Cloudscape Exploration: A Deep Dive into Satellite Imagery with DenseNet121

SUBMITTED BY:	HAMZA RAQEEB (ID) 21031287

INTRODUCTION

Climate change has long been a central topic of interest and a key focus of critical political deliberations and policy decisions. Among the various elements influencing Earth's climate, shallow or low-altitude clouds hold particular significance. However, effectively comprehending and incorporating them into climate models poses considerable challenges. Clouds have an essential role in the control of solar radiation balance and the subsequent emission of radiation into the atmosphere. The continued retention of energy inside the Earth's system directly correlates with the increase in air temperatures, consequently, this leads to a variety of events, including the melting of polar ice caps, which contributes to the phenomenon of global warming. On the other hand, a decrease in the amount of energy that is trapped leads to a decrease in temperatures, resulting in colder conditions. An in-depth comprehension of cloud structures offers valuable insights into the planet's weather patterns, making it of utmost significance to climatologists [1]. Surfaces with a white appearance reflect a substantial amount of energy, indicating a high albedo, whereas darker surfaces have a tendency to absorb more energy, signifying a lower albedo. The Earth's albedo is measured at 0.3, suggesting a factor that contributes to the warming of the climate [2]. The investigation of cloud forms provides significant insights regarding the Earth's climate and the accompanying risks. Satellite imagery of these cloud formations provides an overall perspective of the atmosphere, and the interpretation of such imagery yields vital insights into the present state of the planet's circumstances [3]. The prevailing assumption is that as the Earth's temperature continues to rise, there will be increased evaporation of water from the oceans, leading to the formation of a greater number of clouds with diverse structures and patterns [4]. The extent of climate change might hinge on the overall influence of cloud shapes and other characteristics, such as their abundance, thickness, and altitude positioning. A variety of cloud structures exist to illustrate this complexity further. Updrafts and downdrafts caused by clouds introduce sudden and unpredictable changes in the lift force experienced by aircraft wings, resulting in turbulence. This turbulent phenomenon can lead to the aircraft undergoing abrupt shifts and bouncing during flight, commonly known as turbulence. In experienced pilots may struggle to maintain control of the aircraft in such circumstances, posing potential issues [5]. In contrast, cargo ships heavily rely on sea conditions, which are frequently characterized by unpredictability and constant change. Cargo shipments typically adhere to strict schedules, and any delays can result in significant financial losses, with hundreds of thousands of dollars wasted on increased fuel consumption [6]. In addition, bad weather and storms may increase the occurrence of shipping delays, resulting in substantial financial damages approaching millions of dollars. The prompt and accurate forecasting of storms or changes in weather patterns is of utmost importance, as it serves to not only save human lives but also minimize significant financial damages. Remote sensing and satellite imaging are essential tools in a wide range of fields, such as environmental monitoring, disaster response, and law enforcement. This study presents a methodology that uses deep learning techniques to classify various items and facilities seen in satellite photos from the IARPA Functional Map of the World (fMoW) dataset. The proposed strategy successfully categorizes these objects into 63 distinct groups [7]. In my assignment, I utilized DenseNet-121 for image classification, leveraging its dense interconnections and Adam Optimizer to achieve efficient feature reuse, quick model convergence, and positive trends in reducing loss and improving evaluation metrics. However, I noted potential overfitting issues, suggesting further investigation into fluctuations and adjustments in regularization or data augmentation for optimization.

DATASET

The objective of this task is to do an analysis of imagery from satellites in order to differentiate between various kinds of cloud formations and label them "Fish," "Flower," "Gravel," or "Sugar." Fig.1 Show the value of each class. Images collected from NASA Worldview will be used as part of the competition. The images will cover three distinct locations, each of which will have dimensions of 21 degrees in longitude and 14 degrees in latitude. The images in their natural coloration were taken by the TERRA and AQUA satellites as they flew over their respective study areas once every 24 hours [8]. images are sometimes created by combining the collected data from two different satellite orbits. In these cases, the areas of the earth that are not captured by the combined images are displayed in black.

