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A Novel Neural Network-Based Identification of Flood Regions Using UAV Images

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Abstract: Countless lives have been lost, and numerous buildings and other economic assets have been ruined, all because of floods. People caught in flood zones have no way to go to safety since their houses and other structures have been destroyed along with vital infrastructure. In order to preserve lives, property, and essential city services, it is crucial to create systems that may identify floods in an area and provide help and assistance to those in need as soon as possible. Current methods of detecting floods and damage assessment make use of remote sensing, satellite imaging, GPS systems, and geospatial databases. These strategies use neural networks, machine learning, and deep learning. In light of this, this research employs aerial data captured by unmanned aerial vehicles (UAVs) as part of a Genetic Bilateral Convolutional Neural Network, also known as (GBCNN)-based flood detection algorithm, in order to obtain flood-related characteristics from photos of the disaster area. This technique helps determine the extent of destruction to neighborhood facilities in disaster areas. The research uses UAV imagery gathered before and after a flood in a flood-prone zone. These swaths of the training dataset teach the GBCNN model to identify and extract the places where flooding-related changes have occurred. The model is validated by comparing it to photographs taken before and after a catastrophe; the findings show that it can correctly identify floods 91% of the time. This model may be used by organizations that deal with disaster management to evaluate the extent of damage to essential municipal facilities and other assets throughout the globe. This may aid in the wise administration of cities, ensuring that sudden calamities are dealt with immediately.

Keywords: *Flood detection, Disaster management, UAV, Aerial imagery, and Genetic Bilateral convolutional neural network (GBCNN).*

1. Introduction

During floods, water from rivers and seas surges in vast quantities onto dry ground. In most places, particularly in underdeveloped nations, alterations to water bodies are not meticulously tracked until they cause disastrous floods. Sixty thousand people are killed annually as a result of calamities throughout the world. Also, 40% of all unforeseen catastrophes occur due to floods, making them the most common kind of natural disaster worldwide. The huge increase in flood hazards is mostly attributable to climate change, cyclones, high rainfall, melting glaciers, and snowstorms [1]. Typical floods have caused several hundred million of money in damages and taken the lives of thousands of people. In this age of emphasis on ecology and smart cities, it is crucial to reduce the economic losses caused by natural disasters like floods, which claim not only lives but also significantly damage structures and assets, agricultural fields, crops, and cattle [2]. For instance, eighty-five million individuals were affected by floods in 2016 and 2017, costing an estimated USD 36.7 billion annually. In 2011, floods in the Philippines caused agricultural losses estimated to be in excess of $249 million. Damage to buildings is down by 59%, but animal deaths are up by 87% as a result of these floods. If effective measures are taken to address the crises brought on by the floods, the degree of harm may be contained. According to the National Weather Service (NWS), the 2016 floods caused 126 fatalities and $10 million in property loss, making it one of the worst weather-related catastrophes in US history [3]. Too many people perish because of delayed help and recovery providers because of inaccurate and slow technology that might recognize the onset of flooding in a region. This indicates the need to use cutting-edge digital technology to rapidly and precisely discover flood-affected regions so that rescue efforts may be launched without delay. Having this kind of early warning allows rescue teams to better prepare for the flood and save more lives and money [4]. An external tracking

