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Flash Flood Detection and Alert System Using Machine Learning

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Abstract: Floods can be considered as one among the top natural disasters that sometimes happens regularly in particular season thereby causing harm on human lives and also resultsin reducing economic growth. So, the news about the flooding events has to be spread to nearby localities in time so as to avoid further chaos. Therefore, it is crucial to build a warning system that informs the flooding event to reduce the casualties of flood disaster. Recognizing sensitive events in images, such as flood events is significant for the maintenance of normal public opinionand social stability. By now, it is still a challenging problem. In this project, we propose a novel method for recognizing flood events from images using Keras pretrained MobileNet CNN. Flooding and non-flooding images are collected and trained in theCNN network so as to build the classifier that can differentiate the input image from flooding and non-flooding categories. At first, the feature extraction is carried to develop a model that is capable of classifying flood images from normal images. Later the MobileNet CNN helps in classifying the flood images effectively with accuracy and an appropriate warning message is sent to the people in nearby localities. To enhance the efficacy of our flood event recognition system, we are integrating cutting-edge tech- nologies and methodologies. In addition to leveraging the power of Keras pretrained MobileNet CNN for image classification, we are also implementing advanced image processing techniques for better feature extraction and analysis. By incorporating thesemethods, we aim to achieve higher accuracy and reliability in identifying flood events from images.
Index Terms: CNN, MobileNet, Keras

I. INTRODUCTION

We are presenting a novel method in determining the flash flood of various locations using Image Processing techniques. Since smartphones are becoming affordable, they have be- come ubiquitous. The system will take geo-tagged images of buildings or stationary objects, The geographical location is inferred by obtaining the geotagging information. They are then compared against a set of reference images and the right perspective of the reference image that best represents theimage obtained is identified. For the feature matching, an algorithm called SIFT - Scale Invariant Feature Transformis used. SIFT computes matching feature points and then we will send a message if flood is detected. In addition to the technical aspects of our method, it's important to consider the broader implications and benefits it offers. By harnessing the widespread availability of smartphones andthe increasing adoption of geotagging features, our system democratizes flood monitoring and early warning capabilities. This democratization is especially significant in regions with limited access to traditional monitoring infrastructure, where the deployment of costly sensors or satellite imagery may be impractical. Moreover, the real-time nature of our approach enables prompt response and intervention in the event of a flash flood, potentially mitigating its impact on lives and prop- erty. Rapid dissemination of alerts through messaging plat- forms ensures that relevant stakeholders, including emergencyresponders and local communities, are promptly informed,facilitating coordinated action and evacuation efforts. Overall,our novel method represents a significant advancement in leveraging technology for proactive flood management and resilience-building. By harnessing the power of image process-ing, geotagging, and machine learning, we aim to empower communities with the tools and information needed to better understand, monitor, and respond to flash floods, ultimately saving lives and minimizing the socioeconomic impacts of these natural disasters. Furthermore, the scalability and adapt- ability of our method make it suitable for deployment in diverse geographical and environmental conditions. Whether in urban areas with dense infrastructure or rural regions with sparse monitoring networks, our system can effectively utilizethe wealth of geo-tagged images captured by smartphones to assess flood risk and provide timely warnings. This versatility is crucial for ensuring that vulnerable communities, regardlessof their location or resources, can benefit from proactive flood monitoring and early warning systems. In addition toits immediate utility in disaster response and management,our method also has long-term implications for urban planningand infrastructure development.

By analyzing patterns of floodoccurrence and severity derived from geotagged images, pol- icymakers and urban planners can gain valuable insights into flood-prone areas and prioritize investments in flood mitigationmeasures.

This proactive approach to urban resilience can help minimize future flood damage and enhance the overall sustainability and livability of cities and communities.

