IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Mapping Flood Affected Building And Assessing Depth Using Aerial Imaging

Deban Kumar Shahi, Dheeraj Yadav, Najish MD ,Sadhna S..

BE Students, Dept. of ISE, BIT, Bengaluru, Karnataka, India

Dr. Shilpa M.

Associate Professor, Dept. of ISE, BIT, Bengaluru,

Karnataka, India

Abstract: This study introduces an innovative approach to Flood Damage Assessment (FDA) by integrating advanced technologies, including Remote Sensing (RS), Geographic Information System (GIS), and a state-of-the-art neural network architecture. A custom-designed Convolutional Neural Network (CNN), incorporating a UNET with ResNet-34 as a backbone pretrained on the CIFAR-10 ImageNet model, plays a pivotal role in achieving accurate flood mapping. The utilization of transfer learning enhances the model's ability to discern intricate patterns from high-resolution satellite imagery, addressing challenges in complex landscapes. The proposed methodology, validated with diverse datasets from real-world flood events, demonstrates the effectiveness of the integrated neural network in improving disaster management strategies. This research significantly contributes to advancing flood damage assessment methodologies, showcasing the synergy of RS, GIS, and cutting-edge CNN architectures for timely and accurate disaster response and recovery.

Keywords: Flood Damage Assessment, Remote Sensing, Geographic Information System, Convolutional Neural Network, Transfer Learning, Satellite Imagery, Disaster Management.

I. INTRODUCTION

In the context of disaster response and recovery, this project holds immense utility for its ability to revolutionize the assessment of post-flood damage and the identification of affected buildings. By leveraging remote sensing imagery, the methodology presented here enables a rapid and accurate evaluation of the aftermath of extreme storms and floods. The integration of both aerial and satellite imaging ensures a comprehensive understanding of the landscape's transformation and the impact on structures.

The utilization of ResNet and UNet CNNs enhances the project's practicality by offering a nuanced approach to building identification and damage assessment. ResNet distinguishes between the environment and actual buildings, while UNet produces detailed masks for the identified structures. This combined CNN strategy not only streamlines the identification process but also contributes to a more granular analysis of the affected areas.

The depth assessment model further augments the project's utility, providing critical insights into the extent of flooding by utilizing a range of data sources. This holistic approach, encompassing real satellite images and depth CSVs, ensures a comprehensive understanding of the flood dynamics and the depth to which buildings have been submerged.

The emphasis on data visualization techniques adds a layer of practicality to the project, enabling stakeholders to interpret and communicate the extent of flood damage more effectively. This project's adaptability for real-time applications and resource-constrained environments positions it as a valuable tool for emergency response teams, aiding in the rapid deployment of resources and the formulation of informed recovery strategies. Overall, this research endeavor is not only technically robust but also highly relevant and impactful in addressing the urgent and critical challenges posed by natural disasters.

A. *Computational Requirements*

UNET with Resnet-34 (pertained on cifar-10 imagenet model) are computationally efficient and well-suited for real-time applications due to their relatively low computational demands. They are capable of achieving goodperformance on relatively simple tasks like mapping and object detection . On the other hand, CNNs, especially deep and complex architectures, demand significant computational resources, enhancing their suitability for situations requiringgreat precision is paramount, and computational cost is not alimiting factor.

B. *Use case scenarios*

The Flood Disaster Response and Recovery system plays a pivotal role in enhancing the efficiency and effectiveness of disaster management for multiple stakeholders, including Disaster Management Authorities, Insurance Companies, Government Agencies, and First Responders. By continuously monitoring weather conditions and analyzing real-time satellite imagery, the system provides early warnings to authorities, enabling preparedness measures. In the event of heavy rainfall and flooding, the real-time processing of satellite images allows for immediate identification of adversely affected regions, facilitating rapid response and resource allocation by first responders. The flood mapping model contributes to post-flood analysis, generating detailed reports on the extent of damage, aiding government agencies in the strategic allocation of relief packages for reconstruction. Insurance companies benefit from accurate flood mapping reports for efficient claims verification. With a foundation in deep learning, the system supports data-driven decision-making, prioritizes relief efforts, and ensures efficient resource management during disaster response. Overall, the flood mapping project emerges as an indispensable tool, fostering collaboration among stakeholders and minimizing the impact of floods on communities.

