Deep Flood: Leveraging Deep Learning for Predictive Flood Inundation Modeling and Disaster Management Preparedness

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Abstract

Deep Flood is an integrated approach that incorporates diverse techniques to accurately predicting the floods and assisting requests and streamline coordination by supporting disaster management .By leveraging a wide array of datasets , including historical flood news, rainfall records, image segmentation and spatial data sourced from government portals , open projects and research , the model ensures the robustness and reliability. Furthermore, we develop a user-friendly portal for real-time flood updates and user-initiated assistance for emergency and disaster preparedness initiatives.Through a comprehensive review on existing literature ,this paper outlines the methodology, presents results, and discusses the implications of our approach.

Keywords:

Deep Learning , Image Segmentation , Alert System

1. INTRODUCTION

Floods remain one of the most devastating natural calamities, inflicting widespread damage to infrastructure, claiming lives, and triggering economic crises.Flood-prone communities, e.g. coastal cities, experience frequent flooding due to storm surge, heavy rain, and sea level rise.Conventional flood prediction methods often rely on historical rainfall data and hydrological models, which may lack the granularity and accuracy needed for timely interventions.However, recent advancements in image segmentation and deep learning have opened new avenues for improving flood forecast accuracy. Integrating these technologies with real-time flood news data can provide valuable insights into evolving flood scenarios, enhancing the effectiveness of early warning systems and disaster preparedness strategies.

Earlier literature in flood detection has mostly focused on using satellite imaginary and remote sensing information which does provide high level details regarding scenarios but lacks the proficiency with local details like severity , depth of floodwater on specific road segments and Video surveillance methods analysis.Addressing these limitations requires innovative approaches that leverage diverse data sources and advanced analytical techniques.

The identification of floods by the detection of water regions in photos and movies has been researched in a variety of contexts. In order to guide unmanned vehicles, researchers spatiotemporal information and employed probability models to identify water in videos. Furthermore, the detection and classification of ground-level floods received considerable attention recently. Certain approaches entail the utilization of threshold techniques in order to approximate and calculate the depth and extent of floodwater. Others have suggested using deep learning techniques to classify flood photos by fusing textual data and photos from social media. Studies have also looked at techniques that contrast photos taken prior to and following floods.Dry-flood image comparison-based models use hand selected parameters and compare them with each flood location.

In this paper, our main contributions are:

1.1 Development of an Image Classifier System :

As a critical step towards efficient disaster management, we created an image classifier system in our study to differentiate between photographs of floods and images of dry conditions. We investigated the effectiveness of traditional machine learning techniques as well as deep learning—more especially, MobileNet architecture—for feature extraction..

1.2 Rainfall Prediction System :

We use the Recurrent Neural Network (RNN) model for getting insights of rainfall patterns within a dataset encompassing seasonal, monthly , annual and sub-divisional regions of India. Through this analysis, we sought to examine the effectiveness of RNN models in accurately forecasting rainfall, thereby contributing to advancements in weather prediction methodologies.

The dataset comprises thousands of labeled images sourced from various locations with diverse characteristics. These images were obtained from multiple repositories, including Kaggle, data.gov, and an open-source project, to facilitate further research in image classification and flood area segmentation tasks.

For the classification task, we used the following methods for feature extraction: keras pretrained MobileNet CNN deep learning network which is fine-tuned particularly for flood detection. Various deep learning techniques were employed to optimize precision , including Recurrent Neural Network (RNN),Long Short Term Memory (LSTM), and CNN for feature extraction in rainfall prediction model . .Detailed descriptions about these methods are provided in Section II.and III,followed by sample images and briefly discussion on dataset .The Proposed Architecture section outlines the procedures for model training, while Section IV offers a summary of the models' performance and accuracy.

2. BACKGROUND

The existing body of literature indicates that neural networks are an effective approach for rainfall prediction due to their capacity to capture intricate, non-linear relationships among meteorological variables and rainfall patterns. Numerous studies have demonstrated neural networks have the capacity to overcome limitations of machine learning techniques. Nonetheless, the selection of neural network architecture and input variables majorly depend on selective features ,specified problem and dataset.Ensuring the accuracy and dependability of predictions entails thorough data pre-processing and rigorous model evaluation procedures.

