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Iceberg Detection in Satellite Images using Deep Learning Techniques

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Abstract: Iceberg detection is found to be more critical in the previous researchers. High quality satellite monitoring of dangerous ice formations is critical to navigation safety and economic activity in the regions. The satellite images play a crucial role in the identification of the icebergs. In this manuscript, a convolutional neural network (CNN) model is proposed for the iceberg detection from the satellite images. It is based on the satellite dataset for target classification and target identification. The iceberg detection is based on the statistical criteria for finding the satellite images. This model is used to identify automatically whether it is remote sensed target is iceberg or not. Sometimes the iceberg is wrongly classified as ship. This model is done to make accurate about the changes in the detection.

Keywords: Convolutional neural network (CNN), Iceberg detection, satellite images, target classification

I. . INTRODUCTION

At present, numerous organizations and organizations utilize ethereal observation and shore-based help to screen natural conditions and evaluate dangers from ice shelves. Be that as it may, in remote regions with especially unforgiving climate, these strategies are not attainable, and the main feasible checking alternative is through satellite. Progression of earth perception with satellites utilizing remote detecting has opened another road of earth science examine through contribution huge measure of opportunities for better comprehension of the world's condition and aiding quality dynamic. Deep learning is a piece of AI systems that is utilized by the layers to draw out the more significant level highlights from the crude info. So as to get data, remote detecting gave for examining the earth by satellite or high-flying airplane. Recognizing remote detecting pictures gives the better and more noteworthy test for the savvy examine researchers to find the Iceberg acknowledgment in the specific way. Remote detecting frameworks is utilized to distinguish chunks of ice are housed on satellites over the earth.

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The satellite star grouping is utilized to screen the seas. The satellites catch the pictures at the given area of earth's

surface in time at a given moment. The radar works the recurrence that sees through obscurity, cloud, haze, downpour. It discharges the claim vitality to catch pictures day or night. Satellite radar fills in as blips on boats or airplane radar. Iceberg recognition is utilized to identify the ice sheets in the satellite pictures. The fundamental target is to recognize the chunks of ice to build up the various strategies utilizing the satellite radar information and high spatial goals pictures in the range. The strategies for satellite checking speak to a risk to the route and monetary action.

There are three circumstances in the ice sheet discovery in the seas. They are, Icebergs in untamed water, Icebergs in floating ice, Icebergs in quick ice close to calving regions.

II. RELATED WORK

In this section, different techniques are discussed, which are related to iceberg detection using deep learning techniques

Armando Marino et.al., [1] introduced a strategy titled as a new algorithm for iceberg detection with dual-polarimetric SAR data. With regards to ice shelf location with SAR pictures, a broad work was completed for the recognition of huge ice shelves, yet the distinguishing proof of little bergs or target inserted in ocean ice is till troublesome. Right now, new locator is proposing to handle this issue dependent on double polarimetric incongruous pictures. The calculation depends on the rule that little ice shelves are contained in a constrained territory and they should have a volume commitment that is higher contrasted with the ocean or ocean ice foundation. Wolfgang Dierking et.al., [2] utilizes C-Band radar polarimetry. Right now, centered around examinations of polarimetric C-band radar marks of chunks of ice in ocean ice-secured sea locales. The primary target is to evaluate the potential improvement of ice shelf location when utilizing radar polarimetry. The predominant backscattering components of ice sheets are derived by assessing diverse polarimetric parameters. Extents of the cross-polarization proportions, the connection coefficients among HH-and VV-spellbound signs, and the entropy/alpha parameters show a solid commitment of volume dispersing much of the time.