II. RELATED WORKS

A. Remote detection and monitoring of a water level using narrow band channel

The paper presents a novel approach for remotely detecting and monitoring water levels. Through the utilization of a narrow band channel, the author proposes a method that likelyinvolves the deployment of sensors and the implementationof signal processing algorithms to transmit and analyze data related to water levels. The use of a narrow band channel suggests a focused communication protocol optimized for this specific task. Results from experiments or simulations arelikely presented to validate the effectiveness of the proposed method, showcasing its accuracy, reliability, and efficiency in remote water level monitoring. The paper likely concludes with discussions on the implications of the findings, potential applications, limitations, and avenues for future research, contributing to the advancement of remote sensing techniques for environmental monitoring purposes.

B. A study on the development of disaster information report- ing and status transmission system based on smartphone

The paper explores the creation of a system aimed at facilitating disaster information reporting and status transmis- sion through smartphones. The study probably investigates thedesign and implementation of a mobile application or platformthat enables users to report and transmit critical information during disasters, leveraging the widespread availability and connectivity of smartphones. The paper may detail the func- tionalities and features of the proposed system, such as real- time reporting, location tagging, and multimedia capabilities for enhanced communication during emergencies. Moreover, itmay discuss the technical aspects, usability considerations, andpotential challenges associated with deploying such a system in disaster-prone areas. Overall, this paper likely contributes tothe field of disaster management by proposing a technology- driven solution to improve information dissemination and coordination during crises, potentially enhancing emergency response efforts and community resilience.

C. Remote Sensing for Flood Mapping and Monitoring

The paper delves into the application of remote sensing techniques for the mapping and monitoring of floods. It probably discusses various methods and technologies utilized in remote sensing, such as satellite imagery and aerial photog- raphy, to accurately identify flood-prone areas, assess flood extent, and monitor changes over time. The authors likelyexplore the advantages of remote sensing in providing timely and comprehensive flood information, enabling better disaster preparedness, response, and mitigation strategies. Additionally,the paper may highlight challenges and limitations in flood mapping and monitoring using remote sensing data, as wellas potential future research directions to further improve the accuracy and efficiency of such approaches. Overall, this paperlikely contributes valuable insights to the field of disasterresearch by elucidating the role of remote sensing in enhancingflood management and disaster resilience efforts.

D. Flood Susceptibility Mapping Using Image-Based 2D- CNN Deep Learning

The paper explores the application of deep learningtechniques, specifically 2D Convolutional Neural Networks (CNNs), for flood susceptibility mapping in urban areas with limited data availability. The paper likely provides an overview of the methodology, focusing on the use of image-based analysis and multiparametric spatial data to train the CNN model for flood susceptibility assessment. It probably includesa case study demonstrating the application of the proposed approach, showcasing its effectiveness in identifying areasprone to flooding and providing valuable insights for urban planning and disaster management. Additionally, the papermay discuss the advantages of using deep learning methodsfor flood susceptibility mapping, such as their ability to handle complex spatial data and their potential for automation and scalability. Overall, this paper likely contributes to the ad- vancement of flood risk assessment techniques by integrating deep learning with geospatial analysis, particularly in data- scarce urban environments, thereby aiding in more informed decision-making and resilience building against flood hazards.

E. A review of intelligent models for mapping city develop- ment and urban flooding

The paper provides an extensive review of intelligent mod- eling approaches utilized in the mapping of city development and urban flooding. This review probably encompasses varioustypes of intelligent models, including machine learning, arti- ficial intelligence, and geospatial analysis techniques, aimedat understanding and predicting patterns of urban growth and flood susceptibility.

The authors likely discuss the application of these models in assessing the dynamics of urbanization, identifying vulnerable areas to flooding, and informing sus- tainable urban planning strategies.

Moreover, the paper may highlight the strengths and limitations of different intelligent modeling approaches, as well as emerging trends and future research directions in the field. Overall, this review likely offers valuable insights into the use of intelligent models for addressing the complex challenges associated with urban development and flooding, contributing to more resilient and sustainable cities in the face of environmental changes.

