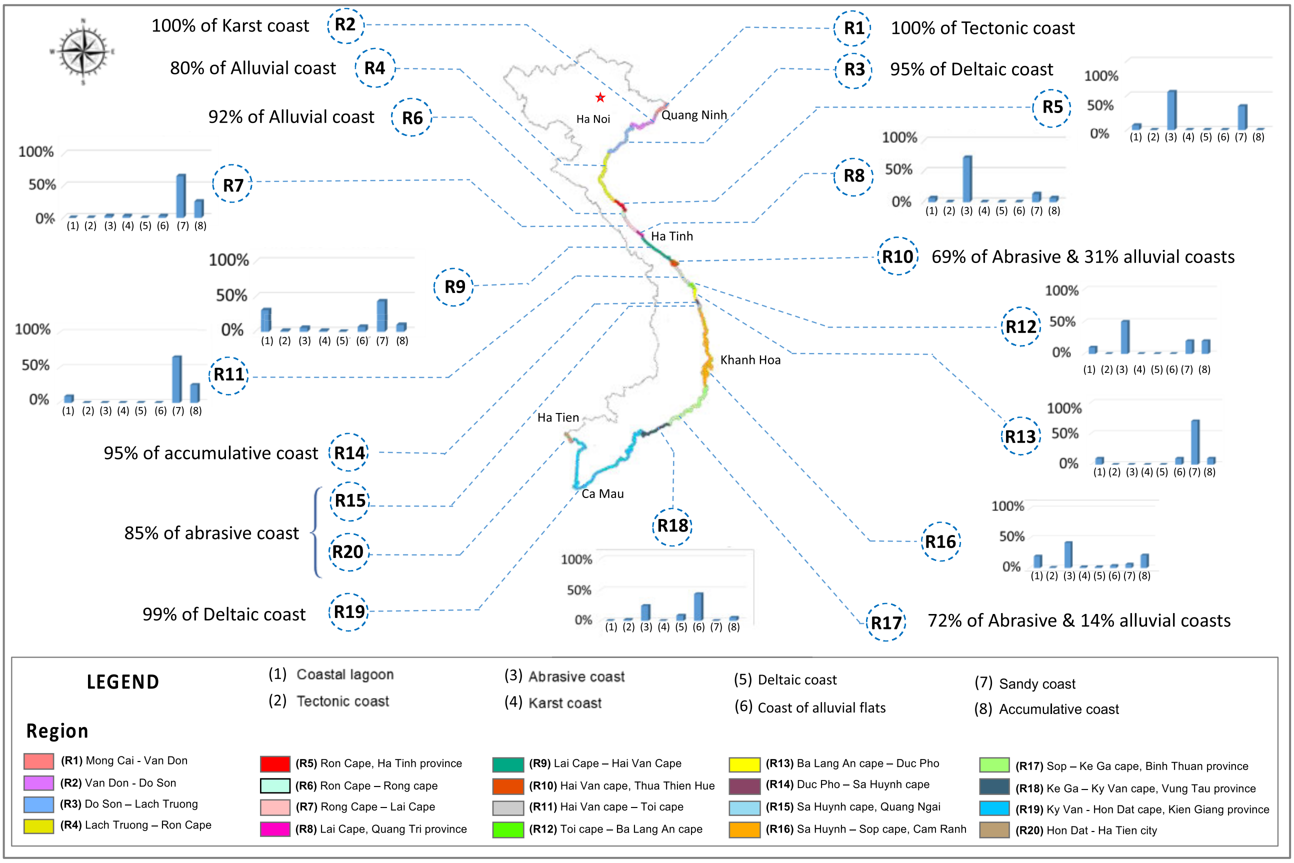

FIGURE 6. A coastal classification system in Vietnam based on the trained ConvNet models.

Meanwhile, it shows similar results with the coastal classification systems of [71]. Whereas the former systems were only classified through expert experience without specific quantitative indicators, the new classification system was generated through the analysis of four geomorphic features in detail. It proved the high potential of the ConvNet models for coastal classification based on geomorphological characteristics. The shape of the geomorphic profile can represent different causes of coasts such as tidal, marine, and alluvial effects.