II. LITERATURE SURVEY

The author [1] employed an integrated methodology for mapping flood extents, combining FCN deep learning and a Remote Sensing and GIS (RG) approach. FCN-8s, applied to high-resolution Unmanned Aerial Vehicle (UAV) imagery, extracts surface flood extents. Data augmentation during FCN-8s training enhances classification results, especially in scenarios with limited datasets. Challenges in areas obscured by dense canopies are addressed through RG, utilizing DEM and water level information. Experimental results underscore the efficacy of the integrated approach in detecting floods in both visible and concealed areas, holding significance for flood emergency response and recovery activities. The research emphasizes the practical application of the integrated methodology, offering a robust solution for challenges in both visible and concealed flood-prone areas.

The author [2] present the FloodNet dataset, designed for post-natural disaster damage assessment. This resource utilizes Unmanned Aerial Vehicles (UAVs) to provide high-resolution and low-altitude imagery crucial for computer vision tasks. The dataset's collection procedure, annotation, and statistics are detailed, addressing challenges in post-disaster scenarios. The paper delves into computer vision tasks on the FloodNet dataset, analyzing image classification, semantic segmentation, and Visual Question Answering (VQA). Challenges with UAVs, especially in detecting small objects, are acknowledged. The experimental results reveal significant challenges in detecting small objects, flooded buildings, and flooded roads. The paper asserts FloodNet's pioneering effort in addressing multiple computer vision tasks simultaneously, emphasizing its role in advancing post-natural disaster damage assessment.

The author [3] introduce MC-WBDN, a Deep Convolutional Neural Network (DCNN) for satellite-based water segmentation. Trained end-to-end through backpropagation, it leverages deep learning to adaptively process diverse datasets, surpassing traditional methods. MC-WBDN directly fuses multiband information within the network, emphasizing multispectral bands like NIR and SWIR for enhanced water extraction. The EASPP module addresses challenges, improving representation integration and performance. S2D/D2S operations enhance reconstruction in the bottom-up phase, offering advantages in pixelwise and region-based classification. MC-WBDN exhibits superior generalization and water body detection, consistently performing across timestamps and varied conditions. This DCNN method stands out for improved segmentation, additional wavelength bands, and robustness, showcasing its potential in remote sensing and hydrological studies. The proposed system represents a significant advancement, highlighting adaptability, accuracy, and consistent results across diverse challenges.

The author [4] conduct a comprehensive study comparing the performance of a rule-based Sentinel-1 flood processor (S-1FS) with five Convolutional Neural Network (CNN) architectures for water and flood mapping. The investigation validates VH or VV-VH polarized data as the preferred input feature for CNN-based water mapping using Sentinel-1 data. The study introduces a novel approach, demonstrating that a linearly weighted combination of the weighted cross entropy loss function and the Lovász loss function yields superior testing results. Insights into the effects of data augmentation on Synthetic Aperture Radar (SAR) data are provided, emphasizing caution with geometric data augmentation. CNN architectures surpass the rule-based S-1FS in water mapping tasks, advocating for CNNs in operational flood mapping scenarios. The study suggests potential transferability to other SAR sensors, highlighting CNN adaptability and potential to outperform rule-based systems in operational environments. Future research avenues include exploring additional information for enhanced model robustness, addressing benchmark dataset inadequacies in flood detection using Sentinel-1 data.

The author [5], address the critical need for efficient flood mapping tools in remote sensing, particularly during emergencies. The latest techniques involve semantic segmentation and deep learning, posing challenges due to the need for substantial datasets and ground truth for effective training. The paper introduces an innovative method for synthesizing patches of synthetic aperture radar (SAR) images depicting open-land flooded areas. Leveraging bitemporal image acquisitions and spatial patterns from elevation data, the approach constructs a large dataset for training deep neural networks to map real-life floods. Using an established U-Net architecture with significantly fewer parameters, the streamlined approach accelerates processing time and proves advantageous from an operational perspective. Empirical segmentation results showcase F1 scores from 0.80 to 0.90, validating the method's effectiveness in mapping flood-affected areas for real-time applications during or after catastrophic events. The proposed solution addresses the challenge of limited datasets, offering a valuable tool for rapid and reliable flood mapping, contributing to improved emergency response capabilities.

