Electronic Letters on Computer Vision and Image Analysis 21(2):63-81, 2022

Rip Current: A Potential Hazard Zones Detection in Saint Martin's Island using Deep Learning and Machine Learning Approach

Md. Ariful Islam* and Mosa. Tania Alim Shampa+

* *Department of Robotics and Mechatronics Engineering, University of Dhaka, Nilkhet Rd, Dhaka-1000, Bangladesh*
+ *Department of Oceanography, University of Dhaka, Nilkhet Rd, Dhaka-1000, Bangladesh*

Received 9 August, 2022; revised 15 October 2022; accepted 17 November 2022

Abstract

Rip current, or reverse current of the sea, is a type of wave that pushes against the shore and moves in the opposite direction, that is, towards the deep sea. The research suggests an approach for something like the automatic detection of rip currents with waves crashing based on convolutional neural networks (CNNs) and machine learning algorithms (MLAs) for classification. Security cameras can be placed at any elevated position around the beach near the coastguard's office, and mobile phones from a certain height have still images of something like the shoreline and represent a possible cause of rip current measurements and management to handle this hazard appropriately. This work is about using CNN and MLAs to build detection systems from still beach images, bathymetric images, and beach parameters. The CNN-based detection model for beach images and bathymetric images has already been put into place. MLAs have been applied to detect rip currents based on beach parameters. Compared to other detection models, detection models based on bathymetric images are much more accurate and precise. The VGG16 model of CNN shows a maximum accuracy of 91.13% (recall = 0.94, F1-score = 0.87) for beach images. For the bathymetric images, the best performance has been found with an accuracy of 96.89% (recall = 0.97, F1-score = 0.92) for the DenseNet model of CNN. The MLA-based model shows an accuracy of 86.98% (recall = 0.89, F1-score = 0.90) for the random forest classifier. Once the potential zone of continuously generating rip current has been identified, the coastal region can be managed accordingly to prevent accidents due to this coastal hazard.

Keywords: Rip Current, Convolutional Neural Network (CNN), Machine Learning Algorithms (MLAs), Coastal Hazards Management, Beach Management

1 Introduction

Research done in the United States of America (USA), Australia, and the United Kingdom (UK) shows that most beachgoers don't know how to spot rip currents, avoid them, and get away from them. Because of this, rip currents kill thousands of people every year, making them a global health risk. At a 90-degree angle from the sea, the waves coming from both sides first hit the beach, then take a narrow path and return to the sea [4]. If someone falls into this current, it will be difficult for him to come back alive.

Correspondence to: <arif.rme@du.ac.bd>

Recommended for acceptance by <Angel D. Sappa>
DOI: https://doi.org/10.5565/rev/elcvia.1604
ELCVIA ISSN:1577-5097
Published by Computer Vision Center / Universitat Autònoma de Barcelona, Barcelona, Spain

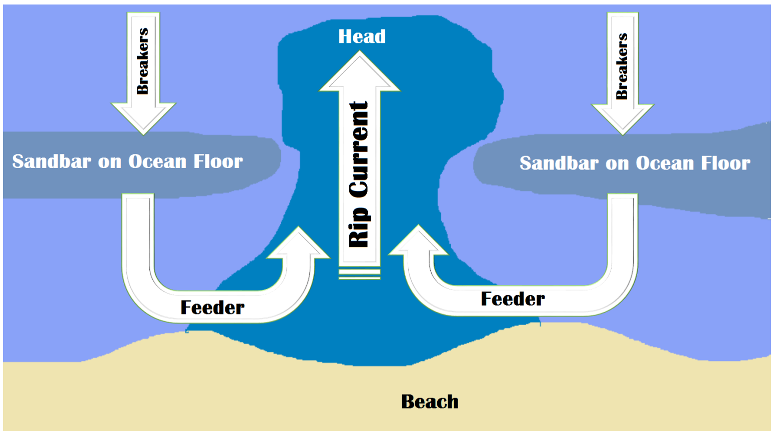

Figure 1: Rip current formation flow

Even though the terms refer to different dangers, some tourists just use them wrong. Also, undercurrents, rip currents, and riptides happen in different places and for different reasons all along the coast. Each of them, however, necessitates distinct techniques for both prevention and evasion. Crashing waves move water up a beach's cliff face, where it eventually drains directly into the sea [8], as shown in Fig. 1.

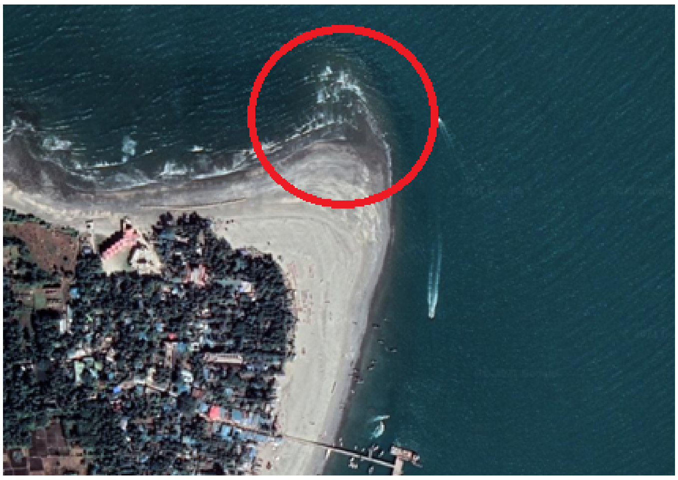

Figure 2: Rip current region of St. Martin Island

The northeast corner of St. Martin, the only coral island in Bangladesh [20], is known as the Rip Current zone (Fig. 2). According to statistics, at least 16 people have drowned on this beach in the last 8–10 years [29]. In 2014, six students at a private university died [29]. This part of St. Martin is a headland area where rip currents are frequent due to natural features [20]. This is because the wind can push water in both directions to create a rip current in its wake [8]. Due to its natural location, there are many large channels through which reverse currents or rip currents flow frequently [20]. A terrifying feature of rip currents or reverse currents is that they look very calm [7]. From above, it appears dark blue. Most tourists or ordinary people have no idea about rip currents [7]. That's why it's important to know if rip currents are created anywhere else in St. Martin, considering the safety of tourists. Rip currents have been found in the northeast corner of St. Martin through a series of accidents [29]. But it is not clear if rip current is often generated anywhere else in St. Martin's.

More than 50,000 people died around the world at this time [29]. This rip current is responsible for approximately 80% of beach deaths [29]. The government has not yet started work to warn tourists about this dangerous issue. Keeping this in mind, this work aims to measure the rip currents on Bangladesh's beaches, particularly on Saint Martin's Island. Undertow, rip current, and riptide are names which are used to characterize current flow with distinct properties [13]. As a result, the vast majority of people, media outlets, and even lexicon terminology misinterpret and confuse various potential threats at surfing beaches [10].