However, due to the former systems were based on expert analysis related to different geological, geomorphological, hydrological and socio-economic characteristics of coasts, these studies distinguished additional coasts such as coral reef coasts and tropical bio-chemical corrosive coasts in islands. These coast types can be identified as tectonic and karst coasts if their coast cut-lines are inputted to the ConvNet models. However, this study does not detect coasts in these islands because of two reasons, including missing data and the requirement of geological material analysis. For further studies using elevation and additional data in islands, coasts can be classified in detail through material characteristics after the coastal classification by the ConvNet models.

Other differences between the new coastal classification system with the previous ones can be found firstly in the coasts from Vung Tau to Cua Tieu/Cua Dai, Tien Giang province. All former systems classified them as the coasts of alluvial flats, whereas the new ones classified them as delta coasts. According to their geomorphic profiles, the coasts in this region has a slight slope and a stable elevation shape. Additionally, the number of alluvial materials in these coasts was provided at about 5 – 7 tons per year from the both Dong Nai and Sai Gon rivers, much higher than those from 0,75 and 2.8 tons per year from the Chu and Ma rivers, respectively [72], [73]. Therefore, the authors identified these coasts as the delta coasts and combined them with the coasts along the Me Kong river delta.

Due to the heterogeneous distribution of the abrasive coasts along the coastline, especially in bed-rock cape, seven parts containing these coasts were separated from the coast parts from Lach Truong, Thanh Hoa province to Sa Huynh, Quang Ngai province (Table 1) (e.g., Mui Rong, Mui Lai, Hai Van, and Nam Cham capes). Meanwhile, Le et al. (2007) and Nguyen et al. (2010) mixed these coast parts and called the abrasive-accumulative coasts (Table 1). Additionally, the coasts from Sa Huynh, Quang Ngai province to Vung Tau, Ba Ria-Vung Tau province that were combined in the former classification systems, whereas it was separated to three parts from Sa Huynh cape, Quang Ngai province to Sop cape, Cam (containing 45% of abrasive coasts and about 45% of accumulative coasts and lagoons); from Sop cape, Khanh Hoa province to Ke Ga cape, Binh Thuan province (containing 72% of abrasive coasts and 14% of alluvial coasts;) and from