The author [6] present DASNet, a novel change detection method for high-resolution remote sensing images. Comparative experiments on CDD and BCDD datasets demonstrate DASNet's superiority over other methods, achieving higher F1 scores and resisting pseudochanges. DASNet employs spatial and channel attention, enhancing feature representations, and employs the WDMC loss for balanced influences on changed and unchanged regions. The Siamese network structure and attention mechanisms contribute to learning change representations effectively. The method addresses challenges in remote sensing change detection, showcasing adaptability to diverse scenarios. Its potential for applications in monitoring urban landscapes, environmental conditions, and disaster-affected regions is highlighted. Future research directions include exploration in small samples, open-world scenarios, and noisy environments to enhance mobility and robustness in change detection.

The author [7] presents a groundbreaking algorithm for mapping floodwater in both rural and built-up areas using 20 m Synthetic Aperture Radar (SAR) data. Leveraging short temporal and perpendicular baselines of Sentinel-1 image pairs, the algorithm utilizes SAR intensity and InSAR coherence data. Tested during the 2017 hurricane season in Houston, Texas, the floodwater maps align closely with high-resolution optical images, overcoming cloud cover limitations. The study highlights the importance of a short temporal baseline for effective coherence exploitation. Validation against Digital Globe crowdsourcing points and FEMA hydrological models shows strong agreement for most affected buildings. The algorithm's potential applications in disaster risk management include updating urban flood models and estimating variables like river discharge. While successful in the Houston case, further verification across diverse scenarios is planned for broader applicability in disaster response and management.

The authors [8] explore the application of deep learning for post-disaster segmentation using the FloodNet dataset. Baseline models U-Net and FCN face challenges in classifying flooded classes, especially smaller objects due to downsampling operations and image resizing. To address this, advanced models like DeepLabv3, PSPNet, and SegFormer are proposed. SegFormer outperforms with the best test Intersection over Union (IoU) of 56.78 (MiT-B4 encoder) and 54.86 (MiT-B0 encoder). Qualitative analysis illustrates superior performance in flooded class identification and finer-detailed masks. Although color jittering in data augmentation shows no significant improvements, preliminary results are promising. Future steps include running models for more epochs, exploring larger pre-trained backbones, customizing loss functions, and considering alternative augmentation strategies to enhance model performance in flooded vs non-flooded distinction and smaller class identification. Ongoing efforts involve extending training duration and implementing a learning rate schedule, with proposed exploration of larger backbones to improve feature mapping.

The author [9] evaluate the ground detection accuracy of an AI-based flood mapping algorithm by comparing its predictions with Sentinel-2 optical satellite imagery during Typhoon Mangkhut-induced flooding in the Philippines (September 2018). The AI model achieved a producer's accuracy of 89.11%, user's accuracy of 90%, and overall accuracy of 89.50%, with a Kappa coefficient of 0.79. Results demonstrated high accuracy for flood and non-flood classifications. The study highlights operationalization in 2018 and 2019, distributing the method to agencies and Local Government Units nationwide, validated through user feedback. Automated flood map production, using Python scripts on DOST-ASTI's High-Performance Computing facility, employs multi-temporal Radar images and RGB color-mixing for flood analysis. The trained AI model, with 90% accuracy, proves valuable for disaster management, successfully detecting large-scale floods during monsoon events in the Philippines and supporting response and recovery operations.

The author [10] address the critical need for accurate flood mapping in flood-prone regions like Pakistan and Kashmir, employing a joint approach using the Multi-Spectral Water Index (MuWI) and Machine Learning classifiers (Support Vector Machine, Classification and Regression Trees, and Random Forest) with Sentinel-2 and Landsat 8 datasets in 2020. Evaluation in Google Earth Engine reveals promising results, with MuWI's role in identifying shadow areas enhancing flood mapping. Sentinel-2 imagery shows SVM outperforming CART and RF, while Landsat-8 indicates comparable effectiveness between SVM and RF. Flood difference maps dynamically visualize flood extent changes. The study underscores the methods' significance for disaster risk management and urban planning, offering valuable insights for informed decision-making and proactive flood mitigation measures. The careful evaluation of satellite imagery sources and machine learning algorithms reflects a data-driven and methodical approach, contributing to the methods' robustness and reliability in remote sensing and disaster management.