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system not dependent on onsite servers may help with catastrophe preparation. If the flood is spotted early by a high-tech exterior monitoring system, emergency measures may be taken right away. Authorities in charge of disaster management and rescue operations would benefit greatly from such an external system's ability to offer detailed, accurate data about the area. One possible method for creating this system is to use photographs acquired by unmanned aerial vehicles (UAVs) connected to 5G or 6G networks to create an emergency map of the impacted area. In order to preserve lives, farmland, property, facilities, and attributes, it is important to estimate the damage caused by floods as soon as possible so that relief efforts may be organized effectively. Scientists may use satellite photography, unmanned aerial vehicles (UAVs), planes, or remote sensing (RS) methods to collect data to create flood maps. Satellite imagery may be used to analyze the region and launch effective relief efforts after a catastrophe. Reduced search efforts and fast access to rescue services make RS an affordable choice [5]. A Geographic Information System (GIS) is crucial for making informed decisions and conducting in-depth analyses during emergencies. It helps the government collect, store, organize, and analyze geographic information in order to respond effectively to disasters. Better flood prediction may be achieved with the use of GIS, which can automatically identify the areas impacted by floods and combine the findings with the existing geographic data. It has been utilized to map evacuation paths and assess transport infrastructure in flood-hit regions. However, this method depends on readily available data concerning the event. A timely reaction is hindered by such data not being made accessible for many days, if not several weeks, after a crisis such as a flood. With a GPS receiver and an unimpeded line of vision to 4 or more GPS satellites, a user may determine their precise position on Earth and get accurate time anyplace on or near the planet. Post-flood disaster management and relief operations have regularly used this technology [6]. Deep learning, which uses methods like Deep Belief Networks (DBN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) for task acknowledgment, identifying objects, and related region classification, has recently become widely used as a result of an increase in complexity. GBCNN has the best performance across the board, including recognizing images, feature extraction, and segmentation, making it the most popular of these methods. Using several layers of cells, CNN can effortlessly acquire information from an extensive repository and perform nonlinear evaluation functions [7]. Therefore, the present work fed UAV-captured aerial photos into GBCNN-based deep-learning models to identify floods. During floods, the UAVs can maneuver through crowded areas and take photographs of houses, businesses, and other structures to help assess the damage. Due to its superior performance in picture categorization and segment tasks, the GBCNN-based deep learning models have been chosen. In this research, we employed deep learning to identify flooded areas in UAV imagery. The goal is to aid emergency response teams in rapidly mapping flooded areas so that rescue and evacuating efforts can get underway as soon as feasible. Unique to this investigation is that the nation under scrutiny is one of the developing worlds.

Here is how the remainder of the paper is structured: The most up-to-date techniques for flood forecasting, detection, and mapping are presented in Section 2. The present investigation makes use of knowledge gained from the study of deep learning algorithms and image processing. The research methods used are discussed in Section 3. The steps involved are: identifying a research field, gathering datasets, designing a CNN architecture, setting up an experiment, training and testing a model, and validating the results. Experiment findings illustrating flood detection output on input test photos are presented in Section 4, and the article is wrapped up in Section 5.