F. Investigation of Flood Monitoring Detection System Using IoT Application

The paper explores the development and implementation of a flood monitoring detection system based on Internet of Things (IoT) technology. This investigation probably involvesthe design and deployment of sensors or monitoring devicesin flood-prone areas to collect real-time data on water levels, weather conditions, and other relevant parameters. The paper may discuss the architecture of the IoT application, including data transmission protocols, data processing techniques, and visualization methods used to analyze and present the flood monitoring data. Furthermore, the authors likely assess the effectiveness and reliability of the proposed system through case studies or experiments, evaluating its potential for early detection, timely warning, and mitigation of flood hazards. Overall, this paper likely contributes to the field of integrated technology by showcasing the practical application of IoT in improving flood monitoring and management, offering insightsinto the design, implementation, and performance of such systems in real-world scenarios.

III. PROPOSED MODEL

The proposed system is designed to effectively classify images as either depicting flooding or non-flooding scenarios. The system operates by taking an image as input and subse- quently generates an output in the form of textual information, clearly indicating whether the depicted scene is associatedwith flooding or not. Additionally, this output includes crucialperformance metrics such as accuracy, F1 score, and precision,providing users with a comprehensive assessment of the classi-fication results. Moreover, in cases where the system identifiesa flooding image, it goes a step further by sending a text message (SMS) alert to notify the user, thereby ensuring timely awareness of potential flood events. proposed system intro- duces a novel approach to flood event recognition, leveraging the power of Keras' pretrained MobileNet convolutional neural network (CNN). Through extensive data collection efforts, we have curated datasets comprising both flooding and non- flooding images, which serve as the foundation for training the CNN model.

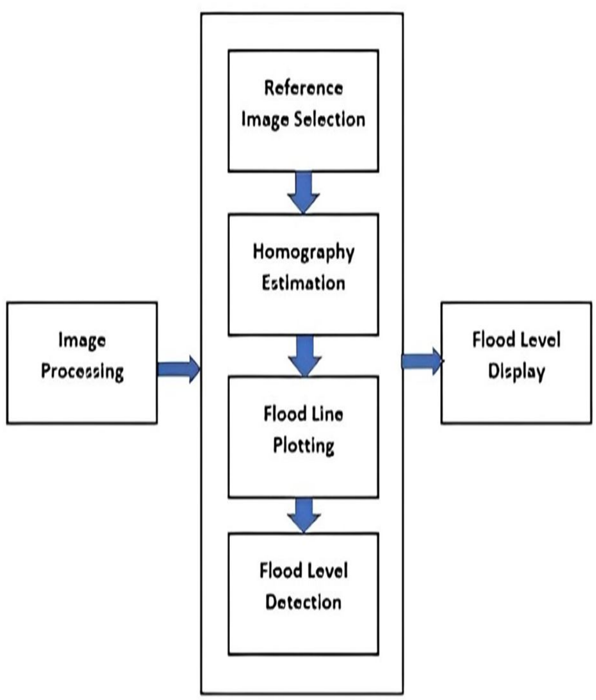


Fig. 1. Implementation Diagram for Machine Training

1) Image Processing: This is the initial step where images are captured and prepared for further analysis. It involves preprocessing tasks such as noise reduction, enhancing image quality, and possibly segmenting the relevant partsof the image.
2) Reference Image Selection: This step involves selectinga reference image, which serves as a baseline for com- parison. The reference image is usually taken when the water level is at a known, non-flood state. This helps in identifying changes in subsequent images.
3) Homography Estimation: Homography is a transforma- tion that maps points from one plane to another. In this context, it is used to align the current image with the reference image, accounting for any perspective changes or distortions. This ensures that the flood level can be accurately measured relative to the reference image.
4) Flood Line Plotting: After aligning the images, the systemidentifies and plots the flood line in the current image. This is the line where water meets the land or otherobjects, indicating the extent of flooding.
5) Flood Level Detection: In this step, the plotted flood line is analyzed to determine the water level. This involves measuring the vertical distance from a known point (often in the reference image) to the flood line. Thismeasurement indicates the flood level.
6) Flood Level Display: The final step is to display thedetected flood level. This can be done through various means such as graphical displays, numerical readouts, or alerts. The display system communicates the current floodlevel to users, allowing for timely and informed decisions.

