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Comparative Analysis on Classification of Coastal Images Using Neural Network

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Abstract:

Despite recent advancements, classifying the coast remains a difficult problem in quantitative `geomorphological and environmental studies. Years passing It is being a serious issue when land is destroyed or lost due to coastal erosion, especially in a nation like India where population growth is exploding .This had motivated researchers to make a thorough study of the Coastal regions. Years later researchers of Machine learning implemented algorithms for coastal image classification. Our paper is a comparative study and classification of coastal images using neural network by implementing different algorithm and architectures which helps you to give best accuracy in classifying these coastal images. The algorithm we have chosen are k-means algorithm and we have used are CNN (convolutional neural network) deep learning algorithm. In this study we have trained samples of coastal images through these algorithms and tried to increase the accuracy by using the best algorithm between these and used GAN model for data Augmentation that makes accuracy much better. This also helps in predicting which areas are danger prone and which are not.

Introduction:

A coastal zone is where both land and water meet. Both marine and terrestrial materials, sustainable and non-renewable, are present. Additionally, links between various natural processes and human actions are important elements in the coastal area. India's coastline, which spans 7500 km and includes its island territories, has a long history. It is significant because of its high ecosystem productivity, resource exploitation, population growth, municipal sewage and trash discharge, expansion of various businesses, increased use of harbours, growth of leisure activities, and, most importantly, petroleum-related research activity. The coastline is a dynamic geomorphological structure that adapts to external forces like waves, tides, nearshore currents, and sediment movement. Accrual or beach growth happens when the net transfer of sediment into a certain place surpasses the net transit of sediment out of the area. Beach erosion, on the other hand, takes place when there is a mismatch between the quantity of sediment entering and departing a particular region. A subfield of artificial intelligence known as "machine learning" concentrates on using algorithms to empirical data, enabling computers to build models for intricate relationships or patterns without needing to be expressly coded. It is predicated on the notion that behaviour can be reproduced and fuelled by a large amount of data. A train dataset, test dataset, and algorithm were needed by the traditional machine learning process in order to build a model for making forecasts. Machine learning has two subcategories as supervised learning and unsupervised learning.

Unsupervised learning, also known as unsupervised machine learning, uses machine learning techniques to analyse and classify unlabelled data. These programs detect hidden patterns or data groups without the need for human intervention.

Using this type of learning helps in handling classification problems. In our paper we have used k-means since we have different parameters like erosion length and erosion area. And we also used CNN for binary classification of images by making image dataset from the official Vedas coastal website.

Contribution:

Machine learning, a branch of artificial intelligence, has been extensively used by academics to develop methods that are more effective in coastal areas. They conducted study on categorization of beaches, arid and wet areas, wave height forecasting, etc. However, no studies have been done to determine which coastal regions are better and which coastal regions are dangerous due to land erosion. In this work, we developed two distinct classification methods for coastal areas. By utilizing various methods, such as K-means clustering and convolutional neural networks, we were able to categorize shoreline pictures as being either dangerous or not dangerous. We also made an effort to demonstrate how these two algorithms vary in terms of precision using silhouette scores, training losses, and validation losses. We also graphically visualized the results that occurred in these algorithms.

Related work:

It was not a simple job to perform a comparative study on classification of coastal images based on neural networks. For this paper much research was done to gain deep insights into the algorithms that we were attempting to apply. We reviewed various study papers released over the last few years on a specific algorithm by different writers. Our study of those algorithms through those papers was extremely beneficial in this paper because we fully grasped the execution of each algorithm and trained all the models to accomplish the paper's goal. The table below includes all the information about the study papers that we used to complete our paper. Creating and training models on the chosen dataset is undoubtedly a difficult task, but these papers have led us and assisted us in resolving the disputes that have emerged while working on this paper.