C. Howell et.al., [3] utilizes the RADARSAT-2 satellite is a propelled C-band engineered gap radar (SAR) with an assortment of new modes including alternatives for polarization blends, goals, and swath width. Right now, analyses the capability of multi polarization information for identifying and segregating boat and icy mass targets Data utilized right now of very much approved airborne Convair-580 SAR and spaceborne ASAR HH/HV and HH/VV. Altogether, the informational collection utilized for assessing discovery and segregation comprises of 901 approved chunks of ice and boat targets.Igor Zakharov et.al., [4] Recent research has affirmed that satellite altimetry can be utilized for distinguishing chunks of ice. With an end goal to approve the altimetry-based methodology, this examination utilized 105 examples of icy masses contained in both satellite altimeter information and ENVISAT-ASAR scenes for the Weddell Sea territory. The issue of separating boats and ice sheets dependent on altimeter estimations was tended to utilizing an outfit of robotized classifiers. A sum of ten highlights were characterized from the altimetry sign to be utilized as indicator factors in managed grouping.

Jerry English et.al., [5] utilizes Space-based Automatic Identification System (S-AIS) information related to satellite Synthetic Aperture Radar (SAR) symbolism for Ship and Iceberg Monitoring. The goals of this work are to misuse S-AIS information for gathering ground truth to improve existing boat/ice sheet segregation calculations and to show the utility of S-AIS information for operational chunk of ice observation.

Armando Marino et.al., [6] proposed a calculation, the calculation proposed depends on a bother investigation in the objective space as of late created and distributed by the creators, which was centered around land-based objective discovery. The calculation can be viewed as a negative channel concentrated on ocean. Thusly, all the highlights which have a polarimetric conduct unique in relation to the ocean are recognized. To exhibit and approve the strategy two Radar Sat. Armando Marino et.al., [7] proposed a method. Right now, procedure dependent on the polarimetric irritation investigation is introduced. The calculation can be viewed as a negative channel concentrated on ocean. Thus, all the highlights which have a polarimetric conduct unique in relation to the ocean are distinguished and considered as targets. Right now, step channel is centered around chunks of ice discovery

Vahid Akbari et.al., [8] proposed another technique for programmed recognizable proof of ice shelves in high goals polarimetric SAR pictures obtained during various seasons. This includes adjusting the calculation to the ocean ice conditions, and confronting difficulties with regards to high chunk of ice thickness, meteorological and oceanographic marvels in the peripheral ice zone causing heterogeneity out of sight mess. Dr. Ch. Rupa et.al., [9] utilizes change procedures-based system has set up for recognizing the chunks of ice in the standard database pictures. This can ready to distinguish not just the bigger ice shelves, can likewise recognize littler and medium chunks of ice. This system has given 96% productive outcomes during the time spent recognition of the chunks of ice. The primary quality of this work is writing study on related works with the examination report on the outcomes.

III. METHODOLOGY AND IMPLEMENTATION

This section shows the system of the proposed approach. Our methodology consists of following they are,

- Data Set Collection
- Data Pre-processing
- Splitting Data as training and testing
- Model Fitting
- Visualize the Results

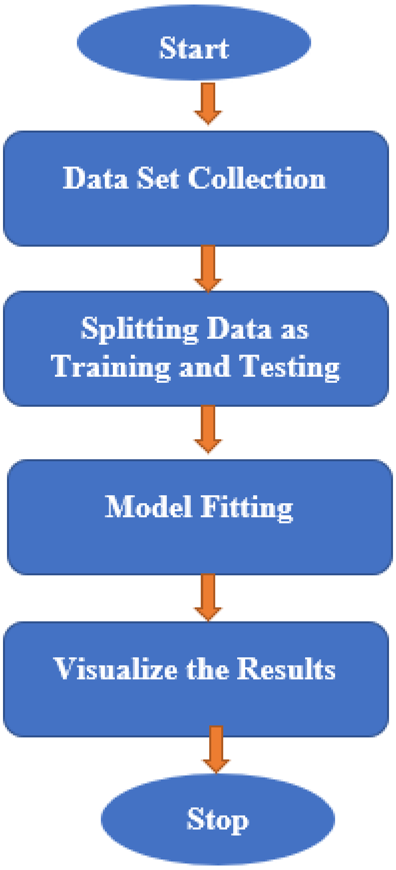

Fig 1. Structure of Proposed Methodology

Data Set Collection

In this, we predict an image contains an iceberg. The names are given by human specialists and geographic information on the objective. All the pictures are 75x75 pictures with two bands. The information (train.json, test.json) is introduced in json group. The records comprise of a rundown of pictures, and for each picture, you can locate the accompanying fields:

- id - the id of the picture
- band_1, band_2 - the smoothed picture information. Each band has 75x75 pixel esteems in the rundown, so the rundown has 5625 components. Note that these qualities are not the typical non-negative whole numbers in picture records since they have physical implications
- inc_angle - the rate edge of which the picture was taken. Note that this field has missing information set apart as "na", and those pictures with "na" rate edges are all in the preparation information to forestall spillage.

- is_iceberg - the objective variable, set to 1 on the off chance that it is an ice sheet, and 0 on the off chance that it is a boat. This field just exists in train.json.

If it's not too much trouble note that we have included machine-produced pictures in the test set to forestall hand marking. They are prohibited in scoring.

A. Data Pre-processing

In this section, we loaded all the libraries and dependencies, the image analysis was performed the Sentinel satellite is fundamentally the same as RISTSAT as it transmits pings in H-polarization and not in V-polarization. H pings when occurrence on an item get dissipated and return as a mix of H-and V-polarizations. As Sentinel has just H-transmitter, the arrival signals are of the structures HH and HV as it were.

Before we utilize the information for investigation to bring significant bits of knowledge, we first pre-process it to evacuate superfluous data present in it. We supplant the lines with tendency point as "na" with a zero. Each preparation test has two groups (HH and HV) related with it. We blend the two groups by averaging the two and making a third channel to get a three-channel RGB comparable. We abuse these basic contrasts to prepare the CNNs to get familiar with the different highlights of boats and icy masses.

B. Splitting Data as Training and Testing

In this section, we loaded the training and testing images in json file format. And we defined the training and testing data. We split the data into 3:1 i.e., we take 75% as training data and 25% as testing data respectively. And, in this we also use different libraries on this training and testing division, different operations was performed, we used sklearn.model_selection module for splitting data as training and testing.

C. Model Fitting

CNN is a class of profound feed-forward counterfeit neural system that is broadly applied in the field of PC vision. CNN is an idea propelled by the structure and network of the neurons in the human cerebrum. With late headways in neural systems, CNNs have demonstrated to be powerful in zones, for example, picture acknowledgment and arrangement. ConvNets have been effective in distinguishing faces, items, and traffic signs separated from controlling vision in robots and self-driving motor vehicles.

Right now, manufacture a CNN containing four primary segments:

- Conv2D layer
- nonlinear activation function (elu)
- pooling layer
- dropout layer

The model was worked with a clump size of 32, which characterizes the quantity of tests engendered through the system per cluster. The model involves four Conv2D layers followed by three thick layers. The CNN additionally was actualized with a 3 × 3 convolutional channels. We utilize a 0.2 dropout layer and 2 × 2 max pool layers after each convolutional layer. All convolutional layers utilized the "same" cushioning strategy and an "elu" activation function.

Before preparing the model is valuable to characterize at least one call backs. Quite convenient one, are: Model Checkpoint and Early Stopping.

Model Checkpoint: when preparing requires a great deal of time to accomplish a decent outcome, regularly numerous emphases are required. Right now, is smarter to spare a duplicate of the best performing model just when an age that improves the measurements closes.

Early Stopping: once in a while, during preparing we can see that the speculation hole begins to increment, rather than diminishing.

This is a side effect of overfitting that can be illuminated from various perspectives (decreasing model limit, expanding preparing information, information enlargement, regularization, dropout, and so forth). Regularly, a viable and proficient arrangement is to quit preparing when the speculation hole is deteriorating.