2. Related Work

The lives of people, their possessions, and the city's infrastructure are all in danger when a flood strikes. While there is no foolproof way to prevent flooding, there are several effective ways to deal with the aftermath of a flood. Locations at risk of flooding must be pinpointed, impacted regions must be quickly identified, rescue routes must be mapped, and logistics must be organized, so rescue operations can begin as soon as feasible. Image recognition and machine learning are two examples of cutting-edge innovations that might be used in flood control. Detecting flood-affected regions from a collection of photos is a challenging problem, but that research proposes an innovative technique that combines image analysis with machine learning [8]. Dams need regular seepage inspections to identify the issues and ensure continued stability. Vegetation, complicated backdrops, a weak signal-to-noise ratio, and a lack of thermogram resolution all have a negative impact on automated outcomes. A UAV equipped with a thermal imaging camera was used to acquire thermograms, and a unique CNN was presented to automatically detect seepage from the surface of dams. In order to limit the number of false alarms produced by "seepage-like" outside disruption on the dams and to reliably detect seepage patterns with defined borders from the smaller thermograms, a different input stream with two specifically built modules was integrated into a U-Net frame [9]. Worldwide flooding has become more common as a result of climate change and human activity. Therefore, disaster management must have accurate maps of the affected regions. That study introduces a new methodology for mapping flood-affected areas using disparate RS data sets. For overflow mapping, the method combines synthetic aperture radar, visual, and altimetry datasets through three main steps: "(1) preprocessing, (2) deep feature extraction based on multiscale residual kernel convolution and convolution neural networks (CNN) parameter optimization by fusing the datasets, and (3) flood detection using the trained model"[10]. Due to their efficiency, ability to fly at lower elevations, and ability to penetrate dangerous areas, UAVs have become an efficient photographing data collecting tool to supply high-resolution pictures swiftly. Flood extent mapping uses image classification algorithms like SVM. CNN-based RS image categorization has improved significantly in recent years. CNNs excel in categorization, extraction of attributes, and separation. Multi-layer CNNs can establish nonlinear decision algorithms and learn features from big datasets effectively. CNN methods are tested for UAV imagery flood extraction. This study employed VGG-based FCN-16s. The method was fine-tuned and tested on the new UAV imaging dataset using k-fold cross-validations [11]. Roads become inaccessible during floods, making community evacuations, the flow of products and services, and rescue operations more difficult and increasing the already high cost of remediation and loss of property. The effectiveness of rescue and cleanup efforts after a flood depends on accurate water level estimates. Conventional flood mappings techniques, such as RS and electronic elevation models, produce significant inaccuracies in urban locations because of altered surface geography, microtopographic changes, and vegetative bias. Pictures of submerged roadways and junctions are used with a deep neural network, Canny identifying edges and the stochastic Hough transform to identify the length of the pole and a prediction of the level of the floodwaters [12]. In that work, they use UAV imagery to examine how various flood-hit regions were impacted. The suggested technique considers the creation of a method based on a neural network, defined with a traditional convolutional layer, processed by a bank of Gabor filters, and carried out using a reverse propagation technique during the training phase. The neural network is taught to identify flood-affected areas in UAV footage. Therefore, we have the flood and non-flood categories. During the learning phase, each patch's characteristic vector is constructed by combining data from the neural layer's output and the HSV representation [13].

3. Proposed Methodology

The field of catastrophe forecasting and management is one where machine learning has recently shown great promise. Deep learning employs a network of multiple layers of neurons to autonomously learn about, identify, and extract information from a picture. In the present research, multispectral aerial photos were taken near the river Indus in Pakistan, and GBCNN was employed with other methods to identify floods. The whole process for detecting floods from aerial photography is shown in Figure 1. UAVs are utilized to capture aerial imagery of the target area for use as training data for the CNN model. Online resources like Google Satellite Image and social media provide another supply of usable images. There is a clear divide between these photographs taken before and after the accident. Both sets of photos have the same spatial data.