III. PROBLEM STATEMENT

To bolster natural disaster response and recovery efforts, it is crucial to maximize the utilization of remote sensing imagery for swift and accurate damage assessments post extreme storms and floods. This entails devising efficient methodologies that harness advanced technologies for the rapid analysis of extensive data. Tackling this challenge is paramount to expediting the assessment process, furnishing timely and precise information crucial for emergency responders and decision-makers. The goal is to strategize and implement effective disaster management measures, ensuring a proactive and well-informed approach to mitigate the impact of natural disasters.

IV. PROPOSED SYSTEM AND ARCHITECTURE

The proposed system consists of three main stages: Preprocessing Step / Resampling ,Constructing the Building Mask and FLood Affected Building Mask and Finding the Depth in Fig.1.

1. PREPROCESSING STEP / RESAMPLING:

In this preprocessing phase, several key technical steps are employed to optimize Very High-Resolution (VHR) satellite imagery for subsequent analysis. Firstly, the original VHR images, initially captured at (1024,1024) resolution, undergo a downsampling process utilizing the BICUBIC resampling technique. This step is crucial for enhancing computational efficiency while preserving crucial image details. Simultaneously, the corresponding image masks, specifying building footprints and flood-affected areas, are upsampled to the same (1024,1024) resolution using BICUBIC interpolation to ensure precise spatial alignment with the images.

To facilitate a more detailed analysis and enhance model training, both the VHR images and masks are further divided into smaller patches of size (512,512). This patching process enables the capture of localized information, providing a finer representation of intricate spatial patterns within the imagery. The entire dataset, comprising both images and masks, is then transformed from integer tensors (ranging from 0 to 255) to floating- point tensors (scaled between 0 and 1). This normalization, carried out using standard ImageNet statistics, mitigates potential numerical instability issues during subsequent model training.

The presented technique carefully balances computational efficiency with information retention, establishing a robust foundation for advanced tasks such as building and flood damage detection in disaster-affected regions. Visualizations of VHR images and corresponding masks illustrate the successful application of these technical steps, underscoring the effectiveness of the preprocessing strategy in preparing the dataset for subsequent sophisticated analyses.

Suppose the function values f and derivatives fx , fy anf fxy are known at four corners(1,0),(0,1),(0,0),(1,1) of the unit square. The interpolated surface can then be written as

$$p(x,y) = \sum_{i=0}^{3} \sum_{j=0}^{3} a_{ij} x^i y^j$$

2. CONSTRUCTING THE BUILDING MASK AND FLOOD AFFECTED BUILDING MASK:

In the proposed workflow, the initial step involves the creation and collection of a dataset using QGIS and Sentinel satellite data. This dataset serves as the foundation for training a semantic segmentation model focused on building detection. The ground truth for building masks is generated through careful annotation using QGIS, providing a reliable basis for model training.

The core architecture for the model is based on a U-Net with a ResNet-34 backbone. The ResNet-34 backbone is pretrained on the CIFAR-10 and ImageNet datasets, offering a transfer of knowledge from diverse image domains to the specific context of satellite imagery. The pretrained weights of the ResNet-34 serve as an initialization for the U-Net encoder, contributing to the model's ability to capture meaningful hierarchical features.

In this comprehensive workflow, real satellite images, along with corresponding building masks, are utilized to train a dedicated model named "BUILDING_MASK." This model is designed to produce accurate masks outlining the footprint of all the buildings present in the satellite imagery. The building masks serve as crucial ground truth annotations during the training process, enabling the model to learn the distinctive features associated with various types of buildings.

Simultaneously, a second model is created using real satellite images paired with flooded building masks. This model, named "FLOOD_MASK," is specifically engineered to generate masks highlighting areas of the satellite imagery where buildings are affected by flooding. The flooded building masks, obtained through a careful process, act as a reference for the model to understand and identify regions impacted by floods within the context of building structures.

During training, the optimization process is facilitated by the Adam optimizer, which dynamically adjusts learning rates for individual model parameters. The adaptive moment estimation (Adam) optimizer updates parameters using the first moment (mean)

mt and the second moment (uncentered variance) vt . The moving averages are then bias-corrected to mt and

vt , and the parameters are updated accordingly.

$$m_t = \beta_1 m_{t-1} + (1-\beta_1) g_t$$
$$v_t = \beta_2 v_{t-1} + (1-\beta_2) g_t^2$$

To further enhance training efficiency, the One Cycle Policy is employed as a scheduling strategy. This policy involves cyclically adjusting learning rates and momentum throughout the training process, contributing to faster convergence and improved generalization.