IV. FLOOD DETECTION

A. Data Collection

In the project, we've established two crucial labels for our image classification system: (1) Flooding and (2) No Flooding. Next, we specify the file paths to our training and validation datasets. To artificially expand our data and improve model robustness, we leverage Keras' powerful ImageDataGenerator function. This function allows us to create batches of augmented images on-the-fly during training.By applying random transformations like rotations, flips, and scaling, we can generate variations of our existing images. This helps the model learn features that are invariant to minor changes in perspective and lighting, ultimately leading to better generalization on unseen data.

B. Data Preprocesing

To ensure compatibility with MobileNet's pre-trainedarchitecture, we adhere to its specific image size requirement of (224, 224) pixels. This ensures all input images are uniformly scaled, allowing the model to effectively extract relevant features. We then leverage Keras' ImageDataGenerator to create batches of these preprocessed images for training. The batch size refers to the number of images processed by the network in a single iteration. Choosing an optimal batch size involves a trade-off between training speed and memory usage. Larger batch sizes can accelerate training but require more GPU memory. We'll likely experiment with different batch sizes to find the sweet spot that maximizes training efficiency for our specific hardware and dataset size.

C. Model Creation

We define the output layer of our fine-tuned model with just2 units, one for each class (Flooding and No Flooding). This replaces the original MobileNet's final layer, which typically has 1000 units for classifying 1000 different categories. To achieve this transformation, we leverage the power of Keras' Model class. We essentially create a new model instance by specifying the original MobileNet model as the input. However, instead of using its existing output layer, we define our new 2-unit output layer on top of the appropriate intermediate layer in the MobileNet architecture. This allows us to reuse the valuable feature extraction capabilities learned by MobileNet on ImageNet, while fine-tuning the final classification stage for our specific flood detection task.

D. Testing and Evaluation

We plot the results using a confusion matrix and also print accuracy score, f1 score, and precision score of our model.If all of the scores are over 98a very good performance. We have trained our model for about 5 minutes (10 epochs on computer with CPU and no GPU) and our training data was also small only around 300 images. Now we will provide our model with images one by one to make it predict what class the image belongs to. We will test it on images which are not from our initial data.

V. EXPERIMENTAL RESULT

Precision	0.9655172413793104
F1 Score	0.9824561403508771
Accuracy	0.9859154929577465

Fig. 2. Successful output in the python program

The precision is the ratio tp/(tp+fp) where tp is the number of true positives and fp the number of false positives. The precision is intuitively the ability of the classifier not to label as positive a sample that is negative. The best value is 1 and the worst value is 0. Precision is one indicator of a machine learning model's performance-the quality of a positive prediction made by the model. In this system it get 96% of precision.

F1-score is one of the most important evaluation metricsin machine learning. It elegantly sums up the predictive performance of a model by combining two otherwise com- peting metrics-precision and recall. The F1-score combinesthe precision and recall of a classifier into a single metric by taking their harmonic mean. It is primarily used to compare the performance of two classifiers. In our system we get 98% of F1-score.

Accuracy is one metric for evaluating classification models.Informally, accuracy is the fraction of predictions our model got right. Accuracy is the division of number of correct predictions and the total number of predictions. In this system, accuracy comes at about 98%.