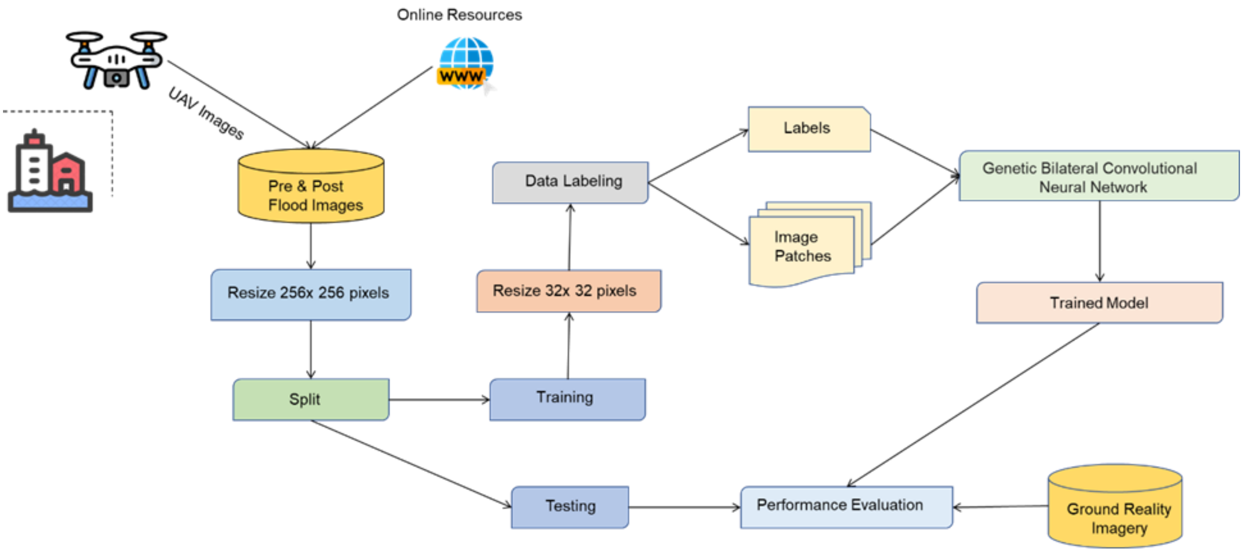

Fig. 1. Proposed Framework

3.1 Data acquisition

The Indus Valley in Pakistan is the research's focal point since it is one of Asia's most significant rivers. Indian, Chinese, and Pakistan are all crossed by its waters. Flooding along the Indus Valley has killed at least 1980 individuals as well as affected an estimated 18 million in Pakistan, based on a United Nations assessment.

Furthermore, the floods have caused the relocation of almost 1.6 million residents whose houses were damaged or destroyed. Damage to homes, commercial property, attributes, and buildings also affects the majority of people directly. As a member of the most vulnerable areas in Pakistan to flooding, the Indus Basin is being studied here to better understand the devastation caused by past floods and better prepare for future calamities. The photos in the dataset come from unmanned aerial vehicle (UAV) footage and internet sources like Google Earth. There are pictures from both before and after the flood. Since the photos in the gathered dataset were of varied sizes and resolutions, they were all scaled down to 256 pixels by 256 pixels before being used in the training process. Every study requires dual sets of pictures. a training set and a testing set. Two thousand one hundred fifty regions across ten different subsets make up the training set. Each of the 14 groups in the evaluation set has 2150 patches. The training collection consists entirely of photos that are all identical in size and location. Images from the before and afterward categories correspond similarly with ground truth photography. This is due to the fact that the system can only accept inputs of a certain complexity. Images with variable brightness may be used for training purposes. The query picture may be generated with variable intensities, alignments, and positions to evaluate the system's responsiveness to a range of inputs.

3.2 Data preprocessing

To improve the input pictures' standard and prepare them for additional analysis, preprocessing the images is a necessary first step. In this step, raw photos captured by the UAV's digital camera are downloaded, saved, processed to remove noise, and orthorectified. Data is preprocessed to accommodate for differences in picture dimensions, form, and luminosity. Thus, pretreatment was conducted after gathering data to eliminate clutter and noise from the collected pictures in the present investigation. Cropping was used to remove distracting backgrounds from the gathered photographs after they had been modified for lighting and size. The suggested GBCNNs underwent data enhancement by random picture cropping and patching, which was then put to use in the whole training process for label formation and flood detection. Additionally, landmark features were extracted from the preprocessed pictures and used in a supervised learning method to aid with choosing parts.

After retrieving landmarks, they are added to the original RGB photos to provide the feature space needed to train a CNN classifier. Additionally, additional test photos are used to assess the classifier's flood detection abilities. The structure of confusion obtained during validation is then used to evaluate performance.

3.3 Training datasets

Most natural pictures are represented in RGB, among the most used compression schemes. In order to train the GBCNN, we first extracted highlight characteristics from the filtered images utilizing a supervised learning technique. Then we utilized the initial one, pictures in RGB, to train the GBCNN. The gathered dataset included the raw RGB photos and the landmarks extracted throughout the process of choosing features. Over-fitting is a common problem for even the highest-performing GBCNNs during training, perhaps because these networks learn to rely too much on the specifics of the images used in the instruction set. To prevent the model from being overfitting, training it with a large enough sample size is crucial. Training specimens are expensive to collect. Thus, methods for augmenting data like image flipping, scaling, and accidental cropping are utilized to compensate. To avoid model over-fitting, it is crucial to raise the number of variability in the gathered pictures by using the earlier augmentation strategies. This is why we employed them in our research.

