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Automatic Identification of Hurricane Damage Using a Transfer Learning Approach with Satellite Images

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Abstract: Satellite imagery may be pre-processed and processed to extract color, texture, and form capabilities, which may then be fed into a CNN version. In education, the CNN version, styles and features that correspond to regions impacted by hurricanes may be discovered, as well as styles and features that correspond to areas no longer impacted. A CNN model also can be constructed using other statistics sorts, such as geographic and meteorological statistics. By combining distinct varieties of records, it's miles possible to enhance the version's accuracy and robustness, as well as offer complete know-how of storm impacts. CNNs can provide treasured insights into the storm harm category in emergency reaction efforts and resource corporations the usage of satellite TV for pc imagery.

Keywords: *CNN - Convolution Neural Network, Satellite imagery, Tensor Flow*

1. Introduction

Assessing as well as other reusing analog digital signals is the subject of signal analysis, a branch of electrical engineering mathematics that interacts with storing, filtering, and operational processes on signals. These signals include, among others, voice, sound, & image signals as well as transmission signals. Image processing, out of all of these signals, an image is created suitable to in which the category of signals and includes an image. As the name suggests, it is about image processing. The other two areas are analog processing of images and processing of digital images.

a) **Analog Image Processing**

Analogue signals are used for analog image processing. In this kind of processing, the electrical signal is changed while the images are being altered. The image on television serves as a frequent illustration.

The processing of digital images has progressively eclipsed analog image processing due to a broader range of applications.

b) **Digital Image Processing**

The focus of processing digital images is the creation of digital systems that regulates a digital picture.

I. Concept for Image Restoration

In unpredictable climates such as gloom, dirt, and haze the visibility of the captured images will be reduced. This is because certain light spectrums transmitted between tracked objects and the camera are taken in and scattered by the suspended particles. As an outcome of these degraded pictures, systems such as object identification systems, hazard detection equipment, monitoring systems as a whole intelligent mode of transportation, and others may work less successfully. A multitude of visibility restoration strategies has been proposed for restoring the visibility of damaged pictures in order to improve system performance during poor weather. To restore visibility, additional information techniques, multiple-image methods, along with single-image techniques can all be employed.

Additional information techniques restore foggy pictures by using the offered scene depth information either by an additional procedure or interaction among users, such as the user-friendly ability to adjust the location among the cameras and through a provided approximate 3-D geometrical model. These algorithms are not well-suited for usage in the actual world because of limitations on the gathering of scene-depth detail data imposed by unknown geography information and extra user action.

A multitude of image techniques utilize numerous photos of the same scene captured using specialized hardware, including a rotating polarizing filtering process, to precisely construct a scene's subsurface data and further perform access restoration of upcoming hazy images. Tan's approach restores picture visibility by maximizing local contrast by utilizing conclusions of scene contrast

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variations. Another approach put forth by Fattal increases the visibility of hazy pictures by estimating the albedo of a scene and identifying the transmission medium. As a result of this discovery, they propose the dark channel prior approach for precisely assessing the amount of the haze data as well as further restoring scene radiance.

Motivated by the described approach, improved techniques founded on this DCP have been developed to recover clarity in damaged photos captured in inclement weather. The method explores the characteristics of the two distinct DCPs together with the multi-scale Retinex methods in order to restore vision in hazy photos. The quantity of the irradiance scattering and even haze relies on an unidentified scene depth, making haze reduction difficult. The haze-free image was created by combining many photographs obtained under varied weather conditions. The darker channel's prior approach is the most advanced way for reducing haze off a single picture. Matlin and Milanfar have suggested removing haze and noise in a single image by employing the BM3D demystifying method and an iterative regression analysis technique.

II. Digital Image Processing

An image has to first be reduced to a collection of computer-process able numbers in order to be digitally processed. For a point operation, the value of a pixel in the output picture is determined by one of the pixels in the input image.

Each input image pixel contributes to the output image pixel value in a global operation. This indicates that each pixel's value as well as the values of its eight closest neighborsare recorded for the noisy image. After these nine values are organized in order of size, the median is picked as the threshold for each pixel of the new picture.

Another type of improvement is contrasting and manipulating others, a specific procedure where the significance of every pixel in the resultant picture is determined only by the value of that pixel of the old image. Another point operation is to assign arbitrary colors to the grey levels of a black-and-white image in order to create the appearance of a color. While object detection finds every instance of a class in an image, for instance, image classification just identifies when a particular group of objects is present.

The methodology used is distinct in that it describes contours with extremely simple, generic segmented lines and ellipse shape primitives, as well as a flexible mechanism for learning discriminative primitive combinations. The line segment represents a straight shape, whereas the elliptical represents a curved contour, hence these primitives are complimentary in nature. They picked an ellipse since it's considered among the simpler circle forms with enough flexibility to depict curved objects [1]. These basic shapes offer an abundance of intriguing characteristics. In contrast with edge-based descriptors, they permit conceptual or visually significant argumentation, which includes parallelism and adjacency [2], [3]. Adjacency and parallelism, for example, enable perceptually meaningful reasoning.

