Flood Detection using Deep Learning Methods from Visual Images

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Abstract. Natural disasters cause devastation, chaos, destruction, death, displacement, and much more when they occur. With the advancement of recent technologies especially in artificial intelligence and deep learning, the severity and impact of natural disasters could be reduced by predicting their occurrence. In this research, the flood detection (using images) system is developed using the proposed architecture of the Deep Convolutional Neural Network (CNN). In this paper, the main aim is to propose an automated System for precision disaster detection, in particular flood detection. The intelligent system will monitor vast problematic areas that are dubbed flood risk areas during the season. The intelligent automated system will systematically take images with real-time processing to detect floods. If a flood is detected, the system will automatically communicate to the ground station with the early warning to issue an early warning to all the inhabitants in the path of the flood. Since this paper will prove a concept, the other main contribution of this paper is a new dataset consisting of 9000 images collected from various sources on the Internet, labeled, and preprocessed. The Deep CNN architectures were trained and tested by constructing a new dataset of more than 9000 labeled images with flood and non-flood collected from different sources. Several experiments are performed with changing CNN architectural design parameters in order to get the best recognition rates. Experimental results show that 92.50% accuracy was achieved using GoogleNet. The second highest performance was achieved using AlexNet with an accuracy of 92.20%.
Keywords. Flood Detection, Drone Flood Images, Deep Learning, Convolutional Neural Networks, GoogleNet

INTRODUCTION

Floods, droughts, hurricanes, tornados, and other natural disasters cause devastation, chaos, destruction, death, displacement, and much more when they occur. The best scenario for reducing the severity and impact of natural disasters would be to predict their occurrence. However, predicting natural disasters has never been accurate and thus natural disasters such as flooding occur with no warning and cause devastation along their path. If floods can at least be detected, then enough time would be available to issue warnings to the towns, houses, and inhabitants along the path so that they can evacuate. This early warning system can save human lives. With the recent advancement in Machine Learning Technology, it is now possible to analyze an image, detect a flood at its origin, and be able to issue early warnings to inhabitants along the path. The affordability of machine learning processing and even the imaging technology (using a drone with a high-resolution camera) makes such a system available even in poor third-world countries. In a 2015 report, Floods were in second place in the top 10 natural disasters by the number of victims after droughts. The number of victims of floods was reported to be 13.71 million people [1]. Studies have been done on the impact of accurate climate information and the role of early warning systems in reducing disaster risk and impact [2].

The added value of flood detection to the current systems in place for early warning can prove to be a comprehensive system that saves lives. The primary motivation of this work is to develop an intelligent machine learning-based system that integrates drone technology and is capable of real-time processing of images to detect floods. The development of such a system will reduce the impact of floods in the devastated areas by minimally ensuring that the inhabitants are evacuated before the arrival of the flood. Though such a system is helpless in reducing the environmental and economic effects of natural disasters, it is a crucial system for saving human lives.

In this paper, the aim is to propose an intelligent Drone System equipped with high-end precision cameras equipped with computing power to run image processing machine learning-based algorithms for precision disaster detection, in particular flood detection. The intelligent system will monitor vast problematic areas that are dubbed flood risk areas during the season. The intelligent system will systematically take images with real-time processing to detect floods. If a flood is detected, the system will automatically communicate to the ground station with the early warning so that early warning can be issued to all the inhabitants in the path of the flood. The proposed system will be a result of a thorough investigation and exploration of different flood detection techniques proposed in the extant literature. It should be noted here that the work in this paper is for proof of concept and thus the dataset designed consists of 9000 images from various sources from the Internet and not necessarily images taken by drones, However, most images are taken from elevated positions similar to those that would be taken by drones.

The main contributions of the paper can be summarized as follows:

- Create a new dataset of flood and no flood images consisting of 9000 images gathered from various serious from the internet.
- The dataset was labeled and preprocessed.
- Proposing an automated system that could potentially be fitted on an elevated area or on a drone to automatically detect floods and give early alerts when floods or potential floods are detected.
- Testing the proposed system and new dataset using various deep learning algorithms.

The rest of the paper is organized as follows: Section 2 highlights the main literature review in the field. Section 3 gives a description of the dataset used in the paper, while section 4 details the methodology. Section 5 details the results and discussion, while section 6 concludes and presents future work. The references are listed in section 7.