Several crucial parameters that influence the rainfall prediction models. These include the historical weather data used for training the algorithms, the choice of climate variables considered for prediction, and the specific location targeted for forecasting. Recent research trends mainly focus on two main aspects: investigating relationships between different weather features and prioritizing the quality of data used to train prediction models.

To uncover hidden patterns that affect the accuracy of rainfall predictions researchers majorly rely on using deep learning techniques. This acknowledgment arises from the understanding that meteorological datasets contain numerous concealed patterns that can influence prediction outcomes. The standard process of selecting a neural network consists of three key stages. Firstly,exploring the algorithms which can be best fit based on the characteristics of the dataset. Next, researchers focus on designing the model framework that complements the chosen

algorithm. This step involves structuring and refining the model to maximize its performance in line with the selected algorithm. Finally, researchers employ various evaluation metrics, optimizing learning methods, making changes in batch size , dense layer or dropout to quantitative precipitation forecasting and rigorously assess the performance of the developed models.

In summary, understanding and addressing these factors and processes are essential for advancing rainfall prediction techniques and enhancing the accuracy and reliability of predictive models.

2.1 MobileNet CNN for Classification Tasks:

Convolutional neural network architecture known as MobileNet was created especially for embedded and mobile vision applications. It is renowned for having an effective structure that is lightweight, making it appropriate for deployment on devices with limited resources. Depthwise separable convolutions, which drastically lower computing costs without sacrificing speed, are how MobileNet becomes so efficient.When it comes to image categorization, MobileNet CNN reliably assigns labels or classes to images, offering insightful information about the images' contents. Additionally, Mobile Net CNN divides images into discrete areas or segments according to semantic resemblances, facilitating in-depth examination and comprehension of image content.Our research aims emphasize the effectiveness of MobileNet CNN in achieving high accuracy and performance while sustaining computational efficiency to minimum cost. The study proves that MobileNet CNN can be a trustworthy and reliable model for image analysis tools, with intriguing prospects for use in a variety of domains.

2.2 Optimizing Image Analysis: Transfer Learning & Fine-Tuning Pretrained MobileNet Using Keras

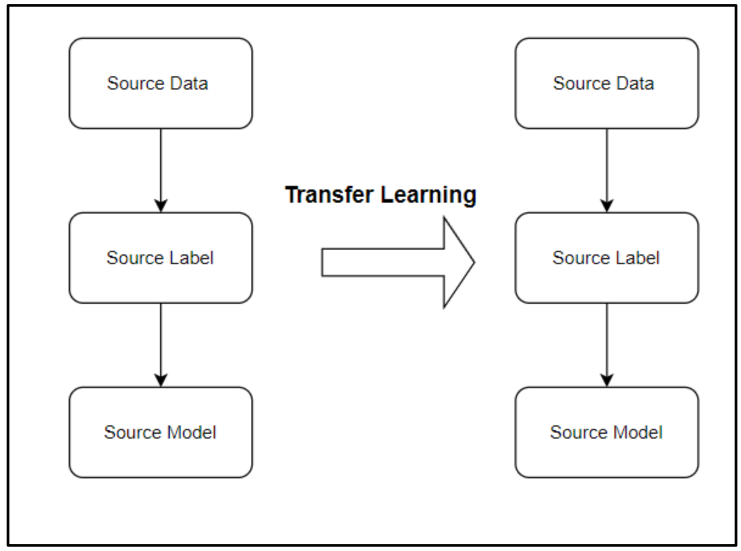

Fig 1. Knowledge Transfer process in Transfer Learning

The aim of the model is to create a valid and precise image classification system that can identify instances of flooding by utilizing Keras to refine the pretrained MobileNet model by using transfer learning using a fine-tuning process, specifically focusing on image classification for detecting flooding and non-flooding scenarios. Initially, the MobileNet model is pretrained on a large dataset to learn general features from diverse images. However, to adapt the model to the specific task of classifying images into flooding and non-flooding categories, fine-tuning is necessary.

The computational layers of the pretrained MobileNet model are retained and used as a feature extractor during fine-tuning, while the final classification layers are changed and trained using the updated dataset. The new dataset consists of pictures that have been labeled as showing floods or not. By means of fine-tuning, the improved MobileNet model enhances its performance for this particular classification job by learning to differentiate the features that separate imagery.

Keras is a Python-written high-level neural network API which has the capability of executing on top of TensorFlow, Theano, or Microsoft Cognitive Toolkit (CNTK) for a framework. Developers can easily prototype and test various designs with Kera's user-friendly interface for creating and training neural networks.