Defining the model:

How about we proceed with characterizing the model. This can be condensed in the below 5 stages:

- I utilized two convolutional layers followed by a max pooling layer which thusly is trailed by another convolutional layer. I have utilized 20% dropout in the middle of to diminish overfitting.
- I rehashed the equivalent for four stacks for better speculation of results.
- Also, I have utilized global max pooling and clump standardization layers to standardize the loads incited from the past layers.
- The last layer is a dense layer with sigmoid as the initiation work.
- Finally, I have utilized Adam as the streamlining agent and twofold cross entropy is utilized as the misfortune work**.**

In this, we train the CNN model for 20 epochs with a batch size of 32 respectively.

D. Visualize the Result

Finally, we visualize the results as in the form of plots, which contains labels of accuracy and model loss with epochs respectively. The visualized results are describing the performance of the iceberg detection in satellite images, which are in the form of json format. The results are as shown in Results and Discussion Section.

II. RESULTS AND DISCSSION

In this section, the CNN structure is streamlined by tuning the hyperparameters to achieve ideal execution during model preparing. Various convolutional layer sizes were tried, and the model giving the most ideal train exactness was chosen. Different get back to capacities were applied to the model while preparing it on 20 epochs.

The CNN model was prepared and tried on an expanded set utilizing a stratified mix split to guarantee that the folds are made by safeguarding the level of tests for each class

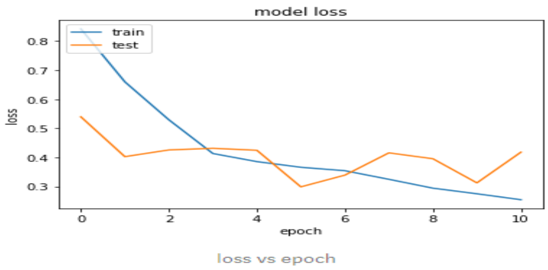

Fig 2. Analysis of CNN model loss vs epoch

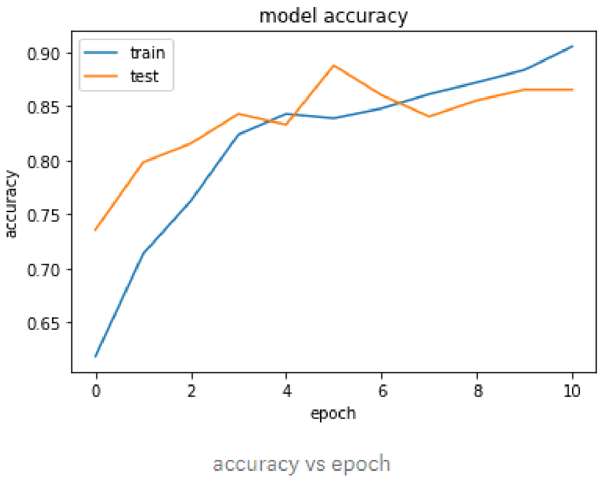

Fig 3. Analysis of CNN model accuracy

III. CONCLUSION

In this paper, we presents the utilization of CNNs for iceberg detection in high-goals satellite pictures. Our work can be additionally improved by investigating the pre-handling of our information. In our examination, we dismissed the rate point that may have tremendously impacted our outcome. We know that rate point can influence the power of the satellite decibel readings and we accept that the combination of this parameter is important to drive the characterization exactness further. Given the log-misfortune scoring strategy utilized right now, blunder can exponentially affect accommodation scores. At long last, we accomplish great precision from examination of chunk of ice discovery in satellite pictures utilizing profound learning procedures. Along these lines, in our future work, we would like to lessen our characterization mistake through different elective information pre-preparing strategies and the investigation of various CNN design and hyperparameters.

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10. The data set was available at https://www.kaggle.com/c/statoil-iceberg-classifier-challenge/data

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