2 Literature Review

De et al. (2021) [1] automated and conducted research on rip current detection. Their publication includes rip current specialist training and testing data. They use Faster R-CNN (F-RCNN) and a custom temporally agglomeration step to identify rip currents from images or videos, with significantly higher verified correctness than humans and other previously described approaches. Mori et al. (2022) [2] offered two strategies that enabled them to identify rip currents while all the other methods flopped. Also, since these methods were made to help people see things, the fact that rip currents exist is naturally emphasized. Most of these plans are based on how rip currents look, like how foamy they are, what color the water is, and where the waves are crashing. Radermacher et al. (2018) [3] conducted an evaluation of anticipated rip currents from either bathymetry that resulted in functionalities for operations and maintenance that present predictions on remote sensing-based bathymetries, with the simulation with in-situ bathymetry serving as a benchmark. Philip et al. (2016) [4] discussed the use of optical flow to identify rip currents. To figure out how fast the water was moving, they used the Lucas-Kanade optical flow algorithm. They modified the color matching method for optical flow to detect rip currents. Pitman et al. (2016) [5] developed a method for automatic rip current detection based on synthetic images. They segmented the "original" images into essential sections, including sand bars, estuaries, coastlines, and the ocean, which are required for the generation of a synthetic image. The pixels of each segment are therefore substituted with the original picture's predominant paint colors. The use of synthetic imagery improved rip detection performance from 81% to 92%. Derian et al. (2017) [6] identified rip currents in a video using concentrated optical flow. The method is helpful because optical streamlines can be directly compared to flow fields based on observations made in the real world.

With the above in mind, a system has been designed that will be able to predict whether there is a rip current elsewhere in St. Martin or a potential rip current location. Rip currents have been found in Bangladesh, St. Martin's Island, and other countries. But its existence has been discovered through various accidents. This paper deals with designing a model using CNN and MLAs to detect whether or not there is a potential for rip currents to occur anywhere in addition to this location. First, the data has been collected by analyzing the beach images (both rip and non-rip), bathymetric images (for both rip and non-rip), and selecting some parameters (e.g., water depth, breaking waves, water nature, backwash current speed, etc.) shown in Table 1 of the beach where the rip and non-rip currents are frequently created. The learning process was then initiated through various MLAs. After that, the testing process was conducted using the beach and bathymetric images as well as the beach parameters of different places in St. Martin as the input to the designed model. Then maybe it will detect whether there is a rip current at different places.

3 Methodology

3.1 Dataset

3.1.1 BeachImages Dataset

The first dataset, entitled "Beach Image Dataset," is comprised of rip and non-rip current beach images gathered from the Internet, photoshopped by one of the authors. Also, the drone-shooting area and the place with the most rip currents were chosen based on what was learned from the previous study. Rip currents were expected to occur in these areas. Instances of rip currents, no rip currents, and potential weak rip currents are included in the compilation. Others with rip currents comprise many sorts of rips, including those with bending, debris jet, a darkish path between beachbreaks, and generating rips [9]. The data set also includes instances of backwash (liquid flowing on the superficial portion of the shoreline after one surge has smashed all the way to the high water mark and can continue up the coast) and reflected waves [7]. Some assortments of beach scenes with non-rip currents are shown in Fig. 3.

Figure 3: Some assortments of beach scenes with non rip currents

Figure 4: Some assortments of beach scenes with rip currents

Some assortments of beach scenes with rip currents are shown in Fig. 4. Due to the novelty of tidal inundation as a research problem in computer vision, any available community imagery libraries containing tidal inundation could not be located. As a result, an entirely new set of labeled training data containing rip current and non-rip current images has been compiled. Google Earth (TM) was a key source of data, allowing for the retrieval of high-resolution aerial footage of tidal inundation and non-rip currents. There are 1463 photographs of tidal inundation and 300 pictures of comparable coastal landscapes without tidal inundation inside the collection. The sizes of the photos vary from 1086 by 916 to 234 by 234 pixels.

3.1.2 BathymetricImages Dataset

As was already said, the near-shore bathymetry is another thing that affects how rip currents form. Consequently, prior to undertaking another study on the research and information interpretation of rip current features, the goal of this paper is to gather the most recent bathymetric records of something like the targeted location.

The measurement of the water depth in oceans, rivers, and lakes is called bathymetry. The overall appearance of bathymetric mapping resembles that of topographic maps, which typically employ routes to depict the contours as well as the height of geographical features. Bathymetric investigations allow us to determine the profundity of a body of water and map its submerged characteristics [11].

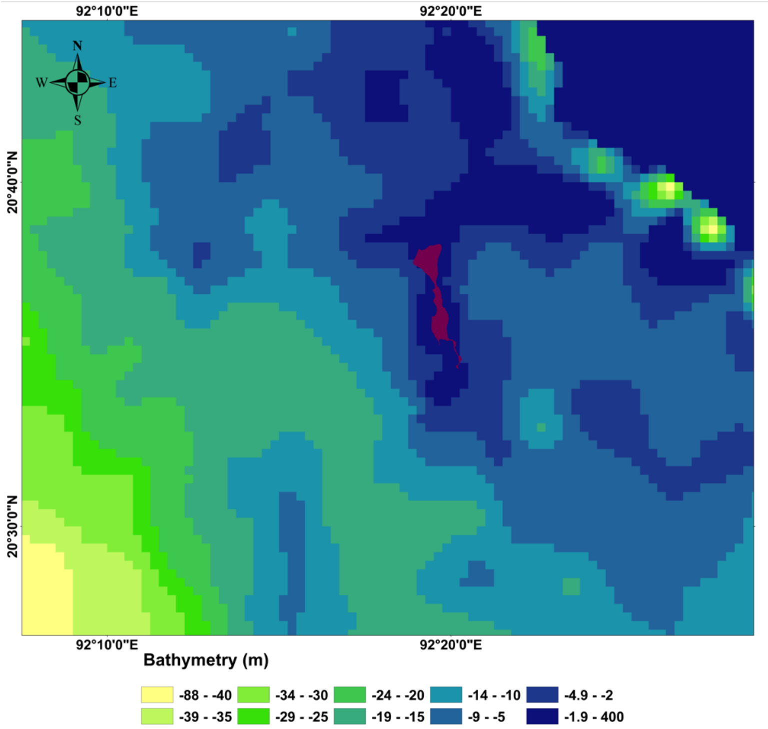

Figure 5: Bathymetric contour map of Saint Martin's Island denoted by red colour

The depths of the regions of the same colour are given in the Fig. 5. The depth conditions around the beach play an important role in the generation of rip currents. This second set of data has bathymetric images of the places where rip currents and non-rip currents are found. These images have been taken from Google Earth [24], manipulated by the writers, or the Gebco Bathymetry website [11]. Firstly, the potential rip current regions have been marked to extract the bathymetric images. For example, Hanakapiai Shoreline [4], located on Kauai's Napali Coastline and only reachable via the Kalalau Trail, is among the most hazardous sites in the world to swim due to tremendous rip waves and currents that have been notorious for sweeping swimmers out to sea. The coastlines of Fraser Island are some of the most treacherous in the world. The bodies of water encompassing the island have large and powerful rip currents. It should come as no surprise that Playa Zipolite [17], which is situated just on the southern coast of Oaxaca state in Mexico and is also renowned as "The Beach of the Dead"[7]. Similarly, the bathymetric images of the islands or sea beaches have been listed and collected to form the dataset named BathymetricImages. Around 346 bathymetric images have been collected. In the compilation, there are situations with rip currents, situations without rip currents, and situations where weak rip currents are likely. As the number of images was small, the bathymetric images have been augmented to increase the number of images. Finally, the dataset has been formed with 1236 bathymetric images after augmentation. Also, the drone-shooting area and the place with the most rip currents were chosen based on what had been studied and found before. Rip currents were likely to occur in these areas. The bathymetric images have been extracted through GIS software [28], known as "bathymetric maps."