The 1cycle policy has three steps:

We progressively increase our learning rate from base_lr to lr_max and at the same time we progressively decrease our momentum from mom_max to mom_min.

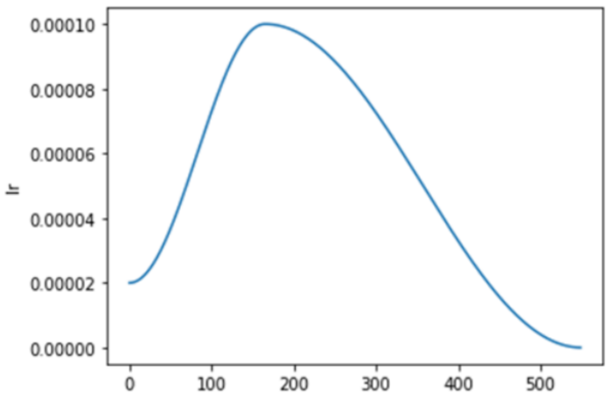

Fig.2 Relation between learning rate and batch size.

We do the exact opposite: we progressively decrease our learning rate from lr_max to (lr_max/div_factor) and at the same time we progressively increase our momentum from mom_min to mom_max.

We further decrease our learning rate from lr_max/div_factor to lr_max/(div_factor x 100) and we keep momentum steady at mom_max.

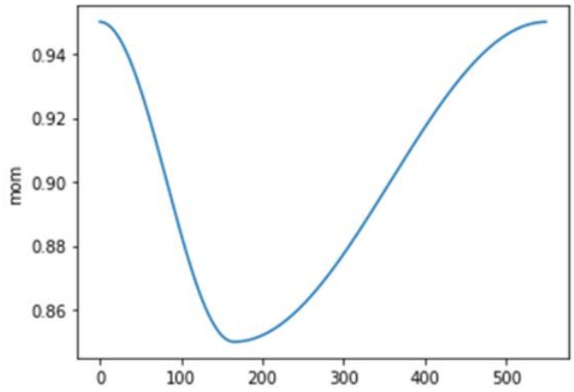

Fig.3 Relation between momentum and batch size.

By training these two models separately, each focused on a distinct aspect (building detection and flood-affected building identification), the workflow aims to develop specialized models for precise segmentation tasks. The BUILDING_MASK model excels at recognizing and delineating the boundaries of buildings, while the FLOOD_MASK model is adept at highlighting areas where buildings intersect with flooded regions.

This dual-model approach enhances the overall capability of the workflow to provide detailed insights into the impact of flooding on buildings in satellite imagery. The models, fine-tuned on real-world data with ground truth annotations, contribute to a more robust and accurate understanding of building dynamics and flood-related changes in the observed areas.

3. Finding the Depth :

This proposed methodology for depth prediction integrates both numerical and image-based features to create a comprehensive predictive model. The dataset includes numeric features such as the number of buildings and the number of flooded buildings, alongside manually generated depth labels derived from visual confirmation, building height information from shape files, and real satellite images. The numeric features are processed using standard scaling, while the image data is preprocessed by resizing and other potential steps. The model architecture combines a ResNet50-based image processing model and a numeric features model. The image model extracts hierarchical features from satellite images, leveraging transfer learning with ResNet50 pretrained on ImageNet. The numeric model processes numerical features through a dense neural network. These two branches are then concatenated and fed into a dense layer for joint feature learning. The model is trained using mean squared error loss and the Adam optimizer, with early stopping to prevent overfitting. The training dataset is split into training and testing sets, and the model is evaluated on the test set. This comprehensive approach aims to leverage both numerical and visual information to accurately predict depth in a given area, combining the strengths of both data types for improved performance.