VI. FUTURE SCOPE

1) Applications supporting computer vision and IoT-based sensor approaches for flood monitoring and mapping include:

- Early warning systems
- Debris flow estimation
- Flood risk management
- Flood inundation mapping
- Surface water velocity assessment

2) Computer vision advantages:

- Covers a broader range
- Treats each point in the field of view (FOV) as a sensorfor water level detection

3) IoT sensor advantages:

- Provides highly accurate point-based readings

4) Shortcomings of computer vision and IoT sensors:

- Computer vision: Less accurate
- IoT sensors: Limited to point-based readings

5) Complementary use of computer vision and IoT sensors:

- Data fusion from both sources improves accuracy andreliability in flood monitoring stations

6) Benefits of integrated approach:

- Enables a comprehensive understanding of flood dy-namics
- Facilitates more informed decision-making by author-ities

- Allows assessment of heavy rainfall impact on water-ways and infrastructure in real time

7) Potential future enhancements:
- Detection of flash floods through measurement of rain-fall intensity and accumulation
- Incorporation of rainfall data into monitoring frame-work for rapid response to emerging flood risks

8) Role of advances in machine learning and data analytics:
- Enhances predictive capabilities of flood monitoringsystems
- Enables more accurate forecasting and early warningof flood events

9) Overall significance:
- Synergistic combination of computer vision and IoT-based sensor technologies represents a powerful ap-proach to flood monitoring and management
- Enhances ability to monitor, map, and respond to floodevents
- Ultimately reduces risk of damage and protects livesand livelihoods in flood-prone areas.