RECENT LITERATURE

The real-time detection of floods or accumulated water bodies that are potential flood origins is crucial in order to evacuate inhabitants who are in danger. This early warning can also lead to the mitigation of both the impact and severity of this natural disaster. Meteorology is a developed science and a lot of research has been done on the prediction of floods. However, there are many challenges in predicting floods and other natural disasters that are still not resolved [3-4]. In addition, the technology for data collection used in prediction systems is not always readily available, especially in struggling third-world countries which are usually where floods occur and where the flood greatly impacts the environmental and economic aspects of these countries the most. In floods, people die, others are displaced, lands are ruined, and homes & farm crops are completely eradicated. Time is of the essence when floods occur because even though it might not be possible to save homes or crops, with enough early warning, human lives can be saved and that is the most important. Studies have been done on the impact of accurate climate information and the role of early warning systems in reducing disaster risk and impact [2]. The extant literature contains research done on various detection techniques.

In [5], the authors propose the use of some machine learning methods and deep learning for real-time flood detection. They used a small dataset that contains only text data. With this small dataset, they reported 98.7% accuracy using the Random Forest (RF). They also reported accuracies of 88.4%, 84.2%, and 87% for Naïve Bayes (NB), J48, and deep learning approach respectively. In [6], the authors propose the use of unmanned aerial vehicles (UAV) imagery along with convolutional neural networks (CNN). They collected images that are UAV-based or from Google Earth. Their final dataset consisted of 10 subsets for training each containing 2150 patches, and 14 set for testing also each containing 2150 patches. They reported an accuracy of 91% in flood detection. In [7], the authors propose a deep learning methodology for flood detection from social media posts. Their proposed model utilizes CNN-based methods for visual feature extraction and a bidirectional Long Short-Term Memory (LSTM) network for semantic feature extraction. They used a dataset from the MediaEval 2017 Multimedia Satellite Task which contains 6600 images extracted from the YFCC100M-dataset. They report poor results of 66% when using images only, 70% when using metadata only, and an improvement of 84% accuracy when they combined both image and metadata information. In [8], they propose a flood-detecting and risk assessment method using multispectral remote sensing data that is provided by SPOT-5 imagery. The report on the possibility and efficiency of using the new type of dataset and the integration of CNN methods. In [9], the authors propose a method to utilize Closed Circuit Television (CCTV) images to detect flooding within cities especially when the sewage system is not equipped for flooding. They developed their own dataset which consisted of 350 CCTV images. They proposed the use of SegNet which is a deep encoder-decoder architecture for the classification process and reported an accuracy between 91.1%-94.3% depending on the camera angle. In [10], the authors propose a deep learning method to predict the flood level severity from video images captured by the inhabitants of the flooded area. They developed their own dataset from scenes in YouTube videos, social media videos, CCTV videos, and others. The final dataset consisted of 749 videos between 10 to 20 seconds each. They also labeled the videos into four categories; low, moderate, high, and very high. They propose the use of gated recurrent (GRU) units and VGG16. They reported an accuracy of 70%. In [11], the authors describe their approach to two tasks dealing with flood image retrieval and flood detection as part of their participation in the

MediaEval 2017 workshop. For flood detection, they employed CNN with 6 dilated convolution layers. The highest accuracy they achieved was reported to be 88.23%. In [12], the authors introduce the concept of populating the datasets using CycleGAN augmentation in order to account for various conditions in flood images; daylight, night, noise, etc. They use residual networks for classification in particular the ResNet50. They reported an accuracy of 86.4% with their proposed method. In [13], the authors analyze and evaluate state-of-the-art existing CNN models used for disaster image classification and proposed an efficient and lightweight CNN model called EmergencyNet for the classification of disaster events using UAV. The proposed model gives ~95.7% of accuracy on low-cost/power devices with multi-resolution images. They developed a large dataset from various sources such as google images, and YouTube using different tags like Ariel view, UAV, or drone. In [14], the authors propose a deep learning model for the classification of high-resolution images obtained from satellite imagery. Due to the nature of the dataset, the proposed system combines both metadata and image features. They used the IARPA functional map of the world (FMoW) dataset which contains 23 classes. Their system has a total accuracy of 83% and is capable of classifying 15 of the classes with an accuracy of 95% or higher. In [15], the authors analyze the existing models used for classifying water/ice/land regions and proposed a new model by employing the light variant of the UNet deep CNN structure with an expanded CNN layer. 32 Landsat-8 images were used for training and 5 images for testing and validation which were randomly collected from different parts of the globe. The proposed method was compared with existing methods for different locations and it performed better according to the metrics used. In [16], the author proposes a hybrid machine learning method for the classification of aerial images of flood-hit areas. The hybrid approach is a combination of both Support Vector Machines (SVM) and K-mean Clustering. 92% accuracy was reported. The dataset used consisted of 200 Ariel images; 100 of flooded areas and 100 of flood-free areas. In [17], the authors propose the use of densely connected recurrent neural networks which is a combination of CNN and Recurrent Neural networks (RNN). Applied to UAV aerial images of Houston TX, the authors report an accuracy of 96%.