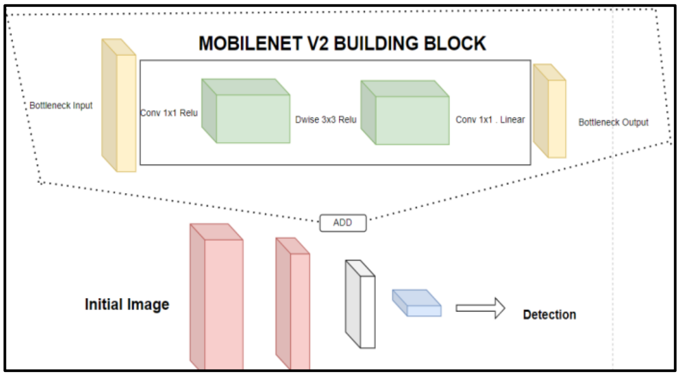

Fig 2. Architecture of MobilenetV2

3. DATASET

The image classification dataset comprises labeled images depicting both flooding and non-flooding scenarios. Every image has a matching mask to identify areas affected by flooding, making accurate categorization easier. To guarantee data integrity and relevance for analysis, the dataset has undergone rigorous preprocessing and cleaning methods.

Description: This table presents the image classification dataset used in the research study. The dataset consists of a total of 2,100 images, with 600 images depicting flooding scenarios and 1,500 images representing non-flooding scenes. Each image is accompanied by a corresponding mask, denoting the flood-affected areas within the image. The availability of masks facilitates precise classification and analysis

Image ID	Image Type	Mask Available
1	Flooding	Yes
2	No Flooding	Yes
…	…	…

Fig 3 : Image Classification Dataset Overview

Description: The table above showcases the rainfall prediction dataset of historical rainfall data that was obtained from the Indian Meteorological Department's (IMD) official website. The dataset, which spans more than a century from 1905 to 2017, contains monthly precipitation measurements, annual rainfall totals, and seasonal features for several states and subdivisions measured in millimeters (mm). Prior to analysis, the dataset has undergone thorough cleaning and preprocessing to ensure data accuracy and reliability.

Year	Seasonal	Subdivision	Monthly	Annual	ID
1905	Sumer	Punjab	…	3373	01
1905	Winter	Punjab	…	3079	02
…	…	…	…	…	03
2017	Winter	West Bengal	…	3282	…

Fig 4 : IMD Rainfall Summary

4. PROPOSED ARCHITECTURE

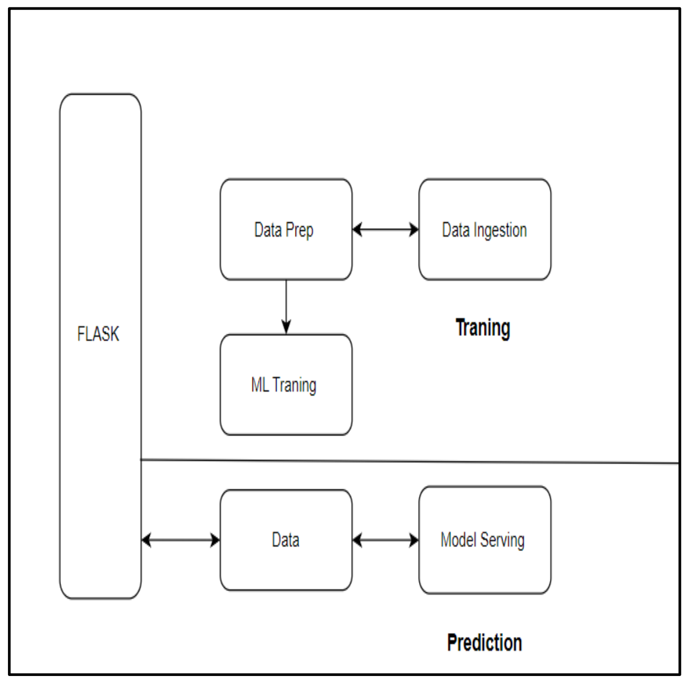

Fig 5 : Model and UI Application Design

We explain our application basic design in this part. The objective of our project is to create a forecasting algorithm that can estimate the total amount of rainfall that will occur in a year. Two main parts make up our application :MobileNetV2 architecture and a Simple Recurrent Neural Network (RNN).The foundation for temporal feature extraction is the Simple RNN, which makes it possible to find and examine relevant patterns in the sequential data. Because it is recurrent, feedback loops can be included, which makes it easier to model the temporal dependencies present in time series data.Conversely, the MobileNetV2 architecture is used because of its superior performance in applications related to picture categorization and prediction. MobileNetV2, a form of convolutional neural networks (CNNs), is highly effective in processing and extracting relevant characteristics from visual data.