The visual analysis of dual sets showed that the pictures in the test set comprise five types of pixels: houses, bridges, roads, dirt, plants, and water. But not all of the instructions were in the training pictures, which led to a mismatch. This issue was fixed using a weighting algorithm based on the average frequency. Equation (1) shows how weight is given for each of the 5-pixel classes that don't appear in a picture.

$$v = \frac{Median(be)}{class\ frequency}$$

(1)

Where ' be ' denotes the overall class frequencies determined by applying Equation (2) to the entire dataset.

$$class\ frequency = \frac{Number\ of\ pixels\ in\ each\ class}{total\ pixels\ in\ the\ image}$$

(2)

The instruction patches are then marked with either a 0 or a 1. If the shift rate, shown by the white area in ground-level reality updates, is below or equivalent to 15%, the number "zero" is given. If the pace of change is more than 10%, the amount "one" is presented. So, 0 means that a significant change happened in the picture, while one means that nothing changed. In simple terms, 0 implies a disaster occurred, while one means there was no catastrophe. After the instruction patches have been labeled, the pictures are preserved and used to teach the GBCNN model. GBCNN has been prepared with data from more than 250,000 trials, and a log of what has been done is kept.

3.4 Testing datasets

In order to plan a successful disaster reaction, it is essential to find and assess the regions affected by disasters during the test phase. In the testing process, the RGB bands of the pre-disaster and post-pictures are first combined into just one picture. This ensures the system works well and gets the results to the user as quickly as possible. Utilizing a scanner that scans over the picture and moves it 16 pixels, the forecast value for the number of disasters is found. From the estimates made in the initial training phase, the "1"-labeled pieces are assembled to make a 32 x 32-pixel square that shows the entire disaster area. For more accuracy, the outcomes of the method are contrasted with actual pictures taken on the ground level that was raster scanned on a 32 x 32-pixel area of interest. After that, precision, recall, and f-score are used to judge the work.

3.5 Genetic Bilateral Convolutional Neural Network (GBCNN)

The overall framework of the present research method for the rapid and precise identification of flooded zones is shown in Figure 2. This study's suggested CNN structure was influenced by AlexNet's design. It has 2 wholly linked layers, 3 pooling layers, and 3 convolution layers. In the architectural diagram, C, P, and FC stand in for the CL, PL, and Fully Connected layers. Images may have their edges and textures extracted using CL. Certain traits are learned from examples of both to correctly classify photos as before or after a flood. An activating function then follows each CL. In this case, convolutional layers are employed using a RELU activation function. In the case of huge photos, PL decreases the number of parameters and hence the dimensions. This shortens the time required to master the material. The result of the preceding layers is then normalized and sent to the FC, which employs an activation function (softmax) to provide the final classification result.

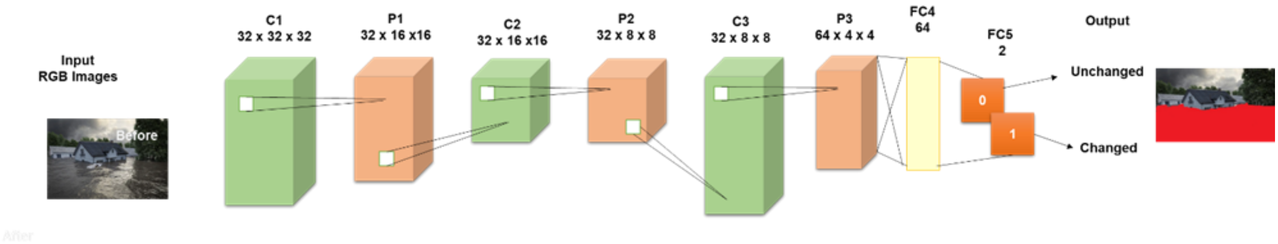

Fig.2. Architecture of GBCNN

The mathematical operation of convolution is widely used in signal and picture processing. A convolution algorithm may be used to extract many characteristics from a picture, including texture and edges. The convolution operators may be used to determine the amount by which two functions ('w' and 'z') overlap. In Equation (3), d' is the third role that can be determined if 'w' is the initial function and 'z' is its mirrored counterpart.