Those maps employ color to represent the depth of the water. In the majority of bathymetric photographs of the ocean, "warm" shades (red, green, and yellow) indicate shallower water, as shown in Fig. 6. As the water becomes deeper, its hue changes from green to blue to violet. Typically, dry terrain is depicted in white. The

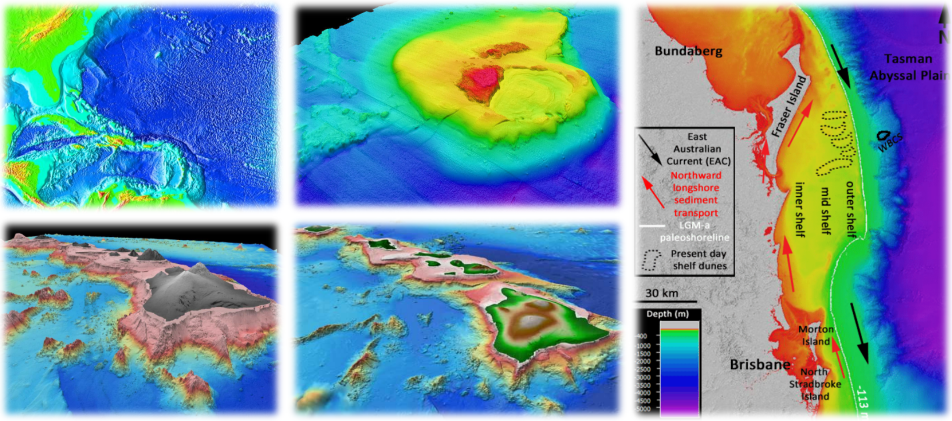

Figure 6: Some assortment of beach's bathymetric conditions with rip and non rip currents formation

sizes of the bathymetric images vary from 1086 by 916 to 234 by 234 pixels.

3.1.3 BeachParameters Dataset

Based on the beach parameters gathered from previous studies or research on the causes of rip current occurrence [7], a dataset dubbed "BeachParameters" was created that takes into account water depth near the beach, the nature of breaking waves, the presence of rocky headlands or grains, the nature of the water, the presence of dark patches, the nature of the water surface, current speed, and the presence of colored or foamy water. Based on the combination, considering that highly correlated parameters cause rip current, the contents of the dataset will be extended step by step. Table 1 displays a subset of the BeachParameters dataset.

Table 1: The part of beach parameters that are compiled to form BeachParameter dataset

Depth of water near beach	High	Medium	Low	Medium
Breaking waves	Fewer	Fewer	Average	Huge
Rocky Headlands and Rocky Groins	Yes	No	No	Yes
Water nature	Calm	Stormy	Windy	Stormy
Deeper dark patches of water	Yes	No	No	Yes
Water surface	Rippled	No rippled	Rippled	Rippled
Backwash current speed	2.5 m/s	0.5 m/s	1m/s	1.5 m/s
Discoloured or foamy water	Yes	No	Yes	Yes
Classification	Rip current	Non rip current	Non rip current	Rip current

3.2 Data Pre-proceesing

The preprocessing stage is indeed a way of eliminating superfluous image data and preserving or highlighting useful data. Regularization and conformal modification are frequently used techniques. In particular, a Gaussian blur kernel [21] is used to soften the image (reduced noise level) as input to the grid points. Then, one or even more picture features are computed using a local derivative procedure [21]. Aside from that, in order to ensure the training impact, this study arbitrarily cuts and reverses the information prior to feeding it to the network. The principle component analysis (PCA) [22], which is a statistical process that turns a collection of possibly correlated experiences into a set of linearly statistically independent values known as principle components. To put it another way, PCA is frequently used to simplify data, minimize ambiguity, and discover unquantified "underlying factors" [22].

3.3 Convolutional Neural Network (CNN)

CNNs, commonly referred to as "ConvNets," are composed of numerous layers and are primarily employed for image analysis and object tracking [23]. In many image recognition tasks, such as object tracking, deep learning models such as those at CNN have outpaced standard algorithms in machine learning [23]. The process of image categorization requires the identification of salient elements in such a picture so that patterns can be identified with training data [23]. Using an Artificial Neural Network (ANN) [31] for picture categorization might result in high computational costs due to the vast size of the learnable parameters [23].

CNN's convolution layer is comprised of many filters that accomplish the convolution function [23]. CNNs have just a ReLU layer enabling element-based computations [23]. The result is a mitigated map of features. The adjusted subset of features is then fed together into a layer for pooling. Pooling is a down-sampling procedure that thus decreases the feature map's dimensionality [23]. Flattening the underlying two-dimensional arrays from either the pooling layer map or the pooling layer transforms them together into a unified, lengthy, uninterrupted, linear vector [23]. Whenever the pooling layer's flattened matrix is provided as input, where it identifies and identification numbers the pictures, a fully linked layer is automatically formed [23]. Fig. 7 an illustration of a CNN-processed image.

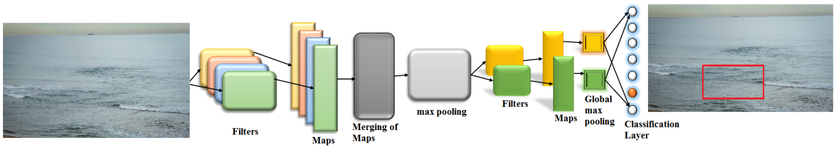

Figure 7: CNN architecture: classification division CNN is the abbreviation for convolutional neural network. The red square mark indicated the rip current

Deep learning techniques known as CNN can train massive datasets with millions of parameters by taking input in the form of 2D images. These images are then convolved using filters to produce the required outputs. The performance of CNN models on image recognition and detection datasets have been evaluated in this paper. Total five CNN algorithms have been used to implement the rip current detection process. Five convolutional layers, three max-pooling layers, two normalization layers, two fully connected layers, and one softmax layer comprise the AlexNet framework [24]. During the first convolutional layer of ZFNet, the number of filters was reduced from 11x11 to 7x7 [25]. VGG16 outperforms AlexNet by substituting huge kernel-size filtration (11 as well as 5 during the first and subsequent convolutional layers, correspondingly) with several 33 kernel-size filtrations in succession [24]. GoogLeNet employs a variety of approaches, including 11 convolution as well as global average pooling, which generates a denser framework. This technology captures 224-by-224 images with RGB color bands [24]. The architectural style of ResNet is influenced by VGG-19, a 34-layer simple network with shortcuts or skipped interconnections that has been implemented [25]. In DenseNet, for every layer, the local features of the previous layers are utilized as inputs, and the following layer uses its very own image features as input data. DenseNets literally connect each layer to every layer, as straightforward as that may sound [24]. That's the central, incredibly potent idea. The input of a layer in DenseNet is the combination of the preceding layers' image features [24].