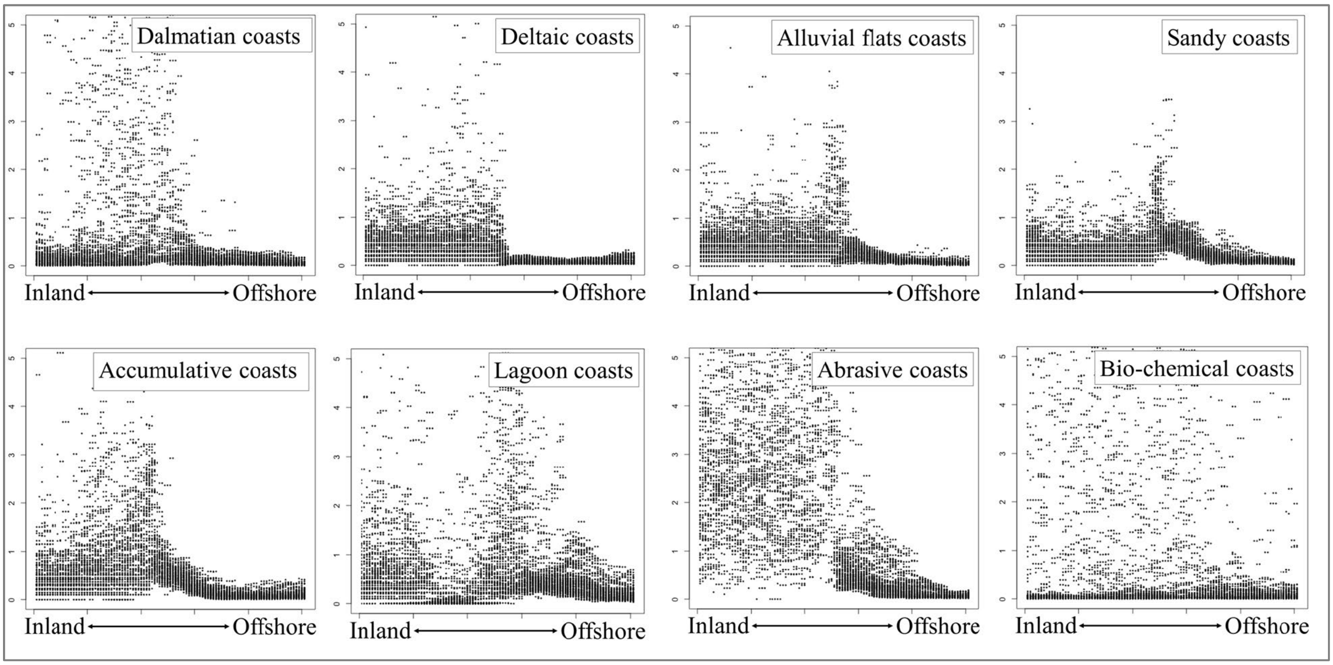

FIGURE 7. Surfaces of slope points from the continent to the sea (from left to right), perpendicular to the coastline in Vietnam. Each sub-figure contains 10100 points of a respective coast type (linked to Table 2).

Ke Ga cape to Ky Van cape, Vung Tau province (containing 30% of abrasive coasts and 45% of alluvial coasts).

Although eight coast types can be separated based on the trained ConvNet, some coast types have not been assessed, such as reef and island coasts. The area of these coast types in Vietnam is too small, resulting in difficulties in collecting samples at the national scale. More samples need to collect at local scales or in other countries to improve data for these coasts. The development of the trained ConvNet for coastal classification is not only useful for coasts in Vietnam but also coasts in different countries and on global scales. Based on the use of DEM data from ALOS and NOAA satellite, scientists only need to (1) calculate geomorphic features in coasts, (2) make cut-lines, (3) prepare input images based on geomorphic profile graphs and (4) run the ConvNet model. The result comparison between three models using three optimizer methods can be a useful method to validate the interpretation before using natural factors.

B. IMPROVEMENT OF COASTAL CLASSIFICATION BASED ON OTHER NATURAL FACTORS

About 10 percent of coasts with complex geomorphic profile graphs are not well classified by the trained ConvNet models. It shows the critical roles of natural factors (e.g., materials, tide, and anthropogenic factors) for the coastal classification. Therefore, some indicators can be used such as material composition, river, wave, tide, and land covers to classify correctly these coasts [13]. Depending on the similar characteristics between the profile graphs, one or a few indicators can be selected in different cases.

Firstly, the geological structure and petrography composition should be chosen to distinguish the tectonic and karst coasts. The karst coasts are mainly generated from limestone in Vietnam during Cambrian, Permian, and Devonian periods. Whereas, materials in the tectonic coasts contains mainly of gritstone, sandstone, and siltstone. The distribution of the karst mountains is more heterogeneous than the tectonic ones (Figure 4). The coastline of the tectonic coasts has a general direction consistent with the direction of the geological structure [6]. Solution (or corrosion) processes were intensified by wave activities, resulting in steep slope surfaces and water levels outside karst mountains. It does not happen in tectonic mountains. According to these characteristics, the tectonic and karst coasts can be completely reclassified.

Secondly, the uncertainty was found in the separation process between delta coasts and coasts of alluvial flats. In this case, the indicator should be the amount of alluvium provided from local rivers. In the delta coasts of Vietnam, the Red and Mekong rivers have produced annual average alluvium materials of 64.34 and 65.94 times more than the rivers in the coasts of alluvial flats. It has resulted in the convex-shaped coasts towards the sea (Figure 4). The moderate amount of alluvium materials in alluvial flats is not large enough to generate a delta. Small dunes are generated along the coastline of alluvial flats due to wave and tide activities. Therefore, the alluvial flats have slight concave surfaces from the coastline to the sea. Regarding the material composition of these two coasts, the delta coasts are covered by silt and clay, whereas the coasts of alluvial flats are covered by mud and fine-grained sand.