$$d(s) = w(s) * z(s) = \int_{-\infty}^{+\infty} w(\tau) z(s-\tau) c\tau \quad (3)$$

In processing pictures, a computer picture is also seen as a 2D function, like ' $w(b,a)$.' So, using a 2D convolution operation, $z(b,a)$. we can use Equation (4) to figure out the result image $d(b,a)$:

$$d(b,a) = w(b,a) * z(b,a) \quad (4)$$

In the same way, a colored image with 3 channels has an input picture of width 'x' and length 'k,' and it has a size of array 'T.' This is found using Equation (5) as follows:

$$T = 3 \times x \times \mathrm{k} \quad (5)$$

The convolutional component yields a feature map as its output. To calculate this, we use Equation (6), which involves adding up all of the synapses' inputs (z_i), multiplying the results by their weights (x_{il}), and then adding in a bias value (u_l) and a function for stimulation.

$$P = \sum_{i=1}^{m} x_{il} \times z_i + u_l \quad (6)$$

In the field of neural networks, the Rectified Linear Unit is a typical activation function. It facilitates training of the model and yields enhanced efficiency. If the input is affirmative, the node will be activated, and its value will be output explicitly; otherwise, the function will return zero. The present investigation makes use of this strategy.

In the present research, a pooling division is introduced right after the convolutional segment to reduce the breadth and height of the test picture. The fewer variables to work with, the easier the calculation will be. Over-fitting is another issue that this fixes. The most common pooling method is called max pooling, and it involves selecting a filter with dimensions "s x s" and performing a most excellent operation over that filtered subset of the picture. Immediately after adding the pooling layer, a wholly linked layer arrives, in which all the neurons get input from all the neurons in the preceding layer. The result is calculated by multiplying a series of matrices by a bias offset. In this research, we want to use grades to categorize images.

3.6 Research Setting

The research used the convolutional structure for the Fast Feature Embedding deep learning platform and the AlexNet CNN's design.

Caffe, a framework for developing DL models, is employed in this system. It's a C++ framework for DL with a Python-like user interface. Created with picture categorization and division in mind, it is optimized for usage with DL models. As a result, it is able to analyze a vast number of photos quickly. Figure 3 shows how the Caffe framework is used to construct a DL method using GBCNN. The pre-and post-flood picture patches are utilized for training a GBCNN Second after the GBCNN learning period is complete, a DL method is implemented using the Caffe platform. The testing step concludes with the application of the Caffe architecture to distinguish between disaster and non-disaster areas in a query picture. Additionally, this model is given a new image labeled as either flooded or not flooded.