Table 1: Study of various papers

Id	Author name	year	Methodology/ algorithm	Dataset	Advantages	Disadvantages
1	Martin SantosRomero, Javier Arellan o-Verd ejo, Hugo E. Lazcan o-Hern andez	2022	Transfer learning method, VGG16, ResNet50, and MobileNetv2 CNN models	Crowd sourcing	It compared all the algorithms and declared the best one for prediction	Ignored other important algorithms that does not talk about sustain of human life.
2	Chang,mona Zhang,han,kim	2020	SVM,Logistic regression	Image dataset	It used exception and inceptions for finding better accuracy	It delt with supervised learning methods. And does not talk about erosion
3	Kinh Bac Dang, Van Bao Dang; Quang Thanh Bui; Van Vuong Nguyen	2020	ConvNet	ALOS,NOAA Satellite	It clearly discriminated the types of coasts in Vietnam	Concentrated only on different types of coats in particular city where other city might have any new coat type.
4	Chengjuan Ren ,Hyunjun Jung, Sukhoon Lee Dongwon Jeong	2021	R-CNN,SSD	Camera captured images	Can clearly identifies any set of objects in sand	Can identify only objects that are defined

Basics of GAN:

Artificial intelligence (AI) has been able to carry out an increasing number of human jobs over the past ten years thanks to Big Data, algorithm optimization, and the continuous advancement of processing power. GAN(Generative Adversarial Network) is a modelling approach used in deep neural networking. It is mainly used for unsupervised type of learning. These work in such a way that it tries and learn the pattern from input data and tries generate images that are like the given set of input. GAN's can imitate any kind of data that might be text,images,videos. This mainly follows two player game ,These GANs use two neural networks they are: (I)Generator (II) discriminator. The generator network creates artificial data that resembles the actual data, such as audio or pictures. It produces a sample of the desired data format after receiving input made up of random noise. The generator's objective is to produce examples that are convincing enough to deceive the discriminator. The discriminator network oversees separating authentic data from false data. It uses both real and produced samples and attempts to distinguish between the real and false ones. The discriminator's objective is to accurately distinguish between genuine and fake data generated by the generator.

Mathematically: the two-player minimax game

The generator *G* and the discriminator *D* are jointly trained in a **two-player minimax game** formulation. The minimax objective function is:

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{\text{data}}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log \left(1 - D_{\theta_d} \left(G_{\theta_g}(z) \right) \right) \right]$$

G(z) is the generator's output given input noise z

D(x) is the discriminator's output given input x (either real or generated)

Pdata(x) is the probability distribution of real data

Pz(z) is the probability distribution of the input noise

E_xPdata and E_zPz are the expected values over the real data and input noise distributions, respectively.

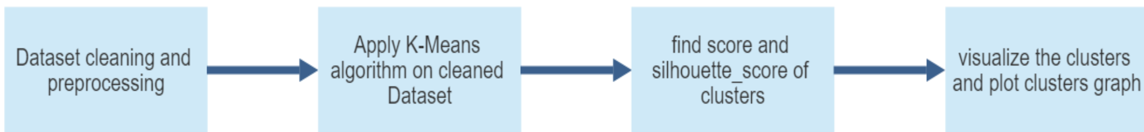
For image recognition and computer vision tasks, convolutional neural networks (CNNs) are a common form of neural network design. Many GAN implementations use CNNs as their fundamental building elements. GANs can also be used in the context of creating and manipulating images. Deconvolutional layers, also referred to as transpose convolutional layers, are frequently used by the generator network in a GAN to produce pictures from a random noise input. These layers can be thought of as the opposite process of the convolutional layers used in CNNs, where the deconvolutional layers learn to up sample the input noise to the desired output shape rather than conducting convolution to extract features. Similarly, CNNs can be used to create the discriminator network in a GAN. A succession of convolutional layers are used by the discriminator to extract features from an incoming picture. In order to determine whether the incoming picture is genuine or fake, these characteristics are then passed through one or more completely connected layers. CNNs are excellent at learning and modelling visual characteristics, which makes them well-suited for tasks like picture generation and manipulation. This is one benefit of using CNNs in GANs. Additionally, CNNs are readily stackable to produce deeper networks, which frequently results in improved performance. The propensity for GANs to experience mode collapse, where the generator produces only a small portion of the possible output data distribution, or for the discriminator to become too strong and overpower the generator are two difficulties that can arise when using CNNs in GANs. Due to these difficulties, a variety of methods for stabilizing and enhancing GAN training have been created, including Wasserstein GANs and conditional GANs, which can be combined with CNN designs to enhance performance. In our paper we use GANs for the purpose of data augmentation since the image dataset is taken manually by us we have used GAN model for larger dataset. Data supplementation produces better models by increasing model ability and having a regularizing effect that reduces generalization error. It creates new, contrived, but believable instances in order to make sense of the primary problem area on which the model is taught. In the case of image data, the techniques are easy and involve cropping, flipping, zooming, and other simple changes of the pictures already present in the training collection. Successful generative modelling provides a distinct, potentially more domain-specific approach for data enrichment. Even though it is not often mentioned, data augmentation is a simplified type of generative modelling.