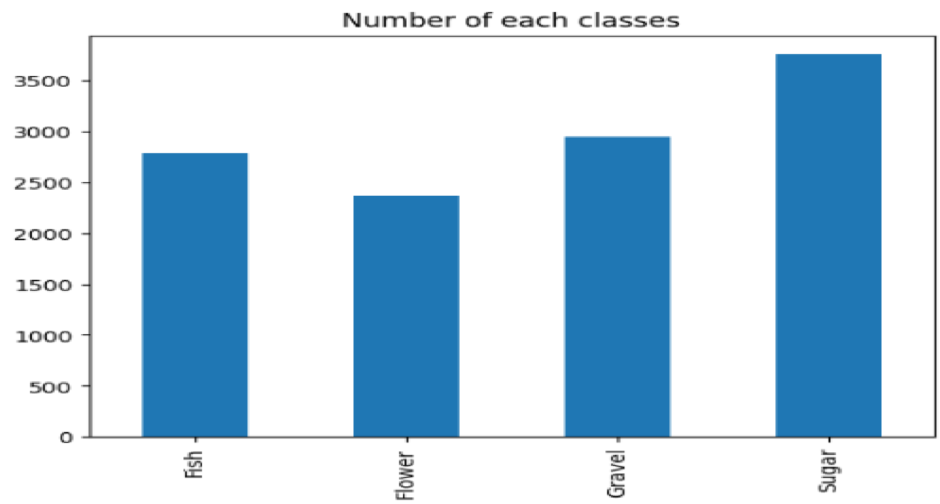


Fig.1 Shows the Number of Values in class in the dataset

EXPLORATORY ANALYSIS OF DATASET

I thoroughly examined the dataset Understanding Clouds from Satellite Images for my dissertation's exploratory study, of the dataset. I conducted a detailed review, counting samples and variables and addressing missing values. I also analyzed data distribution for outliers or skewed trends. Using visualizations like graphs and scatter plots Fig .2 Shows the encoded pixels of labels. Explored variables related to cloud types, image attributes, and metadata, revealing insights into their interrelationships. The provided Google Colab link offers a more comprehensive exploration of the dataset if you see further analysis of the dataset.

	Image_Label	EncodedPixels	Label
0	0011165.jpg_Fish	264918 937 266318 937 267718 937 269118 937 27...	Fish
1	0011165.jpg_Flower	1355565 1002 1356965 1002 1358365 1002 1359765...	Flower
2	0011165.jpg_Gravel	-1	Gravel
3	0011165.jpg_Sugar	-1	Sugar
4	002be4f.jpg_Fish	233813 878 235213 878 236613 878 238010 881 23...	Fish

Fig.2 Image label and their encoded pixels

PARTITIONING REGIONS IN IMAGES.

The process of dividing an image or information into distinct and relevant sections based on specific features such as color, texture, or shape can be described as segmenting regions. This method involves categorizing pixels or data points into groups based on their shared properties. Region segmentation allows you to focus on particular portions of an image or dataset, allowing tasks like object identification, image segmentation, and pattern learning. Figure 3 shows images demonstrating sample segmentation of parts from various images.