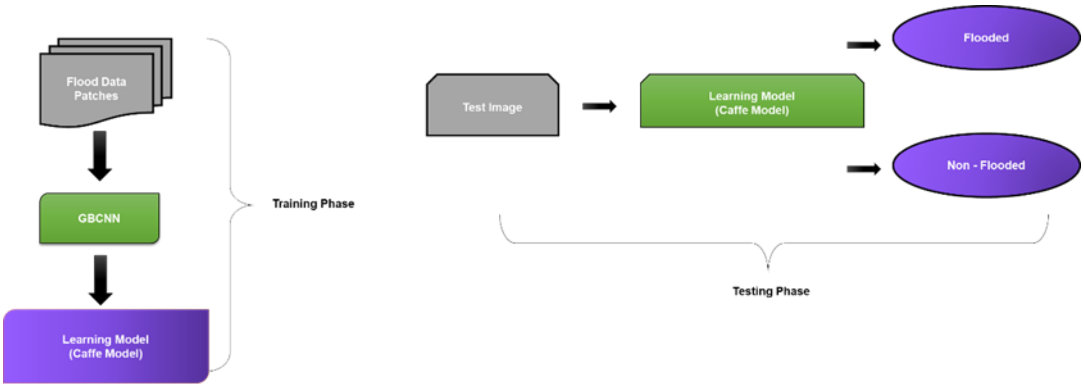

Fig.3. Training and testing process

The GBCNN was trained using a pair of convolution, a layer for pooling, and a pair of fully connected layers, with the first layer receiving pictures from both the flooded and non-flooded classifications. When the idea of GBCNNs is first proposed, data is gathered, and ML algorithms are developed. This research used images from both the flooded and non-flooded categories for data gathering. The next step was to clean and classify the data. Several methods exist for labeling data, such as connecting boxes and segmentation with semantics. Semantic division, a pixel-by-pixel labeling approach, was employed to obtain the water pixels independently from the backdrop pixels. Therefore, this research made use of a refined version of GBCNN. In this case, the final ultimately linked layers only provide two outputs, one indicating whether or not the picture is flooded and the other meaning the opposite. Figure 4 shows the flood and not flood region detection by UAV images.

Fig.4. Flooded and not flooded region detected by UAV

4. Results of Performance Analysis

There are four ways to measure performance: accuracy, precision, memory, and f-score. Accuracy figures out what the actual positive and real negative numbers are. Precision figures out how many optimistic guesses are in the positive class. The recall shows how many correct guesses were made from all the proper specimens. F1-score gives a number value to combine the worries about accuracy and memory.

4.1 Accuracy

Accuracy is a numerical indicator that shows how close an exact or projected value is to the positive or anticipated value. It also has to do with being right or not making a mistake. Accuracy is often used to judge the quality, usefulness, or dependability of systems, designs, or data when considering their efficiency or how well they work. It is calculated by,

$$Accuracy = TP + TN/TP + FN + TN + FP \quad (7)$$

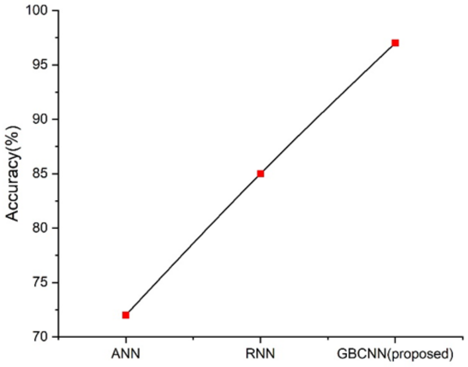

Fig.5. Accuracy of existing and suggested method

Table 1. Comparison of accuracy

Methods	Accuracy (%)
ANN	72
RNN	85
GBCNN(proposed)	97

The above data show that the suggested method may perform better than the present standard study methods, as shown in Figure 5 and Table 1. The recommended approach is more accurate than current methods, such as ANN (72%) and RNN (85%). This shows that our ways (GBCNN 97%) are better than the best methods.

4.2 Precision

"precision" describes the degree of consistency between various measured results. Precision is the fraction of positive samples that are accurately labeled (True Positive) relative to the entire amount of true specimens. A model's ability to avoid making erroneous predictions is measured by its level of accuracy. When the cost of false alarms is high, it's helpful to have a model to make accurate positive predictions. It is calculated by,

$$Precision = TP/TP + FP \quad (8)$$

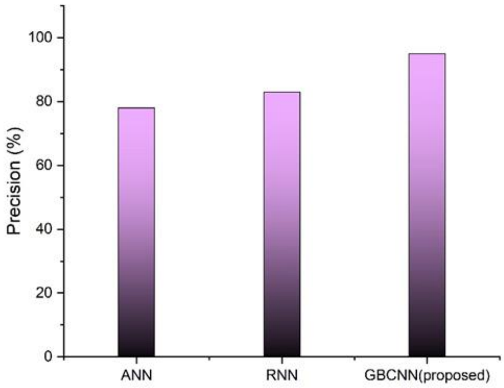

Fig.6. Precision of existing and proposed method

Table 2. Comparison of precision

Methods	Precision (%)
ANN	78
RNN	83
GBCNN(proposed)	95

The precision measures have comparable values, as shown in Table 2 and Figure 6. Compared to commonly used approaches like ANN (78%) and RNN (83%), the suggested method has a better precision of 95%. The system successfully predicts the false category for both real true and genuine false events. When a technique inaccurately indicates a true class, it generates a false positive. A false negative occurs when the method correctly predicts the negative course.