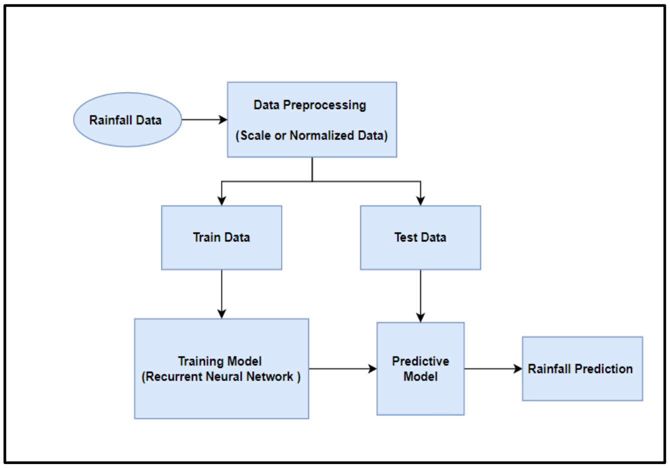

Fig 6 : Rainfall Prediction Model

In feed-forward neural networks (FFNNs),output of every single layer is computed independently of previous outputs. Thus, limiting their ability to capture temporal dependencies.Conversely, Recurrent Neural Networks (RNNs) excel in time series prediction tasks due to their inherent memory connection.In RNNs, the current state (Ct) is decided by both output of the previous time step (Ct-1) and new output.This recursive analogy allows RNNs to sustain and utilize information from past time steps.

The formula to compute the current state (ht) in RNNs is represented by Equation 2:

$$ht = g(ht-1,Xt)$$

where ht represents the current state, ht-1 is the output from the previous state,xt is the new input at time step t, and g is a recursive function. The activation function used for the hidden layers is ReLU, which helps in processing the input and previous state information:

$$ht = ReLU = (wh * ht-1 + wx * xt)$$

Here, wh and wx denotes weight associated with recurrent and input neurons respectively.

For output layer, a linear activation function is applied to determine the output (yt) at each time step:

$$yt = wy * ht$$

Here , yt represents the output and wy denotes the weight at output neuron.

In the context of rainfall data spanning over a century, RNNs are well-suited to capture temporal patterns and dependencies inherent in the data. By leveraging the memory capability of RNNs and incorporating ReLU activation for hidden layers and linear activation for the output layer, we can effectively model and predict rainfall variations over time, facilitating accurate and reliable forecasting.

In order to provide real-time updates, the system continuously monitors weather forecasts and aerial photos. This allows for a smooth workflow. The system's scalability is supported by a cloud-based infrastructure, which makes deployment across many geographic locations simple.

The research presents a sophisticated alert system engineered to automatically dispatch email and SMS notifications in response to potential flooding events. This system harmonizes predictive modeling and aerial image analysis, triggering alerts when both the rainfall prediction model and flood detection algorithm signal heightened risk levels.

Using the smtplib package, the system carefully crafts alerts by meticulously including location information and suggested safety precautions. To make sure that routes of communication are effective, contact information of users is routinely gathered. Then, notifications are sent via email and SMS, which are made possible by the SMS gateway APIs and the smtplib.SMTP protocol, respectively.

To summarize, our alert system demonstrates a proactive approach to flood risk management by skillfully utilizing cutting-edge technologies to provide users with timely and accurate information.

The application is designed to provide users with real-time flood news updates sourced from various online platforms. To achieve this, we employ web scraping techniques such as BeautifulSoup, TextBlob, and others. These tools allow us to extract relevant information, including news article titles and brief descriptions, from websites like Floodlist, Open Weather, India-Water, IMD, and others.

After gathering this information, the application highlights the news updates on its interface so that users can remain up to date on the recent developments concerning flooding incidents. Every news update usually consists of a headline or title that summarizes the content of the story and a short explanation that adds further background information.