3.4 Machine Learning Algorithms(MLAs) for classification

Six machine learning algorithms have been used to implement rip current detection based on beach parameters. A Decision Tree (DT) classifier is a predictor in a tree-like structure, with interior nodes representing the attributes of a dataset, branches representing the rule base, and each child node representing the conclusion of the classification [26]. Logistic regression is a statistical tool as well as a technique for machine learning, both of which are used for classifying difficulties. It is premised on the basis of probability, which is used to solve frameworks to analyze [26]. It is utilized in situations in which the predictor variables being studied (the target) are dichotomous [26]. A Naive Bayes classifier, to put it in more layman's terms, works under the assumption that the existence of one specific factor in a class is independent of the presence of any other characteristic [26]. The fundamentals of support vector machines (SVM), including how the algorithm itself operates, are easiest to grasp with the help of a straightforward illustration, [26]. Imagine for a moment that our data consists of two attributes, x and y, and that we have two tags, rip current and non-rip current. We are looking for a predictor that, when given specific dimensions (x, y), will report whether or not the value is rip current or non-rip current. In general, there are two parts, which we will call "rip current" and "non-rip current." We also have a new sample, which we will call "X." Based on this information, we can determine which of the 2 categories this data point belongs to. We will require the K-NN method in an attempt to remedy an issue of such a nature [26]. With the assistance of K-NN, we are able to quickly ascertain the category or group that a specific dataset belongs to [26]. Imagine there is still a dataset that comprises several different pictures of different types of beach parameters [26]. A random forest classifier is then presented with just this dataset to analyze. The dataset is then segmented into subsets, which are then provided to the various decision trees [27]. Even during a period of training, every decision tree generates a prediction performance [27]. Whenever a novel data item is introduced, the Random Forest classifier makes predictions for the final choice by using the outcomes of the plurality of the decision trees [27].

3.5 Rip current detection process

This paper is about how to use beach images, bathymetric images of the beach, and beach parameters to automatically find rip currents. The three processes are explained below.

3.5.1 Rip current detection using beach images

First, different images of rip currents (Fig. 4) and non-rip currents (Fig. 3) in beach areas have been collected to form the BeachImages dataset. For the prediction process to work, the deep learning algorithms were fed a total of 1,763 pictures of beaches.

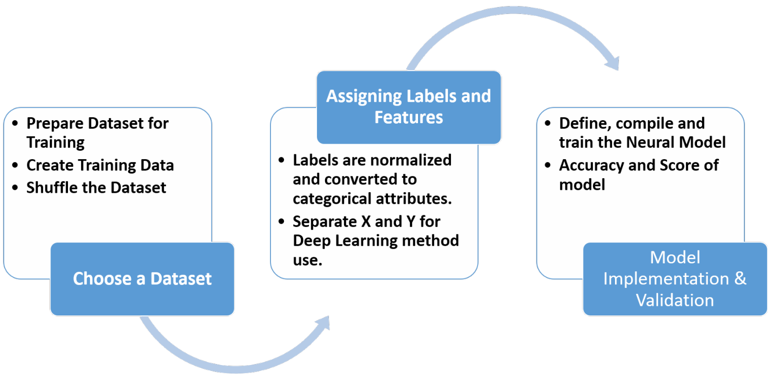

Figure 8: Convolutional Neural Network (CNN) based rip current detection process

Out of these images, 1463 were used to train the networks, and 300 were saved to test the model that was made. Then, we used both ripped and non-ripped images that had already been processed as training data for the CNN learning process. The CNN algorithm extracted some specific features from those beach images, by which it will be understood that the rip current is due to the presence of certain features in the image. These algorithms teach the neural network that a specific feature in an image represents rip current. In this way, we will learn the neural network by labeling the output based on some features of the image. As a result of this learning, the neural network will be able to determine whether or not there is rip current by looking at any unfamiliar image. Choose the BeachImages dataset to use the method for finding rip currents based on beach images. This dataset (CSV) has 1763 augmented beach images (PNG) with rip currents or no rip currents as labels. Fig. 8 represents the working process by which the rip-current detection model can be implemented and validated. Assigning routes, defining classification labels (rip or non-rip current), and scaling the pictures are all necessary steps in building the dataset to train on. The picture was resized to 200 x 200. The collection called training (various beach images containing rip and non-rip currents) includes the picture's pixel values as well as the picture's classification roster indicator. Then the dataset should be shuffled randomly. Then, the features (the input attributes taken from the beach images) and labels (rip current or not) were assigned, normalized, and turned into categorical features. The input and output have been separated for CNN use. The features and labels are then put together, defined, and used to train the CNN model. Finally, the model has been validated in terms of accuracy and score.

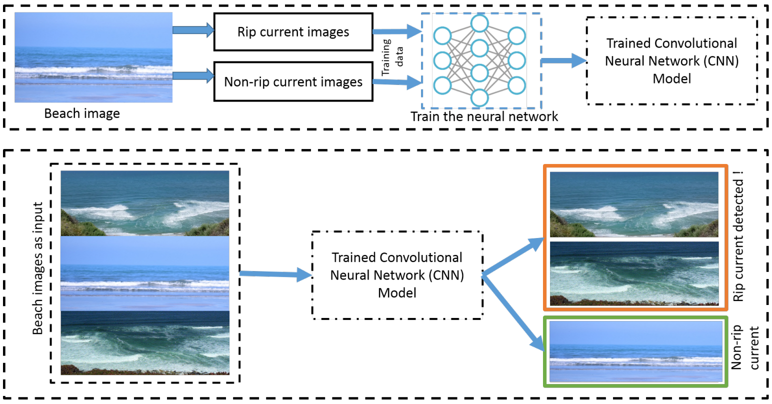

Figure 9: Beach image detection of rip and non-rip current based on CNN

Fig. 9 represents the block diagram of the rip current detection using CNN based on beach images. Once the model has been trained with the training set consisting of rip current and non-rip current images, the model can detect rip current in an image of a particular location. Then, the accuracy and precision of all CNN algorithms were calculated to show which ones were best at finding rip currents based on a test set of beach images. To justify the implemented model, it must be known how well the model detects rip current in unknown beach images. This proposed model showing the best performance has been applied to the images captured from the northeast corner of Saint Martin's Island, shown in Fig. 2.

3.5.2 Rip current detection using bathymetric images

This method has been designed based on the following process mentioned in subsection 3.5.1. But bathymetric images have been considered here instead of beach images. And the rest of the process is the same as explained in subsection 3.5.1.