Recently published studies [1, 7, 8] show that the general character of segments of lines and ellipses provides them a natural capacity to describe complicated forms and systems. Though any one of these primitives can be less distinct on its own, combining many of them allows for a combination that is adequately discriminative. Every one of these pairings is a two-layer primitive abstraction, with learned numbers of form tokens at the following layer with pairs of primitives (known as shape tokens) on the first. It makes it possible for a combination to automatically and flexibly adapt to an object class rather than forcing it to have a predetermined number of shape-tokens. A combination's ability to express a form is influenced by this number, with simple forms requiring fewer shape-tokens than complex ones.

As it turns out, an object class may be described by discriminative combinations of different complexity levels. Exploring the particular form and geometry of an object class, through this combination, and structural limitations.form constraints describe the look of form tokens, whereas geometric constraints specify their organization by space (configurations). Structural restrictions enforce the positions and structures that an object can adopt via relationships (such as an XOR relationship) between shape-tokens.

As a result, these combinations seek to strike a beneficial balance between flexibility, which encourages tolerance for intraclass variance, and prejudice, which makes them resistant to noise in the background and interclass similarity. The capacity of our contour-based recognition approach to provide us with a great degree of flexibility when adding extra picture data is a critical component. It explicitly presents an innovative hybrid recognition approach that extends the contour-based identification method by using form tokens with SIFT characteristics as recognition cues. Shape-tokens and SIFT features tend to be orthogonal, corresponding to sparse salient picture patches and shape boundaries, respectively.

In this circumstance, every learned combination might comprise characteristics that are either 1) complete shape-tokens, 2) total SIFT characteristics, as well as 3) a mix between shape-tokens and SIFT characteristics. automatic operation learning from training pictures teaches the amount and kinds of characteristics to combine, with the most discriminative ones being represented by the training set. As a consequence, discriminative combinations of varied complexity can be used to represent an object class.

Consequently, by incorporating these two levels of variation (in both the number and different kinds of features), give each of them a greater ability to adapt and discriminative potential. Additionally, there was a shortened edition of this paper in [9].

Classification of images:

During the digital processing of images, one of three picture types is employed.

They undertake,

I. Binary format Picture

II. Grayscale Photograph

III. Multicolor Picture

I. Binary format picture

A binary digital photo can only contain a single of pair possible outcomes for each pixel. Binary pictures are normally two colors: black and white, however, any two colors can be used. The colors utilized in the image's foreground and background is unique from one another.

Binary pictures are sometimes known as either bi-level images or two-level images. This implies that each pixel has just one bit (0 or 1).

Algorithm for converting RGB to Binary format

```
# Importingopencv
import cv2
# Importingmatplotlib.pyplot
importmatplotlib.pyplot as plt
# Reading the image
image = cv2.imread(r'C:\Users\tushi\Downloads\PythonGeeks\flower.jpg')
image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
# Displaying the original image
plt.imshow(image)
```

Binary images are highly useful in image processing, as they enable easy separation of an object from the background. Segmentation is the process of labeling each pixel as either a background or object pixel and assigning corresponding intensity values. Binary images are frequently used because they are the simplest images to process, although they offer a limited representation of the image information. They are best utilized when the necessary information can be obtained solely from the silhouette of the object, which can be easily extracted. In digital image processing, binary images are employed as masks or for thresholding purposes.

II. Gray scale photograph

Because the value of every pixel is just one sample in a grayscale picture, all of the information corresponds to intensity. Each of the different shades of grey (from 0 to 255) that are utilized to generate these pictures, commonly known as black-and-white images, are made up of black(0) at the lowest level of brightness and white(255) at the highest.

In contrast with one-bit black-and-white pictures, which are also known as bi-level or binary pictures in the context of technological imaging, grayscale images feature more than two colors. There are many various shades of grey in grayscale photographs. When there isn't any chromatic variation in an image, it is referred to be monochromatic or grayscale.

```
# Importing OpenCV
import cv2
# Reading the image in grayscale mode by setting the flag as 0
img = cv2.imread(r'C:\Users\tushi\Downloads\PythonGeeks\flower.jpg', 0)
(thresh, binary_image) = cv2.threshold(img, 175, 255, cv2.THRESH_BINARY)
# Displaying original grayscale image and binary image
cv2.imshow('Original Image', img)
cv2.imshow('Binary Image', binary_image)
cv2.waitKey(0)
cv2.destroyAllWindows()
```

III. Multicolor picture

An image in digital form that has color data within each pixel is referred to as a (digital) color image. The color that will be displayed at each pixel is determined by its value specifically. The value given is delimited by three different values that indicate the color's breakdown into its three basic elements, Red, Green, and the color blue. This method may be used to depict any hue that the naked eye can perceive. To measure the breakdown of color in all three primary hues, a value around 255 and 0 is utilized.