4.3 Recall

The recall is the fraction of true positives over the overall number of properly labeled positives. How well a model can identify positive samples is measured by its recall. More true samples are picked up as recall increases.is determined by dividing the total number of true specimens by the fraction of those correctly identified as Positive samples. How well a model can identify positive samples is measured by its recall. More true specimens are picked up as recall increases. It is calculated by,

$$Recall = TPTP + FN \quad (9)$$

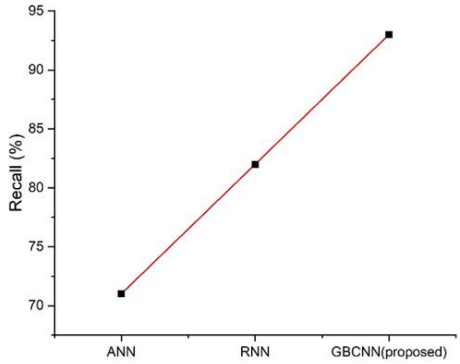

Fig.7. Recall of existing and recommended method

Table 3. Comparison of Recall

Methods	Recall (%)
ANN	71
RNN	82
GBCNN(proposed)	93

The proposed recall technique outperforms existing approaches, as shown in Figure 7, Table 3, and the accompanying image.

4.4 F1-score

A binary categorization model's accuracy in making accurate predictions is measured using the F-score or F1 Score. Precision and recall are used to arrive at this number. It's a metric that combines Precision and Recall into a single number. Since accuracy and recall are equally important, the F1 Score may be computed as the balanced average. It is calculated by,

$$F - Score = 2 \times (Precision \times Recall / \ Precision + Recall \quad (10)$$

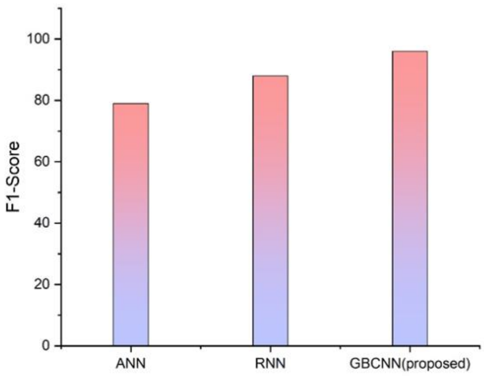

Fig.8. F1-score of existing and suggested method

Table 4. Comparison of F1-score

Methods	F1-Score(%)
ANN	79
RNN	88
CNN(proposed)	96

The GBCNN improves upon the present technique in terms of the F1-score rate. To facilitate comparison, the efficacy of the previous treatment is maintained at the same level across time, whereas the GBCNN procedure is kept fixed within a narrow band. Within its constant state range, the GBCNN technique advances with time. The comparative results are shown in Figure 8 and Table 4.

5. Conclusion

The present research employs UAV-captured photos and a DL technique of GBCNN to successfully identify flooded regions in urban infrastructure with an accuracy of 97%. The findings show significant improvements over the prior flood detection model when contrasted with current approaches. When applied to input photos, the method suggested in this study is able to identify and remove flooded areas accurately. It may be used in all cases of disaster management and utilized by aid agencies worldwide. To quickly select relief routes and deliver aid to those in need in the disaster zone, the model can assist in pinpointing the exact location of the emergency and reduce the region of search. As a result, the number of victims may be minimized, and the appropriate agency can begin rescue efforts immediately. Images obtained by UAVs in the flooded area are as helpful in assessing building damage as cropland. The rapid identification and localization of swamped regions made possible by this study will significantly aid post-flood relief efforts in underdeveloped nations. This method applies to places where floods occur regularly.

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