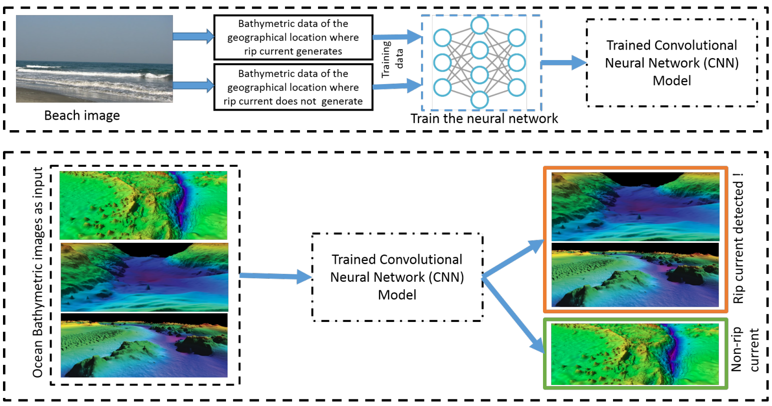

Figure 10: Bathymetric image detection of geo-morphological location causing rip and non-rip current based on CNN

Then, if the proposed model (Fig. 10) detects rip current for the bathymetric image of a particular location, a well-established manual test can be conducted in those locations to see if there is actually rip current being created or if there is a possibility of creating it in the future. This is how the justification for the proposed model will be completed.

3.5.3 Rip current detection using beach parameters

In addition to St. Martin's Rip Current, a data set has been created detailing all the places in the world where rip current has been found, such as water depth near beaches, nature of breaking waves, presence of rocky headlands or grains, nature of the water, presence of dark patches, nature of the water surface, current speed, and presence of colored or foamy water. Table 1 shows a portion of this dataset.

A total of 1123 samples have been compiled to create the BeachParameters dataset. First, the dataset was preprocessed to remove uncorrelated parameters that could be used to detect rip current. To carry out the classification process, highly correlated parameters were used as input features or variables, and rip or non-rip current was used as a target variable. Principle Component Analysis (PCA) was used to extract the highly correlated parameters as input features in detecting rip current. Then the dataset is divided into training and test sets in the ratio of 7:3. Around 786 samples have been selected as the training set, performed in random order. The remaining 337 samples have been considered a validation or test set. The model was then trained using machine learning algorithms like the Random Forest (RF) classifier, the k-Nearest Neighbors (kNN), Naive Bayes (NB) classifier, the Decision Tree (DT) classifier, and the Support Vector Machine (SVM) classifier. The block diagram of the whole process is shown in Fig. 11.

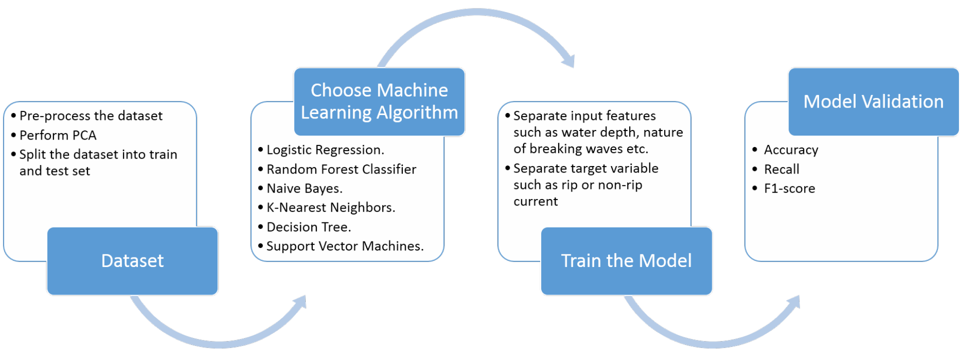

Figure 11: Machine learning based rip current detection process

After the model has been properly trained, the performance metrics have been calculated to find the high-performance algorithm that fits the model accurately. At first, features like the depth of the water near the beach, how the waves break, the presence of rocky headlands or grains, the type of water, the presence of dark spots, the type of water surface, the speed of the current, and whether the water is colored or foamy are fed into the trained machine learning model shown in Fig. 12.

3.6 Classification metrics

Each of the classification indicators evaluates the performance of the proposed model and indicates if the categorization is correct or incorrect. In addition to evaluating different ways to classify things, we will look closely at the following measures:

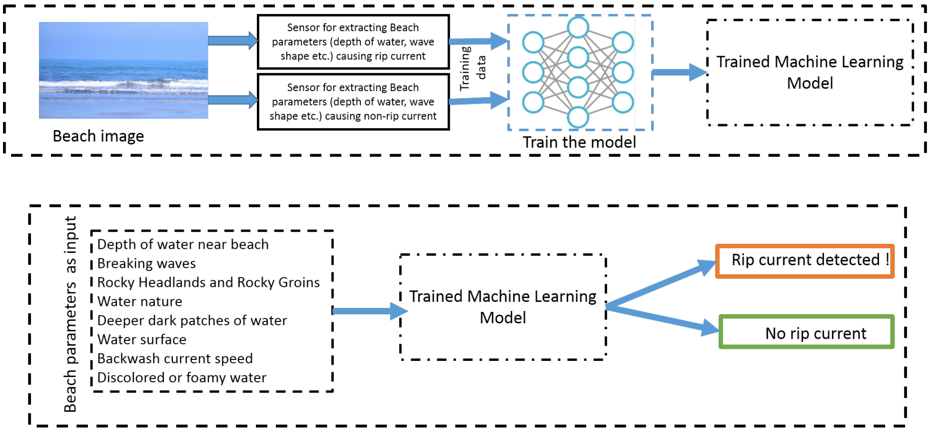

Figure 12: Rip and non-rip current detection using beach parameters based on a machine learning algorithm

		Prediction	
		Rip Current	Non Rip Current
Ground Truth	Rip Current	TP	FP
	Non Rip Current	FN	TN

Figure 13: Confusion matrix for null hypothesis

3.6.1 Accuracy

The effectiveness of a classifier can be measured by the number of correct predictions divided by the number of assumptions multiplied by 100 [28]. This is probably the simplest measurement to use and implement. Either we can do this by continually comparing the current characteristics with the empirical and expected qualities in a loop, or we can utilize the scikit-learn module and let it handle all the grunt work [28].

3.6.2 Confusion Matrix

The Confusion Matrix is a tabular representation of the ground-truth labels relative to the model's expectations [28]. Occurrences that pertain to a final prediction are displayed along the rows of the confusion matrix, whereas real-world incidences are shown along the columns [28]. Although the confusion matrix is not exactly a performance indicator, it serves as the basis for additional measurements to evaluate the outcomes [28].

To fully understand the confusion matrix, you have to guess what the value of the null hypothesis alone is. This might have been of any value. For example, depending on the knowledge we have regarding the detection of rip currents or not (Fig. 13), let's assume that our null hypothesis is "Rip Current has been detected!"