Machine learning can be utilized to help the environment whether for environmental monitoring, environmental protection, or the early warning system. There are many possibilities to integrate the use of machine learning in environmental studies as well. In [18], the authors explain the methods of using machine learning for regulation enforcement for environmental protection. Predictive analysis can be used at facilities to test for water pollution levels. Machine learning can assist in automatic monitoring systems without human intervention which is vital for monitoring agencies. Machine learning is being integrated not only into environmental studies but also into many other sciences whether agriculture [19] or maritime [20], Medicine [21], and all other fields.

EXPERIMENTAL DATASET

For the development of this system, a new dataset was constructed from various sources such as google images and different internet sources. This dataset consists of 9,000 labeled images and sample images are shown in Figure 1. Out of which 5000 thousand flooded and 4000 are non-flooded. The images were RGB images with different dimensions which led to the need for preprocessing the images before feeding them to the network. The total number of output classes is 2 that range from 0 to 1 each representing either flood or No-Flood.

Flood No Flood

FIGURE 1. Samples of Flood and Non-Flood images taken from newly constructed dataset.

Before feeding the dataset to the network, all images are transformed to grayscale 256x256 dimensions to get rid of the extra processing needed for 3 color channels in RGB images. All images were normalized so that the pixel values range from 0 to 1. The dataset was reshaped to meet the format requirements so that it can be fed to CNN. As mentioned, the data set was partitioned into training, validation, and testing sets. This partitioning was done for cross-validation which is a statistical approach to evaluating the performance of Machine Learning (ML) algorithms. The Hold-out cross-validation technique was used which basically splits the data set into three mutually independent sets. This technique is commonly used due to its efficiency and ease of implementation [22]. Since there is a clear guiding rule on the percentage by which the data set is partitioned, one of the commonly used partitioning percentages was selected in this study, which is 20% for testing and 80% for the training set of which 20% is taken for validation.

METHODOLOGY

Due to recent development and success stories of deep learning algorithms in computer vision, we will use CNN which is the most well-known and broadly used in many applications based on [23-25] in identifying and classifying images. The main objective of this research is to design a deep-learning CNN model that would detect floods based on a provided dataset of drone images with a high level of accuracy. The preliminary design of the proposed CNN model would be based on two key layers; convolutional and pooling. A pooling layer will be placed after every convolutional layer [26]. The activation functions are normally used to give the model the ability of nonlinearity, get fitted results, and most importantly get improved accuracy. Therefore, Rectified Linear Unit (ReLU) and Softmax activation functions would be used to get appropriate results. The initial high-level design of the proposed architecture is shown in Figure 2.

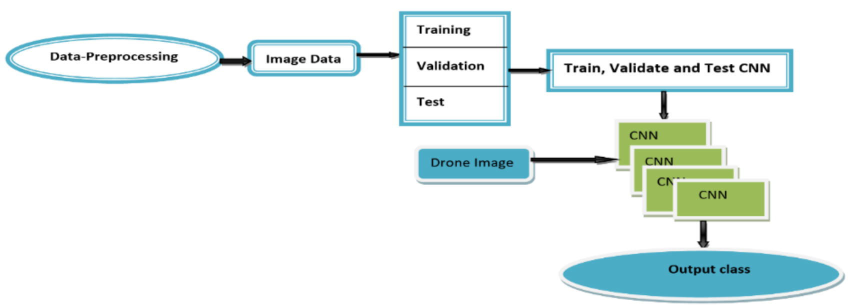

FIGURE 2. Proposed system architecture

Convolutional Neural Networks (CNN)

Recently Computer vision played a significant role in obtaining remarkable results in the success of health care, self-driving cars, or retail which was considered impossible previously. Convolution neural network (CNN) is a major building block behind all these achievements. There are many other applications of CNN, especially in image processing that include image classification, semantic segmentation, and object detection. The success of CNN is evident in the fact that major companies like Facebook, Microsoft, and Google deployed CNN in their products and services. The deep learning community developed several CNN architectures which include VGG16, ResNet, Inception and Xception, MobileNet, SqueezeNet, ShuffleNet, and Efficient Net [27].