V. IMPLEMENTATION

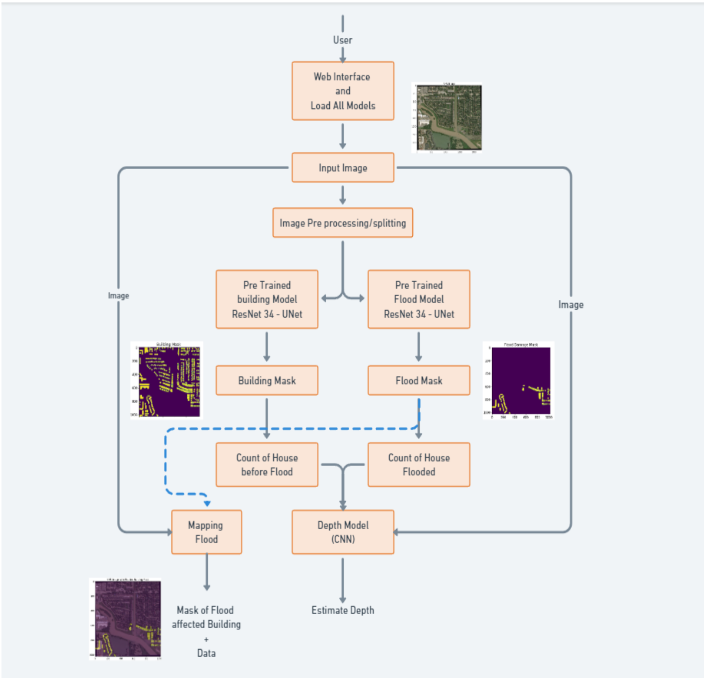

Fig.4 Flow diagram.

Importing Libraries and Module:

First, we import all the necessary libraries and modules required for image processing, machine learning, and deep learning. We import OpenCV as cv2, NumPy as well as TensorFlow and Keras.Various modules from FastAI for vision-related tasks, data handling, and general utilities like scipy library for scientific computing , matplotlib.pyplot for plotting, and numpy for numerical operations. The scipy.ndimage module is imported for multidimensional image processing, and zoom is imported for image zooming.

Pre processing of Input Image :

In this image preprocessing script, the satellite imagery and corresponding masks undergo a series of transformations. The initial step involves loading the high-resolution satellite image (vhr.tif) and two masks (buildings1m.tif and flooded1m.tif) using the FastAI library's PILImage.create and PILMask.create functions. Subsequently, the image is reshaped to a 1024x1024 resolution using bicubic resampling. The reshaped image is then converted into a PyTorch tensor using image2tensor. Further, the tensor is split into four non-overlapping quadrants (z1, z2, z3, z4), each representing a distinct region of the original image. The channels of these quadrants are permuted to achieve the required channel order, and four separate PIL images (im1, im2, im3, im4) are created from the permuted tensors. This preprocessing sequence facilitates the subdivision of the original satellite image into localized quadrants, providing a structured and organized representation for subsequent analyses or specific tasks tailored to individual regions within the image.

Constructing Building Mask and Flood Affected Building Mask:

To generate the building mask and flood-affected building mask, the script utilizes two pre-trained models: BUILDING_PATCH and FLOODED_PATCH which were trained and stored as pkl file to be used. The preprocessed satellite image is divided into four non-overlapping quadrants (im1, im2, im3, im4), each representing a distinct region. For each quadrant, the building mask is obtained by passing it through the model_build (BUILDING_PATCH model), predicting the masks for the individual regions (x1, x2) and concatenating them along the horizontal axis and then vertically (x). Similarly, the flood-affected building mask is generated by processing the quadrants through the model_flood (FLOODED_PATCH model), resulting in individual region predictions (y1, y2) that are concatenated both horizontally and vertically to form the final mask (y). This approach enables the creation of detailed and comprehensive building and flood-affected building masks by leveraging the predictive capabilities of the pre-trained models on localized image regions.

Once the flooded building patches have been generated, they can be overlaid onto the real satellite image by resizing them to the same dimensions. This overlay process involves aligning the flood-affected building patches with the corresponding regions in the original satellite image. By resizing the patches to match the dimensions of the original image, the flood-affected areas can be visually superimposed on the satellite data. This overlay provides a visual representation of the areas impacted by flooding, allowing for a clear identification of buildings affected by the flood. This step enhances the interpretability of the model predictions by presenting the flood damage in the context of the actual satellite imagery, aiding in the assessment and understanding of the flood-affected area.