IV. TensorFlow

The Google TensorFlow deep learning library is the most well-known in the world. Each and every Google product uses machine learning to enhance search engine functionality, picture transcription, or alternatives.

Three elements comprise the tensor flow architecture:

- The data preparation
- Establishing the model
- Training and modeling estimation

2. Related Works

The most significant phase of the software development process is a literature review. Determine the time factor, economy, and company strength prior to developing the tool. The next step is to choose the operating system and language that can be used to develop the tool after these requirements have been met. Once they begin creating the tool, the programmers require a lot of outside assistance. The aforementioned factors are taken into account when creating the proposed system before it is built. A literature review is a body of writing that aims to examine the key elements of current knowledge, including significant discoveries as well as theoretical and methodological contributions to a particular subject. Since they are secondary sources, literature reviews do not just represent any novel or unique experimental work.

Deep learning is being intensively explored for its application in predicting meteorological conditions like rainfall as well as catastrophic events such as earthquakes and typhoons. However, receiving a crisis signal is critical in order to accelerate the first response utilizing deep learning technologies.As a consequence, the suggested deep learning-based method's performance is assessed in this study after it has been applied to a genuine ATSC 3.0 RF signal through a Software Defined Radio (SDR) platform.

The Active Learning is a different approach that allows an ML (Machine Learning) model to pick and identify the information set it needs as it develops without having to manually evaluate each training sample. We investigate whether FL may benefit from the unlabeled data every participant client has been given via AL in this research. In order to achieve this, they employ and assess various AL methods across two distinct application domains in order to put forward an AL-based FL framework.

Effective disaster relief projects rely on precise projections of relief demand, which is challenging owing to reasons such as inadequate instruction samples, incomplete and ambiguous inputs, and incomplete needs. This work describes a co-evolutionary fuzzy transfer learning (CoFDTL) approach for anticipating demand for disaster aid that takes into consideration many objectives (such as predicting typhoons, quakes, and floods). The CoFDTL process is broken into three stages. To begin, a deep fuzzy model of learning is used to learn the unconscious form of the common inputs for all tasks. Second, a co-evolutionary method is used to simultaneously learn the common regressor and task-specific characteristics. In the second stage, the supplied regressor undergoes retraining according to the top outcomes from each job.

Experiments reveal that in terms of performance, CoFDTL exceeds the chosen mainstream fuzzy acquiring knowledge, neural networks, and transfer learning models. This study also discusses the usage of CoFDTL in two actual catastrophes that happened in China in 2018. There are various other challenging multi-task transfer learning situations that may be handled using the suggested CoFDTL, which integrates fuzzy deep learning and multi-task transfer learning, with co-evolutionary development.

Natural catastrophes have hurt millions of individuals and cost society more than three trillion dollars since 1980. Following a natural catastrophe, it is critical to create maps that indicate the harm done to buildings and infrastructure. Many organizations now conduct this activity manually, inferring the degree and amount of damage from pre- and post-disaster photos and well-trained personnel. This difficult task might take many days to accomplish. Suggesting automating this job with post-disaster satellite images.

They employ SegNet, a trained neural network, and substitute its final layer utilising our own damage categorization technique. The network's last layer is retrained using clipped fragments of the disaster's satellite picture.

3. Existing System

Greater amounts of time and effort must be invested in creating and maintaining road networks. Automatic highway extraction is now achievable because too deep learning technology and high-resolution remote sensing imagery.

Road tracking applications with single beginning points frequently leave certain parts inaccessible while doing well in connection, in contrast to segmentation approaches that utilize convolutional neural networks (CNN), which have lately revealed significant transmission concerns. They suggested a tracer that has different starting points and uses either segmentation or tracing techniques.

On satellite images of key cities throughout the world, they compare their method to the most recent tracing techniques and find that it provides an IoU gain of 8%.

4. Proposed System

A two-phase network for disaster classification and identification is proposed in this system. The first network analyses bi-temporal satellite images of urban areas that primarily contain buildings as the topographical features to produce a change map. This framework is based on deep learning in figure1.

The generated change map is further examined to determine the percentage likelihood that a disaster will occur. The additional network then attempts to distinguish the type of disaster between hurricane damage and not if the first network correctly predicted the occurrence of a disaster in figure2.