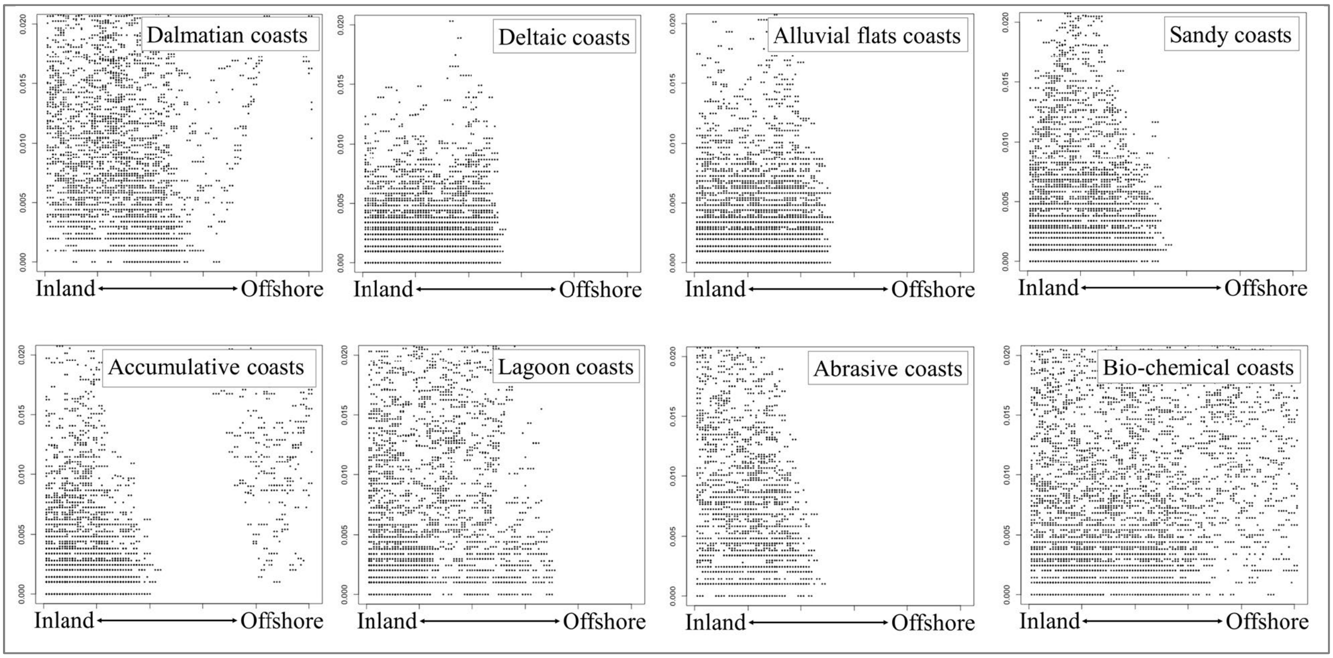

FIGURE 8. Surfaces of flow-length profile points from the continent to the sea (from left to right), perpendicular to the coastline in Vietnam. Each sub-figure contains 10100 points of a respective coast type (linked to Table 2).