Finding Depth :

The depth calculation process involves several steps. First, the flooded building mask is processed using a thresholding technique, where pixels above a specified threshold are considered part of the damaged areas. Subsequently, connected components in the binary mask are identified to represent distinct regions of damage. The count of connected components corresponds to the number of houses in the affected area. This count is obtained through the Connected Components technique, utilizing the measure.label function from the skimage library.

Once the number of houses is determined, along with the number of buildings and the real satellite image, these three inputs are fed into the DEPTH_CALCULATION model. This model is designed to estimate the depth of water in the specified area based on the given information. The integration of house count, building count, and the actual satellite image allows the model to make predictions about the depth of flooding, providing valuable insights into the extent of water damage in the identified regions. This comprehensive approach leverages both image-based information and building statistics to estimate the depth of flooding in a given area

DISPLAYING RESULTS:

The final results are presented in a visual format where an image is generated to illustrate the houses affected by the flood. In this image, all the houses impacted by the flood are distinctly marked, providing a clear visual representation of the affected areas. Additionally, accompanying data is displayed, including the number of houses flooded, the total number of houses in the region, and the estimated depth of the floodwater. This comprehensive presentation offers valuable insights into the extent of the flood damage, allowing for a more detailed understanding of the impact on the affected communities. The combination of visual representation and quantitative data enhances the interpretability of the results, making it easier to assess and respond to the flood-affected areas.

VI. RESULTS AND DISCUSSION

When the code is executed, it processes a sample image and produces an output image that is masked.in Fig.2 In essence, this implementation offers a holistic solution for masking flood affected buildings. The system showcases the power of computer vision in automating masking of flood affected buildings, analysis, and visualization. In contrast to deep learning-based approaches, which have gained prominence in recent years for masking buildings and flood affected buildings have a large layer neural network employed which requires a lot of resources to process along with time , this implementation relies on UNET model with Resnet-34 as a backbone, providing an effective method for identifying flood-affected buildings , offering a distinct set of advantages.

While deep learning methods with multiple layers often require large labeled datasets, and significant computational resources, and may require additional LIDAR dataset, the proposed system excels in simplicity, data efficiency, time efficiency and resource efficiency. It showcases the power of computer vision in automating masking and estimating depth of flood affected buildings and analysis without the need for extensive training data and can calculate depth using given image only.

```
Total Number of BUildings in Image : 334
Number of Buildings Flooded : 39
Predicted Depth: 4.1621317863464355
```

Fig.5: Result produced by the model.