5. System Architecture

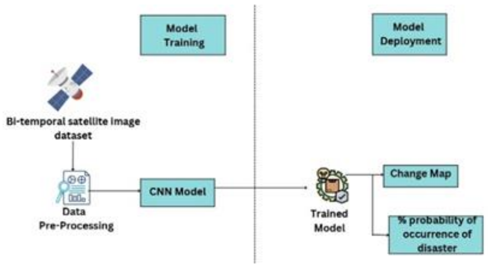

Fig 1: To Predict the Figure 1Probability of Disaster

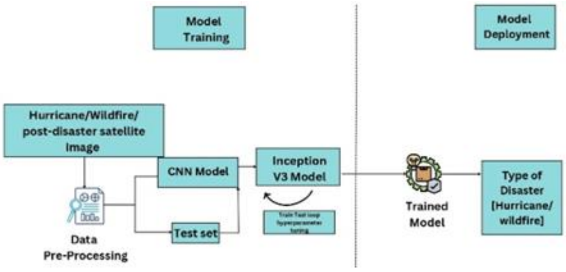

Fig 2: To Predict the Type of Disaster

6. Modules

The dataset is a collection of pre- and post-natural disaster bi-temporal satellite images. Buildings that have been identified as being pre and post disaster images of the same building, with nearly identical resolution and framed in a similar area of the image, are present in almost all images. Before being used to train the CNN model to differentiate between hurricanes and earthquakes, these images are pre-processed. Post-disaster images are produced using pre- and post-disaster bitemporal satellite images of earthquake- and hurricane-affected regions. The classification labels for the pictures are "Hurricane damaged or not damaged." The VGG-19 model, which is based on transfer learning, is used for feature extraction. Two bi-temporal satellite images are used in the model to extract features. The proportion of white pixels in the change map is used to calculate a disaster's probability of occurrence. Using satellite images of the affected areas, the transfer learning-based Inception V3 model is trained to distinguish between hurricane and earthquake disasters. The trained Inception V3 model and an AI change detection model based on the VGG-19 are used to identify disasters that occur between hurricanes and earthquakes. After uploading bi-temporal satellite images, the user is given a change map, a prediction of the likelihood that a disaster will occur, and, if one does, a prediction of the type of disaster, such as hurricane damage or not.

7. Software Requirement

Python

Scripting in Python is largely productive, robust, object-acquainted, and simplified. Python existed aimed to be extremely readable. It employs English terms more frequently than punctuation and has slightest syntactic fabrics than diverse languages.

OpenCV

OpenCV is extensible with a broad number of computer languages and operating platforms, including Linux, OS X, Windows, Android, and iOS. These include C++, Python, Java, and many more. For GPU operations requiring quick communication, user interfaces that utilize CUDA or OpenCL have been actively developed. The best tool for quickly prototyping computer vision issues is OpenCV-Python.

8. CNN Algorithm

The Convolutional Neural Network (CNN) typically comprises three main layers: a convolutional layer, a pooling layer, and a fully connected layer. Figure 3 depicts the overall structure of a deep neural network that includes two convolutional layers (Conv1, Conv2), two pooling layers (Pool1, Pool2), and a Fully Connected Layer (FCL).

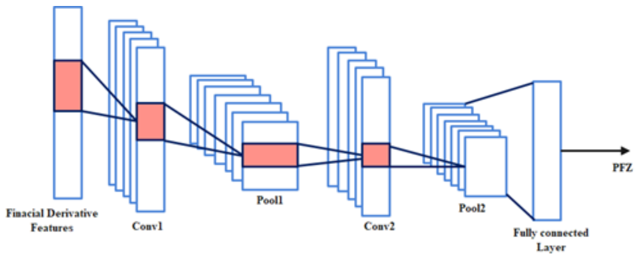

Fig 3: A common architecture of one-dimensional CNN

The convolutional layer is a vital element of a neural network. While in traditional network layers, all neurons of the previous layer are fully connected to the neurons in the next layer, the convolutional layer connects neurons to the local regions of the previous layer. This connection type can be leveraged to determine effective predictors of Hurricane Damage (whatever that refers to). The convolutional layer's structure is influenced by various parameters, such as filter size, filter number, stride, and padding. The filter dimension is the local field of reception, which is an area over the vector[10]. As depicted in Figure 3, the convolutional layer is viewed as a layer stack, and the number of layers depends on the sum of filters chosen. Stride determines how the filter moves via input (local receptive field), while padding is a technique used to add or remove values to the input dimension, allowing the filter to pass over the entire dimension.

The convolutional neural network is structured[11] in a hierarchical layer format. By increasing the number of layers, the network can learn complex input relationships more effectively. The prediction accuracy of the Hurricane Damagemodel is dependent on the input characteristics.Input features $= \delta^1, \delta^2, \dots, \delta^n$, $1 \leq i \leq n, n$ are the input features that can lead to greater performance when the input is sub-set $\beta(\beta \subset \delta)$than the input feature is used. Certain input features may lead to better performance when a subset of input features is used. However, removing some input features from the dataset can result in the loss of important information required for model training. Furthermore, the removal of certain features can significantly affect the forecast accuracy of the model in specific instances and may not be useful in other applications[12].