In essence, CNN is a regularized multilayer perceptron. The majority of the time, multilayer recognitions are complicated systems that are fully coupled. All of the neurons inside the layer here are connected to the neurons in the layer above. Because they are "complete networks," these systems are more prone to preferring information overfitting. CNN, on the other hand, adopts a novel strategy for normalization by using fewer and simpler calculations to produce the desired outcomes. CNN is therefore rated at the lower end of the network and complexity scale. Similar to native neural systems, CNN models can be configured to operate in a parallel framework where adjacent neural units are allowed to communicate with one another. The typical architecture of the CNN model is shown in Figure 3.

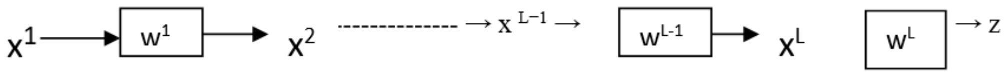

FIGURE 3. A typical architecture of CNN

where x^1 goes to the processing layer with parameters w^1, w^{L-1} is SoftMax transformation. The last layer is as loss layer. If *t* is the ground truth for input x^1 then the loss function z will show the difference between *t* (target) and x^L (prediction) as shown in the below Equation.

$$z = \frac{1}{2} \parallel t - x^L \parallel$$

CNN is trained in two phases, the forward-propagation phase, and the back-propagation phase. Forward-propagation phase is shown in figure 3. Whereas the back-propagation phase starts when the output result is calculated or predicted. In, back-propagation, the weights are updated after finding the minimum value of the error function using gradient descent.

Proposed CNN Model

CNN is designed in such a way that it should have two stages. The first stage objective is to obtain initial reading results that will guide us in the next experiments based on Figure 2. On the bases of the initial results, more experiments are done in the second stage by changing different design parameters in order to come up with the most suitable design for the proposed flood detection system. The convolution operation is performed leading to the pooling layer in reducing the number of computations needed in the training process by reducing the dimension of the image, and therefore the overfitting problem is accounted for.

As shown in Figure 4, the proposed model is based on GoogleNet [28], where the images are input to the first phase consisting of the convolutional layer, max-pooling layer, followed by another convolutional layer, and max-pooling layer. Two inception layers are then integrated followed by a max-pooling layer. Thereafter, four inception layers are integrated followed by a max-pooling layer. Finally, we integrate two more inception layers followed by the average pooling layer. This GoogleNet architecture has the computational efficiency achieved through the minimization of the input images while still keeping the most important spatial features. The max-pooling layers are responsible for down sampling the input through the minimization of both the width and height of the input data.

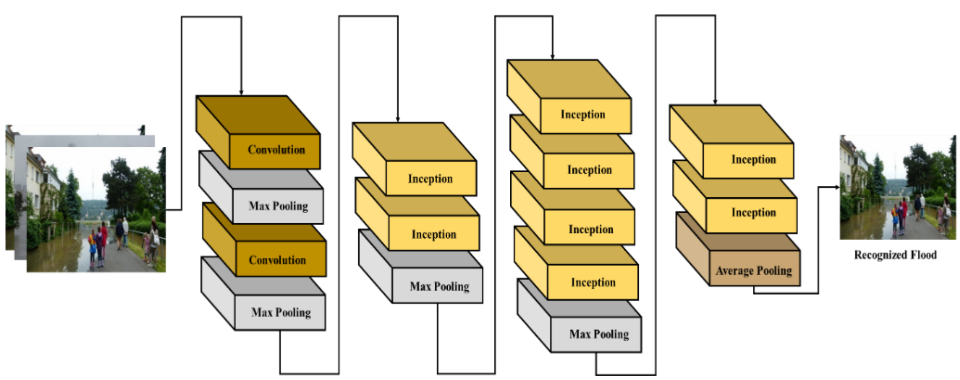

FIGURE 4. GoogleNet CNN Model Architecture with the Inspection Layers

RESULTS AND DISCUSSIONS

To address the imbalance of two classes metrics that are sensitive to imbalanced class distribution is uses such as Recall, precision, and F1-score. The experiments are performed for 100 epochs with batch size of 32 and learning rate of 0.01. The experimental data obtained during the experiments are displayed in Table 1. With an accuracy of 92.5%, precision of 95.90%, recall of 88.8%, F1-Score of 92.21%, and specificity of 96.2%, it is clear that GoogleNet achieved the best accuracy.

The performance of AlexNet [29] was comparable to that of GoogleNet, although GoogleNet still had the best accuracy. The average classification accuracy, precision, recall, F1-score, and specificity for AlexNet were 92.2%, 90.2%, 90.58%, and 94.2%, respectively. As seen in Table 1, LeNet [30] and CNN basic architecture underperformed.