3.6.3 Precision

Precision is the ratio of the number of actual positives to the anticipated number of positives [28]. Equation 1 and 2 shows the expression of precision [28].

$$\mathrm{P} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{1}$$

$$P = \frac{IdentifiedBlueWhaleCorrectly}{IdentifiedBlueWhaleCorrectly + IdentifiedBlueWhaleIncorrectly} \tag{2}$$

3.6.4 Recall/Hit-Rate/Sensitivity

A recall is the fraction of true positives relative to the total number of true positives in the ground truth [28] (Equation 3 and 4).

$$R = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{3}$$

$$R = \frac{IdentifiedBlueWhaleCorrectly}{IdentifiedBlueWhaleCorrectly + LabelledDolphinsasWhalesIncorrectly} \tag{4}$$

3.6.5 F1-score

The F1-score statistic considers both the accuracy and quantity of information retained. In reality, the F1 score is determined by calculating the harmonic mean of two scores [28]. Essentially, the equation 5 for both is as follows:

$$F_1 = \frac{2}{\frac{1}{precision} + \frac{1}{recall}} \tag{5}$$

4 Result and Discussion

4.1 Beach images based rip current detection

The proposed model, which is based on CNN, was able to find the rip current in the beach images taken from the northeast corner of Saint Martin's Island, with only a few false positives. Example recognition outcomes are displayed in Fig. 14.

Figure 14: Detections of rip current on a subset of images from the testing dataset. Red rectangles indicate rip currents that have been accurately recognized. Blue boundary rectangles illustrate the actuality. Without boundary boxes, images never include rip currents.

A well-established manual test has been conducted in those locations to see if there is actually a rip current being created or if there is a possibility of creating one in the future. This is how the justification of our model has been completed.

Figure 15: Exemplary failure scenarios. The false-positives that were found mostly in the beachfront scene (on the right) are tough to explain

The empirical outcomes are presented in Table 2.

Table 2: Performance of the rip current detection model based on beach images

CNN Model	Accuracy	Recall	F1 Score
AlexNet	83.67%	0.84	0.78
ZFNet	85.78%	0.87	0.81
VGG16	93.13%	0.94	0.87
GoogLeNet	92.69%	0.89	0.89
ResNet	87.67%	0.89	0.82
DenseNet	92.27%	0.93	0.90

Furthermore, as indicated in Table 2, compared to other models, the accuracy rate has increased to 93.13%, while the error function depicted in Fig. 16 has dropped, and the gradients now satisfy empirical criteria. The experimental results suggest that the revised VGG16 model presented in this study may have a strong rip current detecting impact. Fig. 14 shows the outcomes of the rip current detection model for beach images that were considered input features and estimated the output, or target label output. The proposed model can be optimized using the confusion matrix. The confusion matrix for the VGG16 algorithm is shown in Fig. 18 (a).

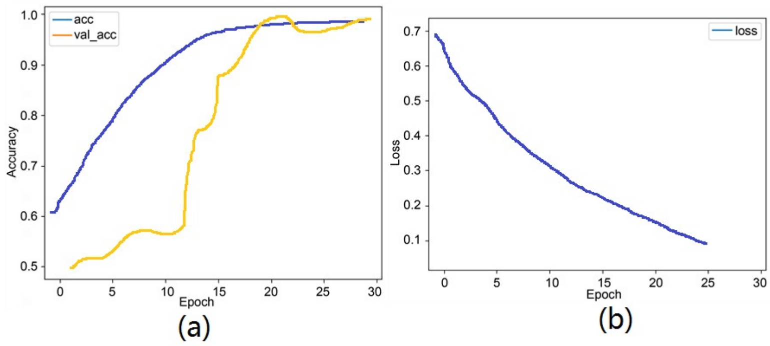

Figure 16: Performance of VGG16 algorithm

This kind of work is quite new on St. Martin. Therefore, comparing with other beach images, it can be seen that the proposed method is able to detect the rip current most accurately as shown in Table 3. The proposed method can detect rip current more accurately than other conventional methods.

Table 3: Comparison between proposed method and existing method

CNN Model	Akila de Silva et al. (2021)	Philip et al. (2016)	Maryan et al. (2019)	This Study
AlexNet	-	-	-	83.67%
ZFNet	-	-	-	85.78%
VGG16	-	-	-	93.13%
GoogLeNet	-	-	-	92.69%
ResNet	-	-	-	87.67%
DenseNet	-	-	-	92.27%
F-RCNN	88.40%	30.70%	72.90%	-

4.2 Bathymetric images based rip current detection

It is essential to have the capability of tracking the changes that take place throughout the coastal area over time in order to forestall the occurrence of any catastrophes that could be caused by rip currents.

As seems to be the case with CNN, this approach may collapse whenever applied to photos that do not reflect the labeled training data. The sets of data predominantly consisted of rip currents distinguished by a hiatus in wave action, the far more typical observable signal for bathymetry-controlled rip currents. Consequently, we anticipate missing rip currents with the other visible cues such as debris booms. As observed, we also anticipate failing when confronted with new visuals, often for no obvious reason.

Furthermore, as indicated in Table 2, compared to other models, the accuracy rate has increased to 96.89%, while the error function depicted in Fig. 17 has dropped, and the gradients now satisfy empirical criteria. The experimental findings indicate that perhaps the revised DenseNet model presented in this research has a strong rip current detecting impact.

Fig. 10 shows the outcomes of the rip current detection model for beach images that were considered as input features and estimated the output or target label output. The proposed model can be optimized using the confusion matrix. The confusion matrix for the VGG16 algorithm is shown in Fig. 18(a).

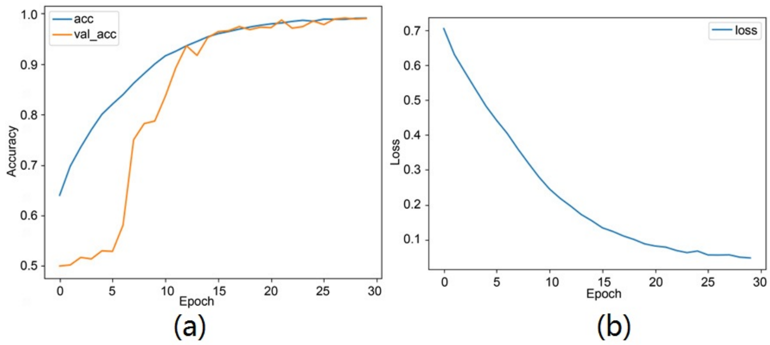

Figure 17: (a) training set accuracy and testing dataset precision, as well as (b) deteriorating gradients of the error function for the DenseNet model

4.3 Beach parameters based rip current detection

The field of machine learning is one of the most rapidly expanding subfields of computer science and has numerous potential applications. It is the process of automatically identifying meaningful patterns in large amounts of data. The goal of the technologies that make up the field of machine learning is to give computer programs with the capacity to learn and adapt. Machine learning has emerged as one of the most important aspects of information technology and, as a result, has become an extremely important, albeit frequently unseen, component of our everyday lives. There is excellent cause to assume that intelligent data analysis of beach parameters will become even more widespread as a crucial ingredient for the progression of technological innovation as the amount of data that is becoming available continues to grow at an exponential rate.

Depending on the beach parameters, such as water depth near the beach, nature of breaking waves, presence of rocky headlands or grains, water nature, presence of dark patches, nature of water surface, current speed, and presence of coloured or foamy water for test set have been applied. The performance metrics are shown in Table 4.

Furthermore, as indicated in Table 4, compared to other models, the accuracy rate has increased to 86.98%. The experimental findings indicate that perhaps the revised Random Forest classifier model presented in this research has a strong rip current detecting impact.