To improve climate pattern representation, we suggest integrating multiple features with mathematical representations. The use of convolutional networks is recommended as it allows for directed input influences to specific locations. This approach can enable deeper network function maps to learn the relationship between input features and Hurricane Damageaccurately without considering all the features of efficiency in Hurricane Damagevariability[13].

A layer of pooling is added to reduce the size of the displayed data. For each specified field, the supreme pooling layer chooses the highest value, while the average pooling layer chooses the average value. When building the network model, each convolutional layer is followed by a pooling layer[14].

CNNs have been commonly used in classification applications. Therefore, several activation functions were used to map the input functions to a number of categories. In this investigation, the output was measured as Hurricane Damage. Sigmoid and hyperbolic tangent were studied in the final layer as they are nonlinear activation functions[15].

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

$$\sigma(\mathrm{z}) = \frac{1}{1 + \mathrm{e}^{-\mathrm{z}}}$$

If z is the result of biased weights and inputs of a connected layer, where the weight of the connected layer, xk is is the input of the complete layer, and b is the bias, then c represents the weights and inputs of the fully connected layer. In this case, z acts as an input of the complete layer connector. Additional layers are often used as flattening layers to convert the input into one dimension with varying sizes. To prevent over fitting, drop-out is usually employed. The dataset is typically divided into training, validation, and testing sets. The CNN[15] training process is illustrated in algorithm 1, where a number of functions may be used during the training phase. As shown in algorithm 1, a test point is used to improve performance on the validation dataset in order to maintain network weights in algorithm1.

Algorithm 1: CNN Training Process

Input: Training and Validation dataset

Output: Trained CNN

1: Prepare the network weights and bias

2: For each epoch:

3: Process the records of the training data cases

4: Equate the actual values to predicted values

5: Compute the loss function

6: Back propagate the error through the layers and adjust the network weights

7: Check the validation dataset

8: If better loss value obtained

9: Save the network weights

10: End

11: End

12: Return the trained CNN

9. Convolution

1. An RGB picture, also known as an "input image,"As opposed to neural networks, which require a vector as input, multi-channeled images (in this case, three channels) do not in figure4.

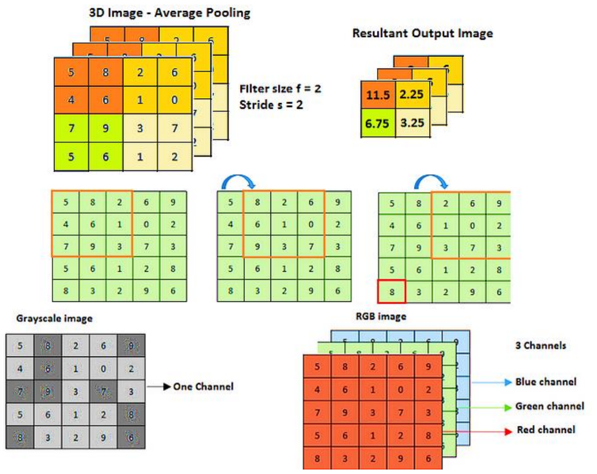

Fig 4: Convolution process

The Convolution Layer:

- Accepts a volume of size $W_1 x H_1 x D_1$
- Requires four hyperparameters:

- Number of filters K,
- their spatial extent F,
- the stride S,
- the amount of zero padding P.
- Produces a volume of size $W_2 x H_2 x D_2$ where:
- $W_2 = (W_1 - F \quad + 2P)/S + 1$
- $H_2 = (H_1 - F \quad + 2P)/S + 1$ (i.e. width and height are computed equally by symmetry)
- $D_Z = K$
- With parameter sharing, it introduces F·F·D1weights per filter, for a total of $(F - F - D_1) - K$weights and K biases.
- In the output volume, the $d - th$ depth slice (of size $W_2 x H_2$ is the result of performing a valid convolution of the $d - th$ filter over the input volume with a stride of S, and then offset by $d - th$ bias.

A common setting of the hyperparametersis $F = 3, S = 1, P = 1$. However, there are common conventions and rules of thumb that motivate these hyperparameters[16].

2. Integrating a filter to distort a picture

Applying the 5*5*3 filters to the full picture, we take the dots that are produced when we go through the filter area and various input image regions in figure5.