TABLE 1. Comparison of the experimental Results for Different CNN based Models

Method	Accuracy	Precision	Recall	F1-score	Specificity
GoogleNet	92.50%	95.90%	88.80%	92.21%	96.20%
AlexNet	92.20%	90.58%	94.20%	92.35%	90.20%
LeNet	61.80%	60.65%	67.20%	63.76%	56.40%
CNN [26]	65.20%	65.20%	64.80%	65.06%	65.60%

The GoogleNet confusion matrix is displayed in Figure 5. The classification of Flood for 88.8% of the photos matches the actual situation. The ground truth and the classification of No-flood for 96.2% of the photos agree. Just 3.8% of flooded photos and 11.2% of non-flooded images were incorrectly classified.

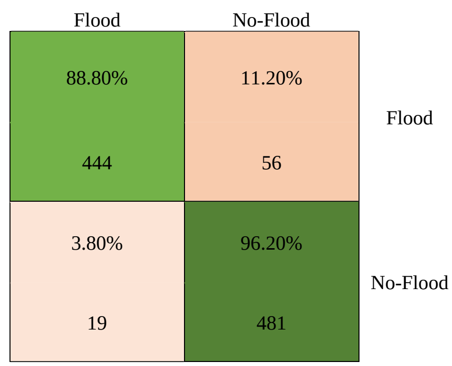

FIGURE 5. Confusion Matrix of the Flood and no-Flood detection using GoogleNet Model

The 110 iterations of the GoogleNet model's training accuracy and validation accuracy are trended in Figure 6. It is noted that the graph's trend, which is expanding rapidly and reaching saturation, is exactly what is expected of a successful model and demonstrates that the overfitting and underfitting issues were taken into consideration.

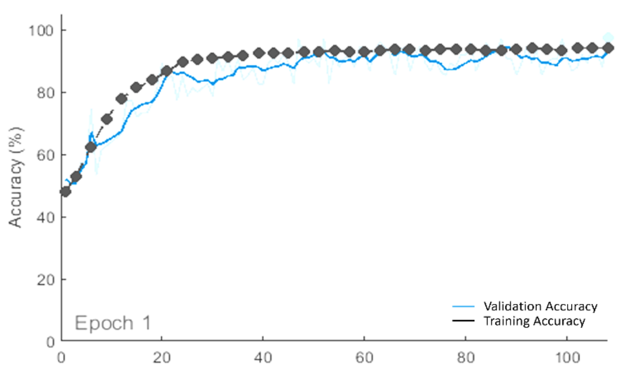

FIGURE 6. Comparison between Training Accuracy and Validation Accuracy for 110 iterations of the GoogleNet Model.

Figure 7's result demonstrates yet another outcome demonstrating the model's suitability and ability to account for both overfitting and underfitting. Figure 7 displays the GoogleNet model's 110 iterations' training loss and validation loss. The graph's trend, which shows how the iterations go closer and closer to 0 until reaching a steady position, is exactly what is expected of a solid model.

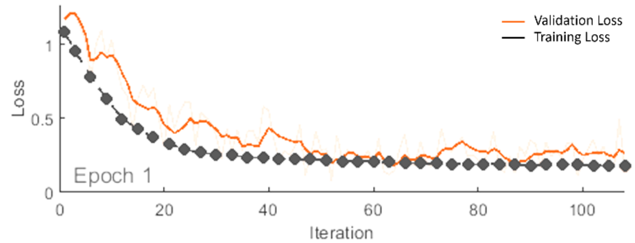

FIGURE 7. Comparison between Training Loss and Validation Loss for 110 iterations of the GoogleNet Model.

CONCLUSION AND FUTURE DIRECTIONS

The experimental results show that GoogleNet achieves an excellent accuracy of 92.5%. The flood detection system is intended to utilize several technologies such as Drone Technology fitted with Raspberry PI capable of computing power for taking real-time images and either processing them locally or sending them to a ground station that can process them in Realtime using CNN models to classify and detect flooding. The early warning might be instrumental in saving the lives of humans, and animals, or even saving possessions. With early warning, the population in the path of the flood could be warned so that they can evacuate the area well before danger arrives. In this work, we constructed a dataset from multiple sources. The resulting dataset consisted of over 9,000 images of which 9,000 were labeled as flooded. Before feeding the dataset to CNN it was preprocessed as detailed. Now that we have constructed a dataset and tested it using various CNN models, we can continue expanding the dataset and use it for further research in the field. One of the main objectives we have in the future is not only to classify flooded and non-flooded areas but to also be able to predict floods before they occur based on images and other related data. Flood prediction will offer advantages far beyond what is stated in the current research because it will give residents and governments enough time to take real action that can save both lives and property. We also plan on developing machine learning and deep learning combinations that can produce better accuracies than stated in the current work.

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