Fig.6: Original Input Image

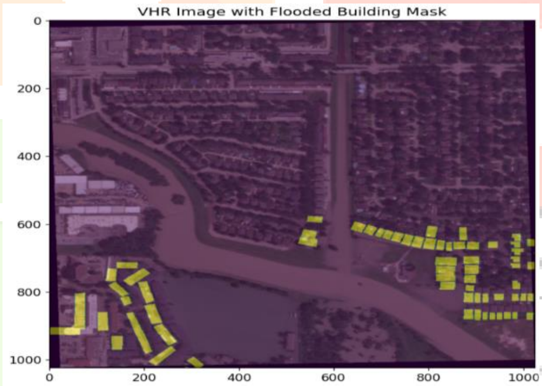

Fig.7: Masking the affected areas in the image

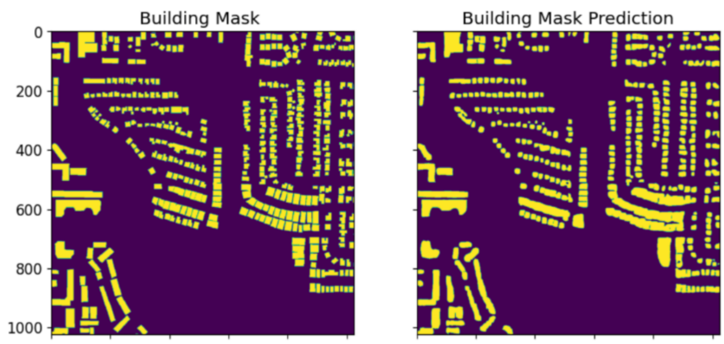

Fig.8: Building mask expected vs obtained

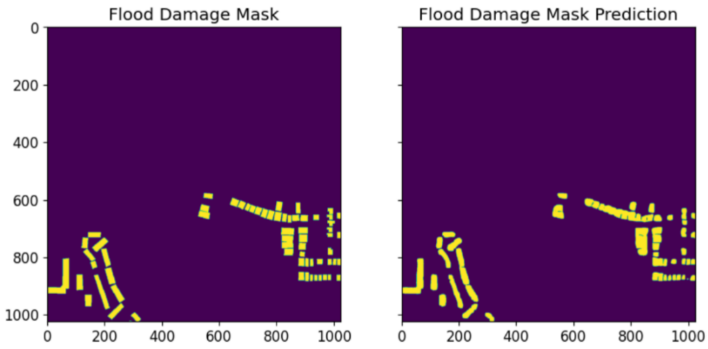

Fig.9: Flood mask expected vs obtained

Results:

Table 6.1: Accuracy of masking models

EVALUATION METRICS	BUILDING MODEL	FLOOD MODEL
ACCURACY	92.9%	93.1%
PRECISION	0.920	0.91
RECALL	0.910	0.93
F1-SCORE	0.912	0.934
IoU	0.85	0.83
DICE COEF.	0.88	0.91

Table 6.2: Accuracy of depth models

EVALUATION METRICS	DEPTH MODEL
Mean Absolute Error (MAE): 0.38	0.38
Mean Squared Error (MSE)	0.20
Root Mean Squared Error (RMSE)	0.45
R-squared (R^2)	84.76%

The dataset comprises 930 image tiles, with 469 allocated for training and 461 for testing. Extracted from the Sentinel dataset, it features Very High-Resolution Images (1973x2263 pixels, 0.5m per pixel) and corresponding masks (960x960 pixels, 1m per pixel) for building and damage detection. Based on this testing dataset, we have calculated the accuracy, precision, IoU , Dice coefficient and recall values for our model -

Accuracy: In the context of image segmentation, accuracy is a metric used to assess the overall correctness of the model's predictions. It is calculated as the ratio of the number of correctly classified pixels (both true positives and true negatives) to the total number of pixels in the image. Represented as *(TP+TN)/(TP+FP+FN+TN).*

Precision: is a metric that assesses the accuracy of positive predictions made by a model. Precision is calculated as the ratio of true positive pixels to the total number of pixels predicted as positive by the model. It is represented by *TP/(TP+FP).*.

Recall is the fraction of detected water pixels compared to all water pixels.

Recall=TP/(TP+FN)

Recall=417/(417+8) ≈ 0.981 The recall is approximately **0.981**, signifying that the model successfully identified

98.1% of the actual flood water pixels.

F1-score is a metric that combines both precision and recall into a single value to provide a balanced measure of a model's performance. The F1-score is the harmonic mean of precision and recall and is represented by *2*Precision*Recall/(Precision + Recall).*

Intersection Over Union (IoU): Measures the ratio of the intersection between the reference mask and the segmentation mask over their union. Represented as

IoU= Area of Intersection of two boxes / Area of union of two boxes.

Dice Coefficient: Measures the similarity between the predicted and true masks. It's calculated as twice the intersection divided by the sum of the areas.

VII. FUTURE WORK

In future developments, our project aims to enhance its capabilities by incorporating precise house coordinates into the mapping system, enabling more accurate location-based information. Additionally, we plan to identify isolated houses that require immediate assistance, facilitating swift and targeted rescue operations. The next phase involves implementing a robust system for calculating the required resources and manpower, providing a comprehensive understanding of the scale of assistance needed.

To cater to diverse urban layouts and topographical variations, we envision training multiple models specific to different city structures. This adaptive approach ensures the effectiveness of our solution across various geographical settings. Furthermore, we plan to mark high-risk areas to raise awareness and enable proactive disaster preparedness.

Refining our depth prediction capabilities is another priority, focusing on more precise building height calculations based on coordinates. This improvement contributes to a more accurate assessment of flood severity.

Ultimately, our future goal involves deploying the project for public access and use by non-governmental organizations (NGOs), fostering collaborative efforts in disaster response and recovery.

ACKNOWLEDGMENT

We convey our sincere thanks to Rajya Vokkaligara Sangha, Bangalore and our guide Dr. Shilpa M. ,Associate Professor, Department of Information Science and Engineering, Bangalore Institute of Technology, without whose direction, this would not have been possible. We also express our gratitude to our team members whose team participation resulted in successful completion of the paper.

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