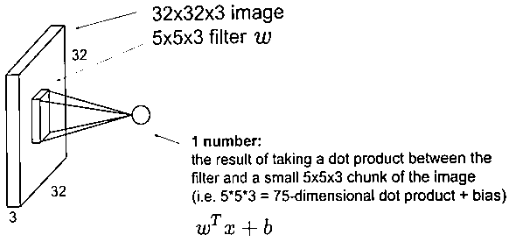

Fig 5: Integrating a filter to distort a picture

3. There is a scalar output for each dot product that is taken in figure6.

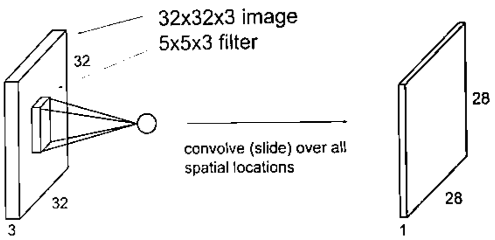

Fig 6: Layer visualization in Convolution Layer

4.The basic component of the convolution neural network is the convolution layer in figure7.

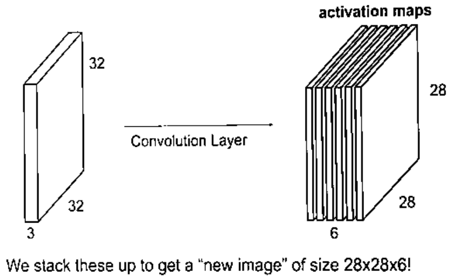

Fig 7: component of the convolution neural network

10. Convolution Layer

A collection of independent filters—six in the example shown—make up the convolution layer. Six feature maps with the dimensions 28*28*1 result from the independent convolution of each filter with the image in figure8.

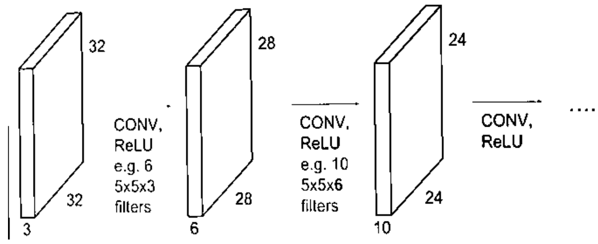

Fig 8: Collection of independent filters

11. Convolution Layers in Order

Each of these filters is set up at random and acts as the network's initial learning parameters in figure9.

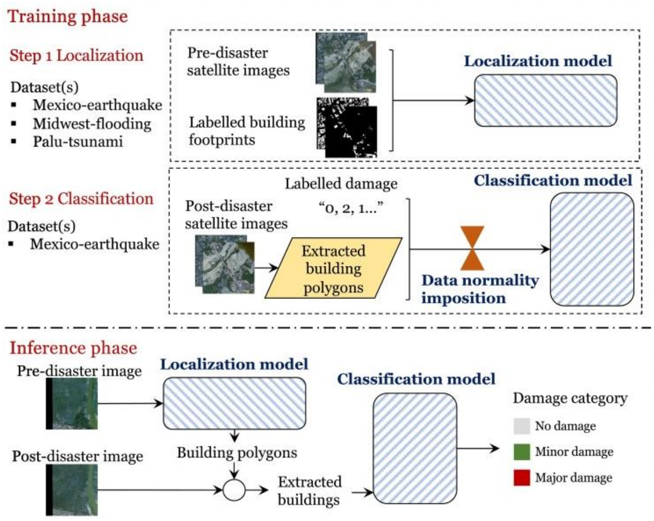

Fig 9: A trained network scenario

12. Filters on a Trained Network

Take a glance through the 5*5*3 filters in the uppermost layer. Through back propagation, they have tailored themselves to form blobs of colored edges and fragments. As we go further into additional convolution layers, the filters are doing dots based on the input data of the prior convolution layers. They employ tiny colored bits or edges to combine into bigger one[17]s.

Considering the 28*28*1 field to represent a pattern of 28*28 neurons and look for picture 4. Each neuron has the same weight for connections and is attached to a tiny fraction of the input picture for a specific attribute map, which can be the result of convolving the picture with a certain filter. Now let's discuss how a CNN and neural networks in general differ from one another in figure10.

The phrases "local connectivity" and "parameter sharing" are frequently employed by CNNs.All of the neurons in a specific feature map share weights through parameter sharing[18].

Local connection describes the concept that each neuron is only linked to a subset of the input picture, in contrast to neural networks wherein each of its neurons is totally coupled. Reducing the total number of parameters in the system, this improves the computations.

13. Pooling Layers

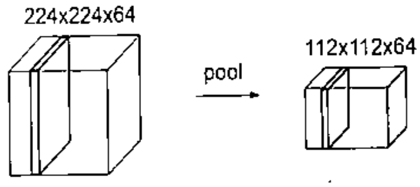

Fig 10: Pooling layer function

Pooling

The ultimate objective is to gradually reduce back the network's calculations and parameters by reducing the spatial size of the representation. The pooling layer handles every feature map separately.The pooling technique that is most often employed is max pooling[19].