Proposed model:

This comparative study of machine learning algorithms compares and evaluates how well various machine learning algorithms perform on predicting the shoreline images as danger prone or not. The goal is to select the best algorithm that gives better accuracy. It is possible to choose the optimal algorithm by comparing the results of different algorithms parameters like, Performance Evaluation: This study can provide a quantifiable evaluation of the efficacy of several and can help in figuring out which method is the most accurate, efficient, and trustworthy for finding effect on the shoreline. Model selection and optimization can be aided by understanding which model parameters or hyperparameters are effective for a given technique in the research. Improvement of the Field: The results of the research can be used to advance the field of machine learning by adding new algorithms, improving existing algorithms, or combining algorithms to create hybrid models. The results of a comparative study must be interpreted in light of the specific subject, information, and evaluation strategy used; as a result, the conclusions may not generalize to other contexts or datasets.

PROCESS FLOW OF THE TWO ALGORITHMS:

(I) K-MEANS CLUSTERING:



Algorithm:

Input: Image Dataset Output: comparative analysis on classification of images
Step 1:Start Step 2: clean and pre-process the datasets Step 3:Apply K-means algorithm Step 4:Train the dataset Step 5:Find the score and silhouette score of the clusters Step 6: visualize the clusters in graph Step 7:stop

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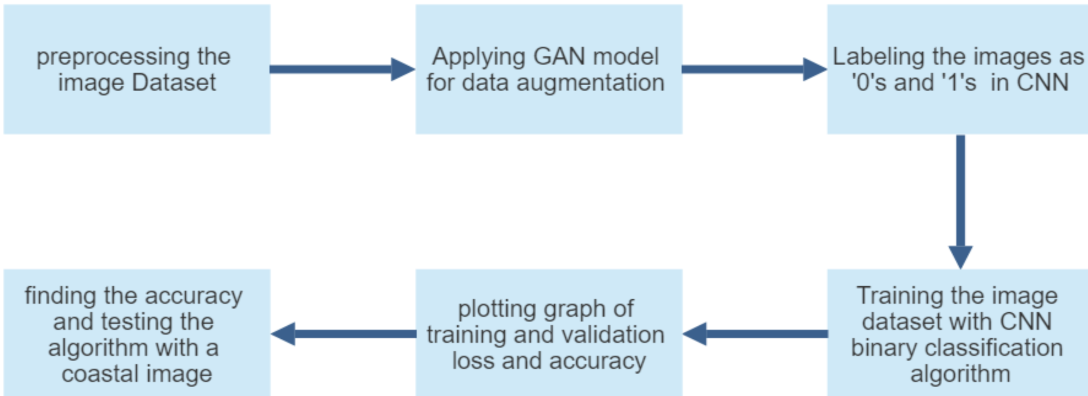
a(II)CONVOLUTIONAL NEURAL NETWORK:



Algorithm:

Input: Image Dataset Output: comparative analysis on classification of images
Step 1:Start Step 2: clean and pre-process the image dataset Step 3:Apply CNN binary classifier algorithm Step 4:label the images as 0's and 1's Step 5:Train and test the dataset Step 6: plot the graph for training and validation accuracy and loss Step 7:Find the accuracy and test with a coastal image Step 8:stop

In this paper we have used machine learning algorithms for classifying the coastal images. This paper methodology is to use the two algorithms K-means clustering and CNN binary classifier. And tries to train the algorithm that gives better accuracy in identifying the coastal images as danger prone or not danger. The process of collecting the image dataset, data cleaning, splitting the datasets into training and testing are already explained in the paper. Accuracy, Score, and silhouette score are the parameters that are taken into consideration for the algorithms' performance. Graphs are also plotted for visual observation. The CNN binary classifier gives the better accuracy than the K-means. So, CNN algorithm is considered as better algorithm in classifying the coastal images.