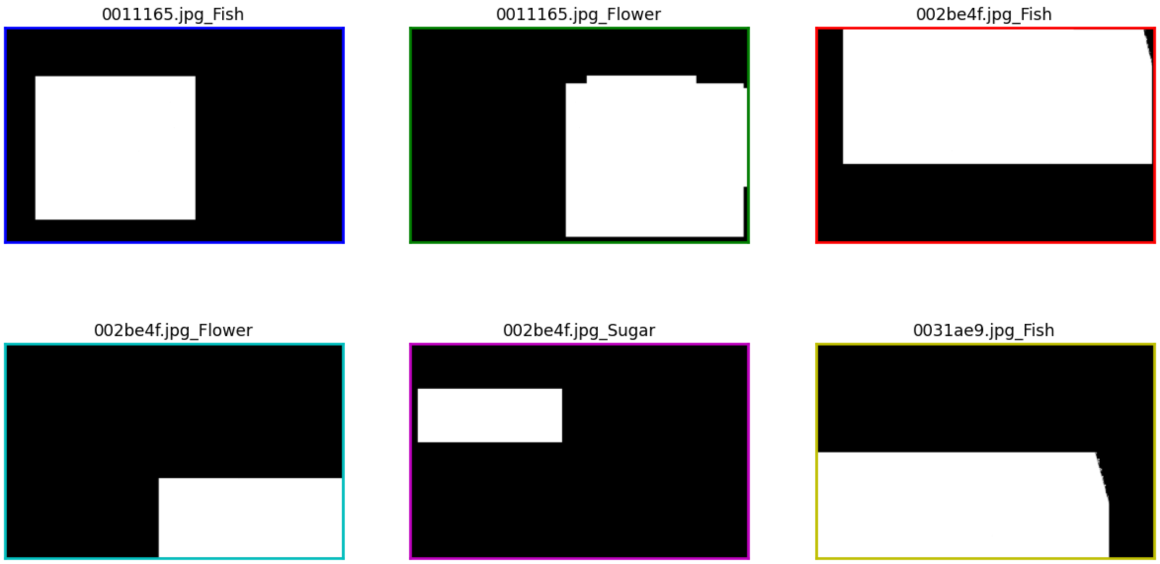


Fig.3 Shows Images Segmenting Regions.

An image showcasing superimposed masks

Sample images are provided alongside associated masks that identify labeled regions of interest, such as distinct cloud types. As depicted in Figure 4, these masks are superimposed onto the original images. This overlay serves the purpose of visually emphasizing and distinguishing the regions of interest, facilitating their analysis for classification.

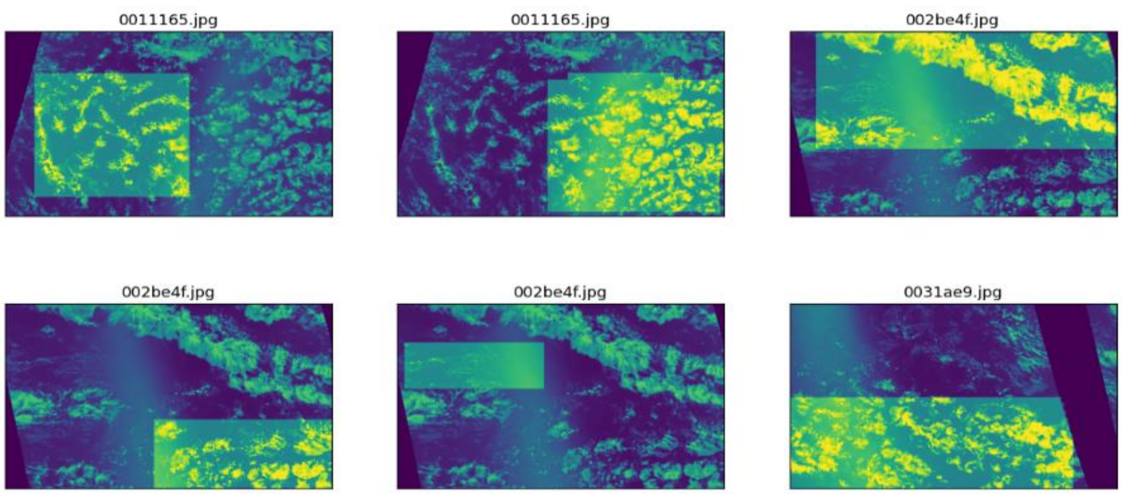


Fig.4 Shows a Sample image with masks overlayed

Densenet-121 Model

This assignment, utilized the DenseNet-121 model, a powerful convolutional neural network architecture, particularly well-suited for image classification tasks due to its dense interconnections between layers, which enhance feature reuse and training efficiency. It overcomes the vanishing gradient problem and achieves state-of-the-art performance with fewer parameters compared to other architectures like VGG or ResNet. Also apply the Adam Optimizer, a widely adopted optimization algorithm that adjusts learning rates efficiently, facilitating quicker model convergence during training. Fig. 5 Show line graph of the results. Additionally, consider using the sigmoid activation function, which effectively maps input values to a 0-1 range, making it valuable for binary classification tasks aiming to predict between two classes in machine learning or deep learning projects.