Steps for convolution

```
train_datagen = ImageDataGenerator(rescale
        = 1/255)

train_generator
= train_datagen.flow_from_directory('dataset',

# This is the source directory for training images target_size
= (128,128),

# All images will be resized to 200 x 200 batch_size
        = batch_size,

classes = ['affected','not_affected'], class_mode
        = 'categorical')

import tensorflow as tf

model
= tf.keras.models.Sequential([tf.keras.layers.

Conv2D(16, (3,3), activation = 'relu', input_shape
        = (128,128, 3))

tf.keras.layers.MaxPooling2D(2, 2),

tf.keras.layers.Conv2D(32, (3,3), activation
= 'relu'), tf.keras.layers.MaxPooling2D(2,2),

tf.keras.layers.Conv2D(64, (3,3), activation
= 'relu'), tf.keras.layers.MaxPooling2D(2,2),

tf.keras.layers.Conv2D(64, (3,3), activation
        = 'relu'),
        tf.keras.layers.MaxPooling2D(2,2),

tf.keras.layers.Conv2D(64, (3,3), activation
= 'relu'), tf.keras.layers.MaxPooling2D(2,2),

tf.keras.layers.Flatten(),

tf.keras.layers.Dense(128, activation
= 'relu'), tf.keras.layers.Dense(2, activation
= 'softmax') ])

model.summary()

from tensorflow.keras.optimizers import RMSprop

model.compile(loss
= 'categorical_crossentropy', optimizer
= RMSprop(lr = 0.001),

metrics = ['acc']) total_sample = train_generate

n_epochs = 30

hist = model.fit_generator(

train_generator,

steps_per_epoch = int(total_sample/batch_size),

epochs = n_epochs,

 verbose = 1)

model.save('model.h5')

history_dict = hist.history

print(history_dict.keys())

plt.figure()

plt.title("Accuracy") plt.plot(hist.history['acc'], 'r', label
= 'Training') plt.legend()

plt.show()

plt.figure()

plt.title("Loss")

plt.plot(hist.history['loss'], 'r', label
        = 'Training') plt.legend()

plt.show()
```

$$Output\ hgt = (Input\ hgt + padding\ hgtt\ top + padding\ hgt\ bottom - kernel\ hgt) / (stride\ hgt) + 1.$$

14. Sample Dataset

You can see the satellite images collected before and after the disaster, along with the corresponding ground truth mask, displayed in the figure below, from left to right. The color of the buildings in the images shows the level of destruction they have suffered, where blue indicates "no damage" and red indicates "totally destroyed" figure11.

Fig 11: Example of xView Dataset

After thoroughly inspecting the original dataset, we noticed that it can be difficult to distinguish between certain categories such as “no damage”-“minor damage” and “major damage”-“destroyed”. Additionally, some damages[20] to structures may not be visible from a satellite top view. Therefore, we decided to simplify the approach to war damages in Hurricane Damage by combining those classes into two categories: “no-damage” and “damaged” in figure 12.

Fig 12: Example of xView Dataset

To enhance the accuracy of the developed solution and apply it in practical situations, we require a more generalized dataset. During our work, we utilized as many data sources as possible, with the main purpose of using the transfer-learning approach. For training, we used available open-source data, and for testing and validation, we created a custom dataset sourced from various image sources, primarily Google Earth Engine in figure13.

Fig 13: Example of xView Dataset

To expand the dataset, we attempted to extract building polygons from Google Maps or OpenStreetMaps and use them as a ground truth mask for segmentation model training. However, we encountered some issues during this process. For instance, there was a significant misalignment between the extracted building masks and the satellite views in Google Maps refer to Figure14,15,16,17,18.

Fig 14: Google Maps Satellite view, Google Maps’ view, Extracted Building Masks from google maps (left to right)

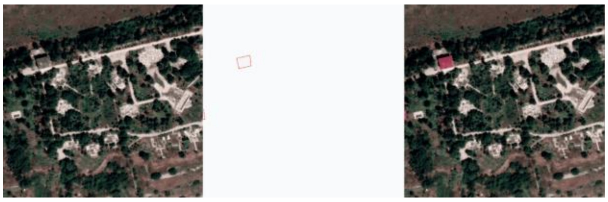

Fig 15: Google Maps Satellite view, Google Maps’ view, Extracted Building Masks from google maps (left to right)

Fig 16: From left to right, the text describes Google Maps Satellite view, Google Maps view, and Extracted Building Masks from Google Maps