Experiments and Results:

Table-2

Mno	Model name	Accuracy	score	Silhouette_score
1	K-means clustering	-	-4597.46	0.523
2	CNN Binary classifier	70.87%	-	-

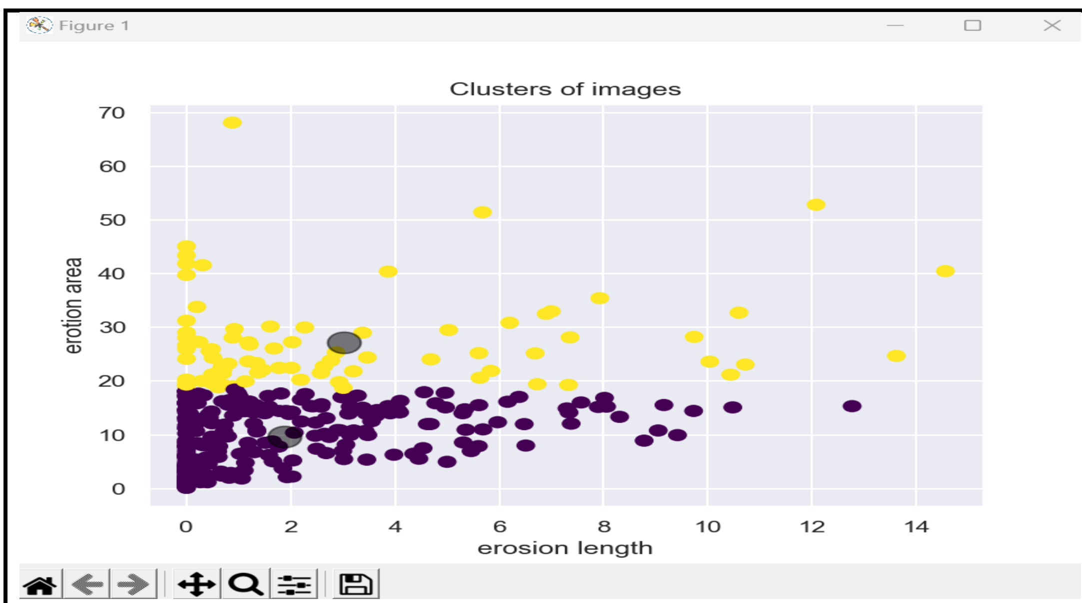


Figure 1:Represents clusters of coastal images

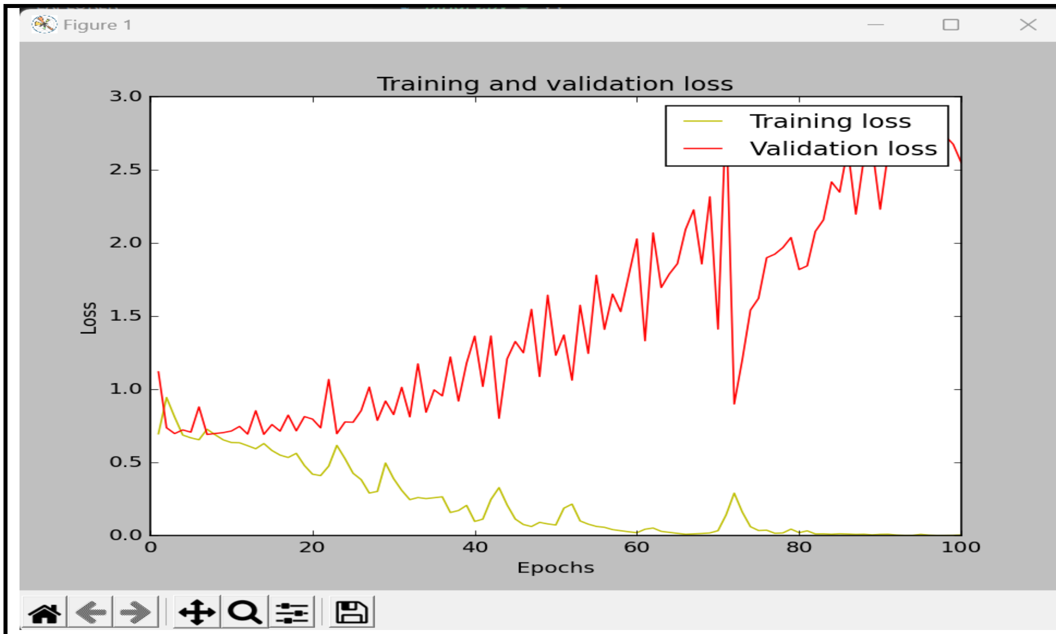


Figure 2:Figure represents training and validation loss of coastal images

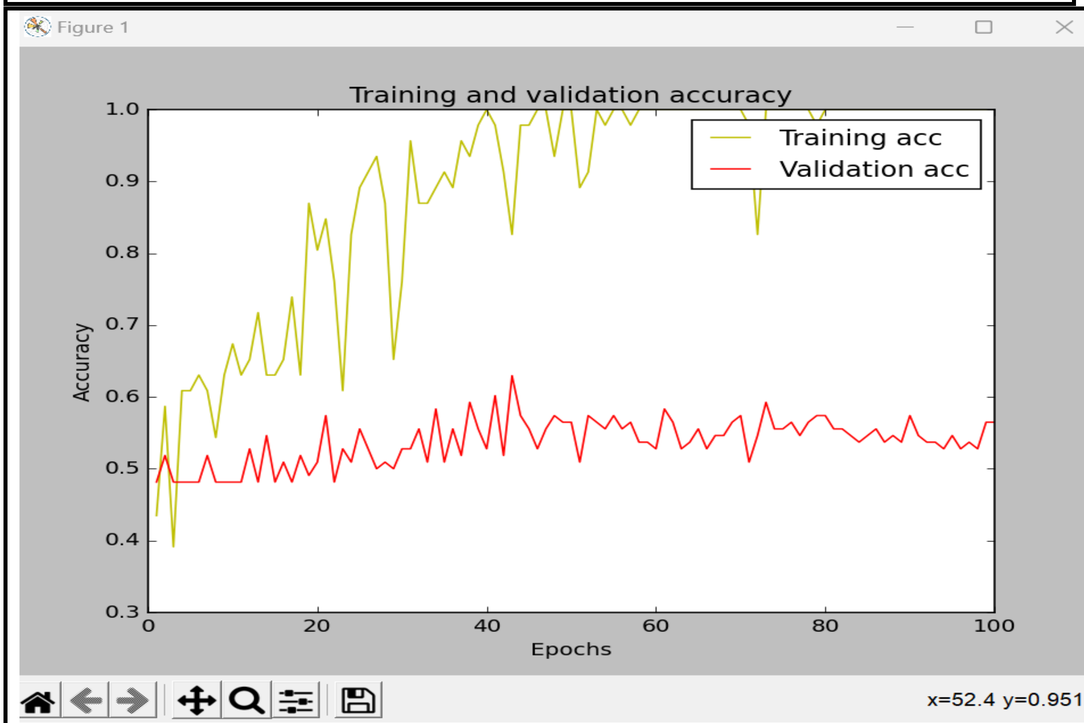


Figure 3:Figure represents training and validation accuracy of coastal images

Conclusions:

The performance of two different machine learning models for the classification of coastal images using neural network is compared in this study. We have seen K-means clustering algorithm which has a silhouette score of 0.523 which means the clusters are better in distinguishing each other and a score of -4597.46 which means it calculates the negative of the sum of squared distances between the data points and their closest cluster centers. Since the value it lesser we can state that the datapoints are distingued in a better way. And the accuracy found to be 70% using CNN binary classifier which mean the algorithm distinguished images in a better way.so we conclude that using CNN binary classifier and data augmentation through GAN helps you in getting better accuracy.

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