Table. 1 Shown Training Accuracy and Loss of Five Epoch

Epochs	LOSS	IOU_SCORE	F1-SCORE	VAL_LOSS	VAL_IOU_SCORE	VAL_F1 SCORE	LR
1	0.9064	0.3604	0.5144	1.5938	0.1341	0.2144	20
2	0.8341	0.4008	0.5575	0.9424	0.3650	0.5096	20
3	0.8053	0.4188	0.5757	0.9430	0.3473	0.4863	20
4	0.7833	0.4332	0.5902	0.9510	0.3343	0.4673	20
5	0.7651	0.4455	0.6021	0.8943	0.3571	0.4914	20

Table 2. Shows Model Accuracy

Loss	0.8996315598487854
IoU	0.3540029227733612
F1:	0.4881959557533264

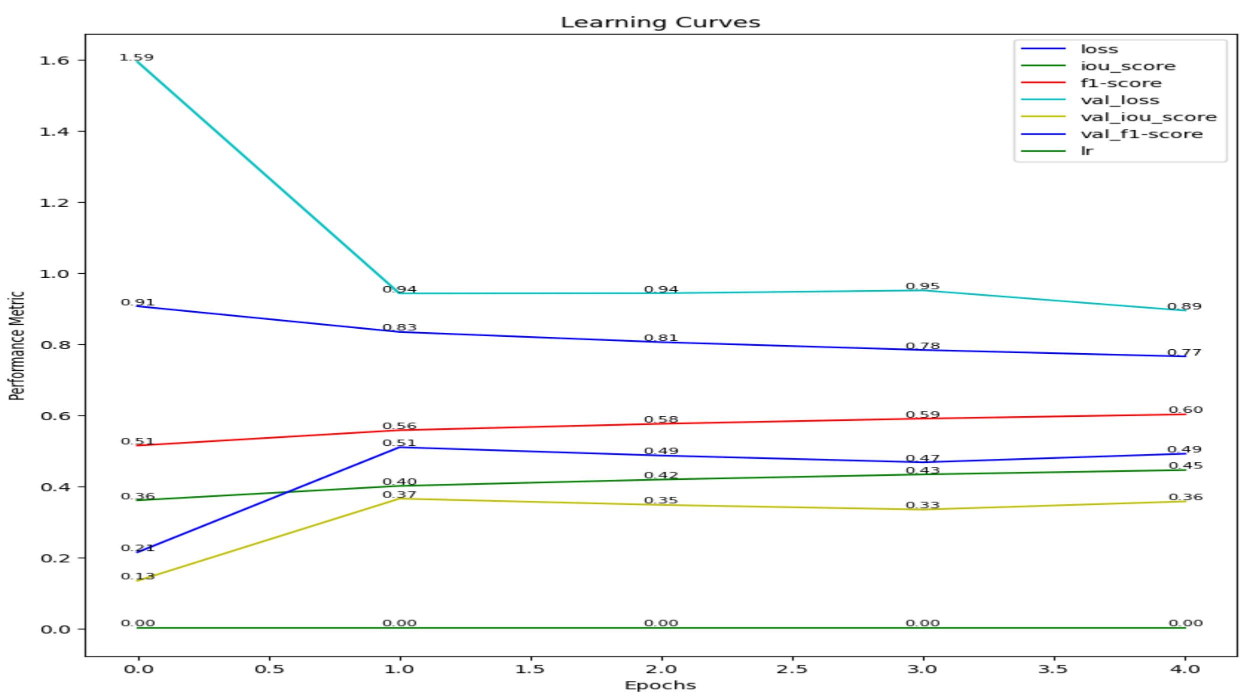


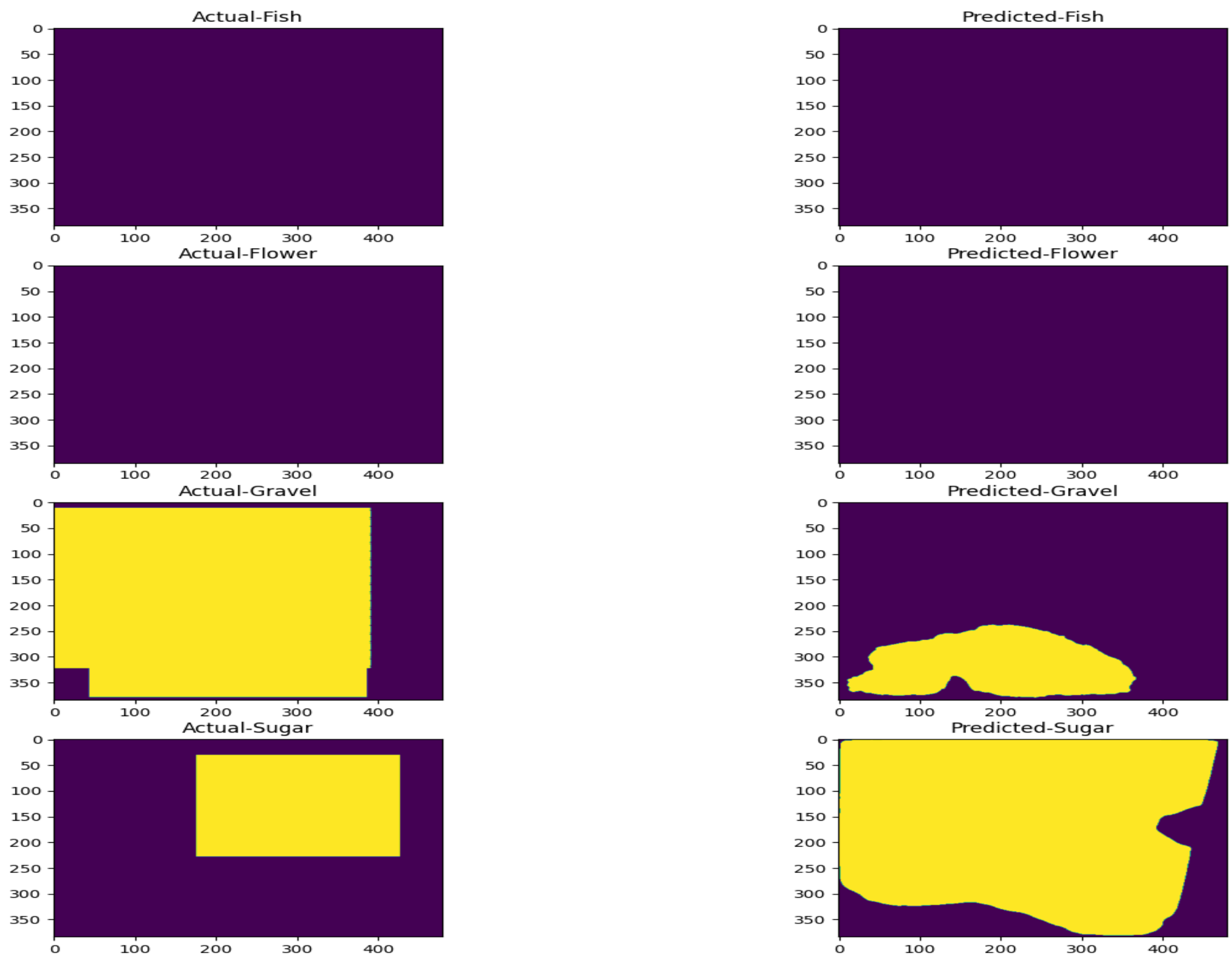
Fig.5 Show Line Graph of the Results

Critical Analysis of the Results

DenseNet-121 Model for image classification is used in my assignment, leveraging its dense interconnections for efficient feature reuse. The model effectively addresses challenges like the vanishing gradient problem, showcasing state-of-the-art performance with fewer parameters compared to other architectures. The use of the Adam Optimizer is fitting, promoting quicker model convergence through adaptive learning rates. In my assignment the analysis of training results reveals positive trends in reducing loss, improving IoU and F1 scores, and indicating effective learning. However, attention should be given to potential overfitting, especially with a slight decrease in validation IoU and F1 scores in later epochs. Exploring the reasons behind these fluctuations, considering challenges in generalization, and potential adjustments in regularization or data augmentation strategies is crucial. Additionally, a careful examination of learning rate dynamics is advised to ensure optimal training performance. My assignment demonstrates a well-considered model architecture and training strategy, with room for further optimization and exploration of potential overfitting.

Images and Their Corresponding Predictions

In the 'Understanding Clouds from Satellite Images' dataset, images are consistently accompanied by predictions derived from machine learning models utilizing the DenseNet121 architecture. Regrettably, due to limitations in this report's space, presenting the complete set of DenseNet121 predictions is impractical. For a thorough examination of the predictions, please refer to the attached Google Colab link.



Google Colab Link:

https://colab.research.google.com/drive/1O91C4C7FsVxS4fIfqBS9rZI5MJqOSaxU?usp=sharing

GitHub Link: https://github.com/HHamaz123/My-New-Assignment-

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