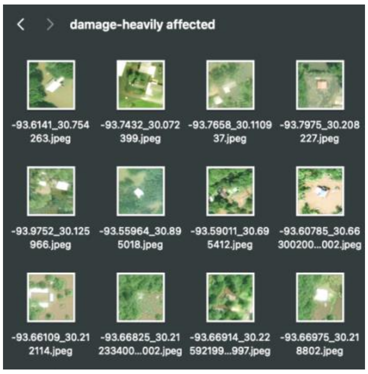

Fig 17: Affected Data Set

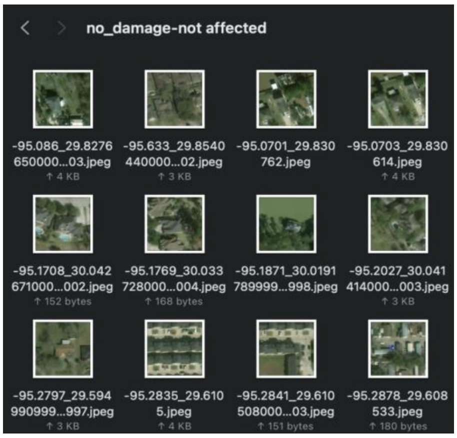

Fig 18 – Not Affected Data Set

15. Sample Output

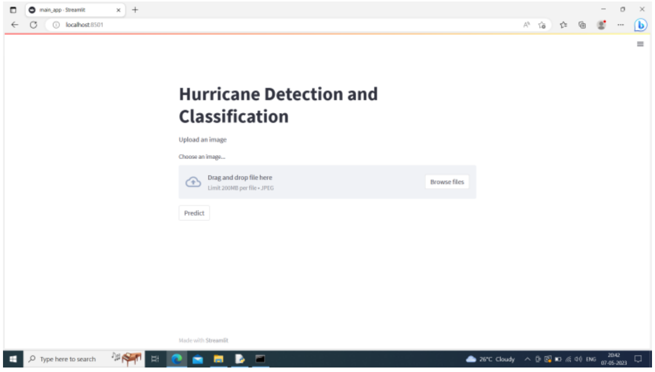

Fig 13 : Main Page

Fig 14 : Affected

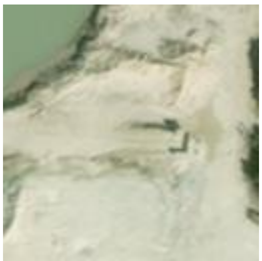

Fig 15 : Not Affected

16. Results and Discussion

In this research, the best transfer learning model is compared with commonly used machine learning algorithms. The model achieved an accuracy of 78% with the optimizer and 23,000 satellite images. Hurricanes are often accompanied by floods, and most authors have studied floods using machine learning algorithms figure16. Naive Bayes achieved an accuracy of 78.51% and Support Vector Machine achieved an accuracy of 91% when applied to 7500 images. Random forest attained an accuracy of 82% when applied to 201 images, while it attained an accuracy of 92% on 255 flood images. The machine learning results are better since the analysis has been conducted on lower numbers of images figure17. However, the deep learning transfer learning models proposed in this paper have used a greater number of images, which involved 23,000 images.

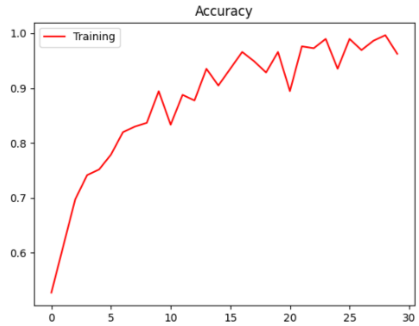

Fig16 : Accuracy of the Occurrence of Disaster

To improve the accuracy of automated damage assessment in Ukraine, we need to use more data from the damaged areas. Our initial results have shown that a transfer-learning approach can be used to identify war damages by training on natural disasters. However, we have noticed that even a small amount of domain-specific data (war damages) can significantly improve the model results. With the availability of actual data (satellite images of real battlefield locations with damaged structures), we can further enhance the existing results.

Developing a pipeline for automatic damage assessment is the first step in building resilient and efficient responses to both natural and human-made disasters. Quick and accurate damage identification can be used in various risk assessments such as cost assessment, migration planning, and restoration assessment.

17. Conclusion

In conclusion, using CNNs to classify hurricane damage is a promising strategy that may enhance the effectiveness and efficiency of emergency response operations in impacted areas. We can classify new, unseen locations based on their features and offer useful insights to aid organizations and emergency responders by training a CNN model on labeled examples of places affected by hurricanes and those that have not.

For this kind of project, satellite imagery serves as the main source of data, and combining different types of data can increase the model's accuracy and robustness. The framework can be enhanced and its performance in terms of generalization can be improved by means of methods like data augmentation, transfer learning, and fine-tuning.

Multi-modal data fusion, transfer learning and fine-tuning, semi-supervised and unsupervised learning, real-time monitoring, and prediction are some potential areas of focus for future research in this area. Enhancements in these areas might have a significant impact on disaster response organizations and humanitarian organizations, which would ultimately help save lives and lessen the effects of hurricanes.

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