Fig. 14 shows the outcomes of the rip current detection model for beach images that were considered as input features and estimated the output or target label output. The proposed model can be optimized using the

Table 4: Performance of rip current detection based on machine learning algorithm

Machine Learning based classifier	Accuracy	Recall	F1 Score
Decision Tree	78.98%	0.80	0.82
Logistic Regression	83.98%	0.82	0.86
Naïve Bayes	84.57%	0.87	0.89
Random Forest	86.98%	0.89	0.90
KNN	80.38%	0.81	0.86
SVM	86.77%	0.82	0.84

confusion matrix. The confusion matrix for the Random Forest classifier algorithm is shown in Fig. 18(c).

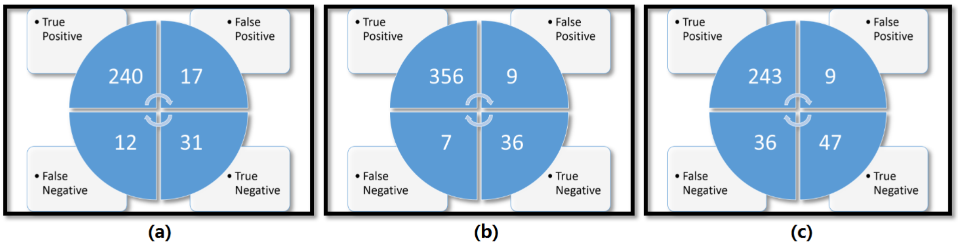

Figure 18: Confusion matrix for (a) VGG16, (b) DenseNet, (c) Random Forest classifier algorithm in the rip current detection method

It is clear from the confusion matrix (Fig. 18(a)) that the detection model is able to detect 240 beach images labeled as rip current presence, while 31 beach images are labeled as non-rip current. The model makes a total of 29 false detections. The model predicted 12 beach images as non-rip current, but originally those images contained the presence of rip current, which is the limitation of the proposed method. Because this false detection can impact beach goers more dangerously than the 17 false detection incidents. The detection model is able to detect 356 bathymetric images (Fig. 18(b)) labeled as rip current presence, and 36 bathymetric images are labeled as non-rip current correctly. The model makes a total of 16 false detections. The model predicted 7 bathymetric images as non-rip current, but originally those images contained the presence of rip current, which is the limitation of the proposed method. Because this false detection can impact beach goers more dangerously than the 9 false detection incidents. The detection model is able to detect 243 samples successfully as rip current and 47 as non rip current (Fig. 18(c)). The model makes a total of 37 false detections. The model predicted 36 beaches of rip current as non-rip current, but originally those images contained the presence of rip current, which is the limitation of the proposed method. Because this false detection can impact beach goers more dangerously than the 7 false detection incidents.

5 Beach Hazard Safety Implications

When applied to pictures that do not correspond to the training data set, our approach has the potential to fail, just like any other machine learning model. The majority of the rip currents in our data sets were denoted by a gap in the waves crashing, which is the most prevalent type of visual indicator for bathymetry- controlled rip currents. We should therefore anticipate missing rip currents when looking for other visible clues, such as sediment plumes. We also anticipate that our predictions will be incorrect when we are shown new footage, and sometimes they will be incorrect for no obvious reason at all.

Since rip currents are a coastal hazard, they must be managed through the coastal management system to abate their severe consequences. By making sure there is good governance, educating the public, getting stakeholders involved, etc., these risks can be eliminated.

Saint Martin's Island is often the scene of drownings. It is possible to avoid this accident with a little care. Moreover, it is important to know how to get out in case of danger. The potential zone producing rip current found from the result of the proposed method can be managed by appropriate governance implications. If we can figure out where rips are likely to happen along the coast of Saint Martin's Island, the Bangladesh government can take the right steps to keep them safe.

In some places on the beach, the tide is very high. On the way back after the ocean waves hit, the submerged sand dunes are blocked. If we look closely, we can see that the waves in the sea form waves before they hit the beach. This is where the sand dunes and the water depth between these two waves are higher than normal, meaning it is like a canal. In some spots, these dunes have gaps, and the water goes back to the sea that way. Since a lot of water goes through this small gap, there is a lot of tidal current or tension from the beach along this place. It is not possible for a skilled swimmer to swim against this current. This is called "rip current." The problem is, the position of this rip current is not fixed at any particular place; it changes continuously with the current wave. At low tide, the red flag is flown in front of the watchtowers. The restrictions have to be observed not to dive into the water at this time in the rip-prone area.

For the purposes of rigorous scientific investigation and community safety, especially in coastal regions, an infrastructure of webcams for seaside observation can then be established in the rip-prone coastal area. To achieve such, a consistent data collection and data approach will be developed in order to offer stakeholders, including rescuers, emergency responders, and coastal management staff, actionable insights from camera video. Moreover, an alarm system can be implemented by which the person tapped by rip current can be easily noticeable when the system generates a command signal to turn on the ringing devices.

Our three approaches have been applied to the rip-prone area of Saint Martin's Island. All of our three approaches have successfully detected the north-east corner of Saint Martin's Island. That means our method is capable of identifying the rip current zone. If we apply our proposed model to all regions of Saint Martin's Island, then we may find many potential rip-prone areas that we can't recognize manually. If any rip-prone areas have been labelled as rip current, then we can test those regions manually by fluorescent dye solution injection to justify our model. If this manual process also returns the same outcome, we can declare that regions as rip-prone areas and proper steps must be taken accordingly.

6 Conclusion

This paper suggests using CNNs and MLAs to automatically detect rip currents with crashing waves. Three datasets, including BeachImages, BathymetricImages, and BeachParameters, have been generated and then conducted the rip current detection process, through which it will be possible to identify different places of possible rip current in Saint Martin's Island. This work includes expert-tagged rip current training and test data. Then the datasets have been divided into test and training sets to implement the training procedure of the proposed methods. After that, the trained model was evaluated using the test set and then recorded the performance metrics for classification. A CNN-based detection algorithm has been implemented for beach and bathymetric photos. Using beach parameters, MLAs have been used to identify rip currents. Some real images have been captured from the suspected rip current generation region in Saint Martin's Island to validate the model, showing the highest accuracy and precision. Analysis reveals that bathymetric image-based detection models are more accurate and precise. So this model can be used to identify the potential rip current regions on Saint Martin's Island. Due to a lack of funding, we could not collect much data and create advanced datasets. If we can gather more information by in situ experimentation, surely we can enhance our dataset and hence the performance of the model based on beach images and beach parameters. Besides, there is another way to enhance the accuracy of the proposed model. As the dataset consists of a very small amount of data, we can apply a few-shot learning method in the future to train the method accurately with a very small amount of data.

7 Acknowledgement

We are grateful to the Coast Guard and Life Guards of St. Martin. They assisted in the work of this project with various pieces of information and helped to find the location of the rip current created in the north-east corner.

8 Source of Funding

We had no funding for this work. We have done this small work with our personal initiative and funding.