If users find a particular news item of interest, they have the option to click on it for more details. Upon selecting a news update, the application can redirect users to the corresponding webpage where the full article is hosted. This enables users to access comprehensive information about the flooding event from reputable sources directly.

5. RESULTS

In this section, we summarize our test results.For image segmentation we have used precision, recall and F1-scores as performance measures which are derived from the confusion matrix. On the other hand, rainfall prediction we have used mean absolute error , mean absolute percentage error and accuracy to measure performance of the model

5.1 Analysis of Test Result : Image Segmentation

		Prediction	
		$\hat{y} = 0$	$\hat{y} = 1$
True label	y=0	True Negative	False Positive
	y=1	False Negative	True Positive

Fig 7 : Confusion Matrix for Image Segmentation

Precision = True positives / True Positive + False Positive

Recall = True Positive / True Positive + False Negative

F1 = 2 * Precision * Recall / Precision + Recall

Metrics	Value
Precision	96 %
Recall	98 %
F1	98 %

Fig 8 : Performance Measures of Image Classification

These metrics demonstrate the high precision, F1 score, and accuracy of our segmentation model in accurately identifying flooded areas within images. The precision of 0.9615 indicates that the model correctly identifies flooded pixels 96.15% of the time, minimizing false positives. The F1 score of 0.9804 highlights the balance between precision and recall, with a value close to 1 indicating excellent performance. Moreover, the high accuracy of 0.9853 reflects the overall effectiveness of our segmentation model in accurately classifying flooded and non-flooded areas.

5.2 Analysis of Test Result : Rainfall Prediction Model

Metrics	Value
Mean Absolute Error	0.156
Mean Absolute Percentage Error	0.000106
Accuracy	99 %

Fig 9 : Performance Measures of Rainfall Model.

Our analysis reveals that the predictive models achieved a low MAE of 0.156, indicating that, on average, the models' predictions deviated from the actual values by 0.156 units. The MAPE value of 0.00% signifies that the predictions had an excellent relative error of 0.00 %. Furthermore, the accuracy of 99.9% highlights the model's ability to make correct predictions in all the cases.

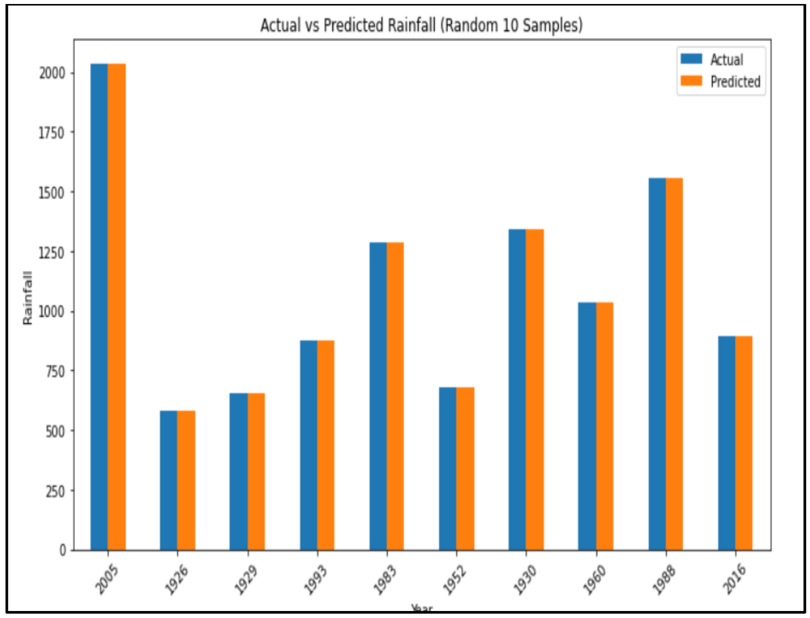

Fig 10 : Comparison between Actual VS Predicted Rainfall Data.

5. CONCULSION

In this research paper, we employed image classification and rainfall prediction to study flood inundation. Furthermore, we proposed an integrated approach that incorporates flood news and a message alert system.As further work, we will investigate extracting more information from the floodwater such as flood severity level and water depth estimation and work on improving the model for water reflection cases [1].Considering more deep learning techniques and new features such as (landslides) which is one of the major negative consequences of flooding , crop harvesting and its impact due to floods and how we can prevent this by taking proactive measures to take minimum damage from disaster.

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