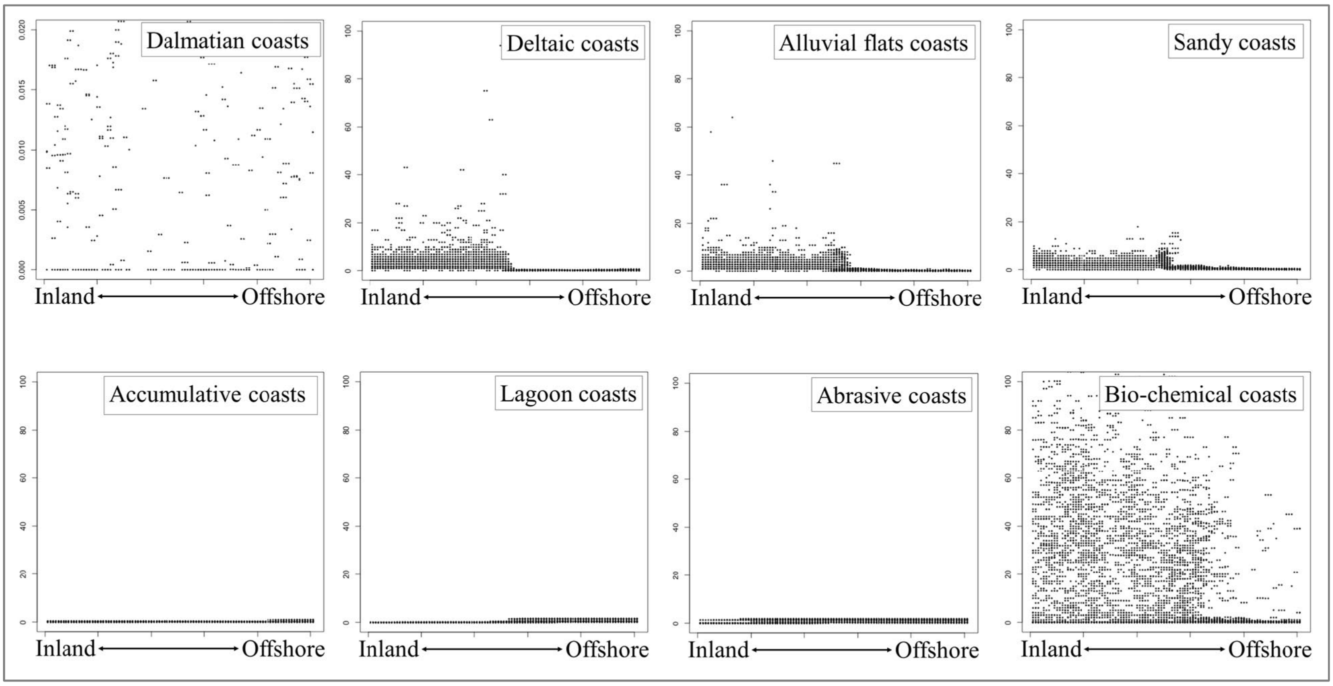

FIGURE 9. Surfaces of relative elevation profile points from the continent to the sea (from left to right), perpendicular to the coastline in Vietnam. Each sub-figure contains 10100 points of a respective coast type (linked to Table 2).

The third error was found due to similarities between the sandy and accumulative coasts (Figure 4). Sediment materials are accumulated in both coasts, leading to the movement of coastline towards the sea. The sandy coasts contain long young dunes that have been generated since the Holocene period. Whereas the accumulative coasts have created since the Pleistocene period. The accumulative coasts also have young sandy dunes, but they are narrower than dunes in the sandy coasts. In the accumulative coasts, rivers (or dune slacks) have been generated in the transitional zone between young and old dunes. Therefore, accumulative banks contain both marine and river materials, whereas material composition in the sandy coasts is only coastal sediments.

Lastly, some cut-lines cannot be defined as a lagoon or accumulative coasts. These undefined cut-lines mainly located in the transitional zones between clear lagoon or accumulative coasts. In both coast types, dunes along the coastline have an average elevation of 20-30m (Figure 4). Additionally, these cut-lines have rivers and lakes behind coastal dunes. It is challenging to select a suitable type for these coasts. It is similar when cut-lines locate in transitional zones affected by waves and river runoffs. Therefore, a new coast type named "transitional coasts" should be added in this study. However, the geomorphic profile graphs of these coasts are very complicated, and the number of these cut-lines is not enough to make a new type. It can be a new issue for studies in the future.

V. CONCLUSION

Based on the use of a Convolutional Neural Network to classify coasts in Vietnam, the individual research questions raised in the introduction section are answered as follows:

- **How many types of the coast can be identified in Vietnam?** According to the former coastal classification systems, ten main coast types were identified in Vietnam. However, these coast types can be grouped into eight types based on the differences between their geomorphic characteristics. They include delta, alluvial, accumulative, abrasive, sandy, lagoon, tectonic, and karst coasts.
- **Is it feasible and effective to apply convolutional neural networks for coastal classification based on geomorphic features?** Yes, the geomorphic characteristics of eight coast types were recorded from the trained ConvNet model for coastal classification with high accuracy and low loss function. Three trained models were used to classify coasts in Vietnam, and it can be used to classify global coasts in the future.
- **How do coast types distribute in Vietnam?** Eight coast types spread heterogeneously along the coastline of Vietnam, especially in the middle part. The coasts in the northern and southern parts contain mainly tectonic, karst, alluvial, and delta coasts. However, 10% of Vietnamese coasts have not been defined in this study. It is necessary to have further studies to analyze geomorphic profile graphs in the transitional areas between defined coasts.

APPENDIX

See Figs.7, 8, and 9.

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