References

[1] Silva, A., Mori, I., Dusek, G., Davis, J. & Pang, A. Automated rip current detection with region based convolutional neural networks. *Coastal Engineering*. **166** pp. 103859 (2021)

[2] Mori, I., Silva, A., Dusek, G., Davis, J. & Pang, A. Flow-Based Rip Current Detection and Visualization. *IEEE Access*. **10** pp. 6483-6495 (2022)

[3] Radermacher, M., De Schipper, M. & Reniers, A. Sensitivity of rip current forecasts to errors in remotely-sensed bathymetry. *Coastal Engineering*. **135** pp. 66-76 (2018)

[4] Philip, S. Rip Current Detection using Optical Flow.

[5] Pitman, S., Gallop, S., Haigh, I., Mahmoodi, S., Masselink, G. & Ranasinghe, R. Synthetic imagery for the automated detection of rip currents. *Journal Of Coastal Research*., 912-916 (2016)

[6] Dérian, P. & Almar, R. Wavelet-based optical flow estimation of instant surface currents from shore-based and UAV videos. *IEEE Transactions On Geoscience And Remote Sensing*. **55**, 5790-5797 (2017)

[7] MacMahan, J., Thornton, E. & Reniers, A. Rip current review. *Coastal Engineering*. **53**, 191-208 (2006)

[8] Castelle, B., Scott, T., Brander, R. & McCarroll, R. Rip current types, circulation and hazard. *Earth-Science Reviews*. **163** pp. 1-21 (2016)

[9] MacMahan, J., Thornton, E., Stanton, T. & Reniers, A. RIPEX: Observations of a rip current system. *Marine Geology*. **218**, 113-134 (2005)

[10] Austin, M., Scott, T., Russell, P. & Masselink, G. Rip current prediction: development, validation, and evaluation of an operational tool. *Journal Of Coastal Research*. **29**, 283-300 (2013)

[11] Benassai, G., Aucelli, P., Budillon, G., De Stefano, M., Di Luccio, D., Di Paola, G., Montella, R., Mucerino, L., Sica, M. & Pennetta, M. Rip current evidence by hydrodynamic simulations, bathymetric surveys and UAV observation. *Natural Hazards And Earth System Sciences*. **17**, 1493-1503 (2017)

[12] Ishikawa, T., Shimada, R., Sawagashira, R. & Komine, T. Proposal and verification of rip current detection using AI. (2021)

[13] Arun Kumar, S. & Prasad, K. Rip current-related fatalities in India: a new predictive risk scale for forecasting rip currents. *Natural Hazards*. **70**, 313-335 (2014)

[14] Trimble, S. Addressing the International Rip Current Health Hazard. (2017)

[15] Kim, T. Detection of rip current using camera monitoring techniques. *American Geophysical Union*. **2016** pp. EC14C-0996 (2016)

[16] Sembiring, L., Van Dongeren, A., Winter, G., Van Ormondt, M., Briere, C. & Roelvink, D. Nearshore bathymetry from video and the application to rip current predictions for the Dutch Coast. *Journal Of Coastal Research*., 354-359 (2014)

[17] Schönhofer, J. & Dudkowska, A. Rip currents in the southern Baltic Sea multi-bar nearshore zone. *Continental Shelf Research*. **212** pp. 104324 (2021)

[18] Maryan, C., Hoque, M., Michael, C., Ioup, E. & Abdelguerfi, M. Machine learning applications in detecting rip channels from images. *Applied Soft Computing*. **78** pp. 84-93 (2019)

[19] Reinhart, B. & Pfaff, S. Wave analysis for rip current forecasting in Southeast North Carolina. *Technical Attachments, National Oceanic And Atmospheric Administration*. (2016)

[20] Shampa, T. A Field Report on Saint Martin's Island, Cox's Bazar Bangladesh. (University of Dhaka,2020)

[21] Hummel, R., Kimia, B. & Zucker, S. Deblurring gaussian blur. *Computer Vision, Graphics, And Image Processing*. **38**, 66-80 (1987)

[22] Daffertshofer, A., Lamoth, C., Meijer, O. & Beek, P. PCA in studying coordination and variability: a tutorial. *Clinical Biomechanics*. **19**, 415-428 (2004)

[23] Sun, Y., Xue, B., Zhang, M., Yen, G. & Lv, J. Automatically designing CNN architectures using the genetic algorithm for image classification. *IEEE Transactions On Cybernetics*. **50**, 3840-3854 (2020)

[24] Gu, J., Wang, Z., Kuen, J., Ma, L., Shahroudy, A., Shuai, B., Liu, T., Wang, X., Wang, G., Cai, J. & Others Recent advances in convolutional neural networks. *Pattern Recognition*. **77** pp. 354-377 (2018)

[25] Kim, P. Convolutional neural network. *MATLAB Deep Learning*. pp. 121-147 (2017)

[26] Mahesh, B. Machine learning algorithms-a review. *International Journal Of Science And Research (IJSR).[Internet]*. **9** pp. 381-386 (2020)

[27] Bonaccorso, G. Machine learning algorithms. (Packt Publishing Ltd,2017)

[28] Erickson, B. & Kitamura, F. Magician's corner: 9. Performance metrics for machine learning models. *Radiology: Artificial Intelligence*. **3** (2021)

[29] Correspondent, S. Unsafe Cox's Bazar, Saint Martin — Prothom Alo. *Prothomalo*. (2014,4), https://en.prothomalo.com

[30] Correspondent, C. 2 die, 4 missing in Saint Martin's Island. *Bdnews24.com*. (2014)

[31] Akhter, T., Islam, M. & Islam, S. Artificial Neural Network based COVID-19 Suspected Area Identification. *Journal Of Engineering Advancements*. **1**, 188-194 (2020)

[32] Islam, M., Hasan, M. & Begum, A. Improvement of the Handover Performance and Channel Allocation Scheme using Fuzzy Logic, Artificial Neural Network and Neuro-Fuzzy System to Reduce Call Drop in Cellular Network. *Journal Of Engineering Advancements*. **1**, 130-138 (2020)

[33] Kar, P., Islam, M. & Paul, A. Experimental Circuit Model for Increasing the Signal Strength level of a Mobile Phone into a Lift. *International Journal*. **10** (2021)

[34] Islam, M., Akhter, T., Begum, A., Hasan, M. & Rafi, F. Brain Tumor Detection from MRI Images using Image Processing.

[35] Hasan, M., Islam, M., Rahman, S., Frater, M. & Arnold, J. No-Reference Quality Assessment of Transmitted Stereoscopic Videos Based on Human Visual System. *Applied Sciences*. **12**, 10090 (2022)

[36] Kar, P., Islam, M., Chakraborti, J. & Sutradhar, S. Mathematical Performance Analysis of the Absorbing Sun Light for Rotating and Non-rotating solar cell panel.. *Journal Of Theoretical And Applied Information Technology*. **100** (2021)

[37] Islam, M., Shampa, M., Alim, T. & Others Convolutional Neural Network based Marine Cetaceans Detection around the Swatch of No Ground in the Bay of Bengal. *International Journal Of Computing And Digital System*. (2021)

[38] Islam, M., Begum, A. & Hasan, M. Mathematical Analysis of Improving the System Capacity and Signal to Interference Ratio in Cellular Mobile Communication. *Journal Of Engineering Advancements*. **2**, 24-34 (2021)