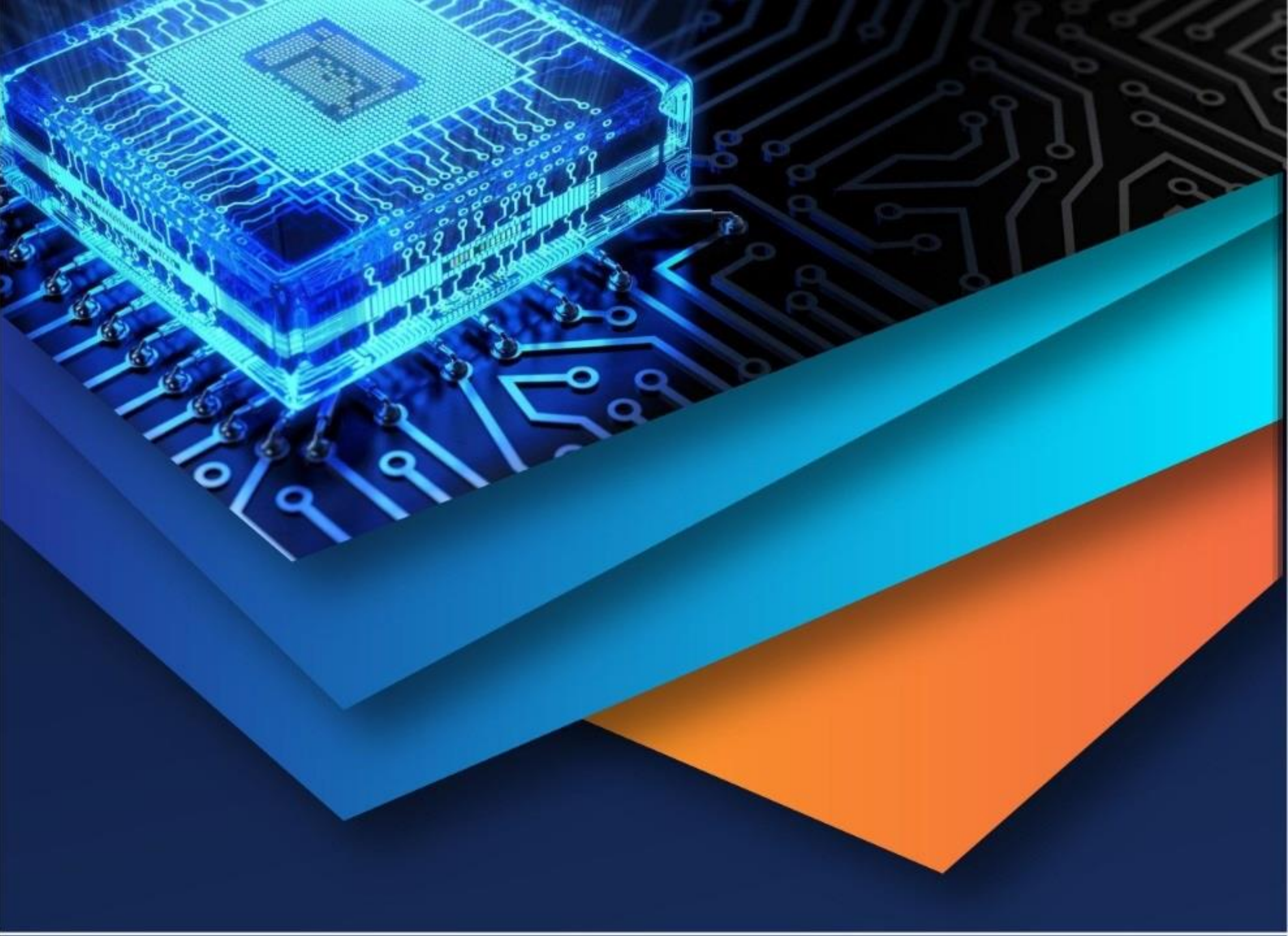
VII. CONCLUSION

The project entails the development of a sophisticated system aimed at monitoring and managing flood occurrences in nearby areas. By leveraging advanced technology, such as image recognition, we have successfully implemented a mech-anism to swiftly identify and differentiate between flooded andnon-flooded regions. This achievement aligns seamlessly withthe outlined objectives, ensuring that both local authorities and residents remain informed about the current status of flooding in their vicinity. One of the key strengths of our system lies in its exceptional accuracy, which has been achieved with minimal effort. Through meticulous design and rigorous testing, we have optimized the system to deliver reliable results consistently. This accuracy is crucial in facilitating timelyresponses to flood events, allowing for effective mitigation measures and resource allocation. In summary, our project represents a significant advancement in flood management andmonitoring. Furthermore, our system is equipped with real-time data collection capabilities, integrating seamlessly with existing weather monitoring networks and satellite imaging systems. This integration enables us to not only detect ongoing flood events but also anticipate and track potential flood risks based on meteorological forecasts and historical patterns. By harnessing the power of predictive analytics, our system can provide early warnings to communities and authorities, empowering them to take proactive measures to safeguard livesand property. In essence, our project represents not only a technological breakthrough but also a testament to the power of innovation in addressing pressing environmental issues. By harnessing the latest advancements in image recognition, data analytics, and remote sensing, we are paving the way for moreresilient and sustainable communities in the face of climate uncertainty.

REFERENCES

[1] H. H. Jaehyoung Yu, “Remote detection and monitoring of a water level using narrow band channel,” Journal of Information Science and Engineering 26,71-82, 2010.
[2] H. D. Y. Dong Hui, “Research of image matching algorithm based on surf features,” International Conference on Computer Science and Information Processing, 2012.
[3] S.Hyong ,et al.,”A study on the development of disaster information reporting and status transmission system based on smart phone,”In proceedings of 2011 International conference on ICT Convergence,2011.
[4] Hsu, M.-H.; Lin, S.-H.; Fu, J.-C.; Chung, S.-F.; Chen, A.S. Longitudinalstage profiles forecasting in rivers for flash floods. J. Hydrol.
[5] Rizwan Sadiq, Muhammad Imran ,Ferda Ofli ,”Remote Sensing for Flood Mapping and Monitoring”, in Emerging Advances In International Handbook of Disaster Research , pp 1-19,2023.
[6] Muhammad Syafiq Zainal Norazlianie Sazali, ”Investigation of Flood Monitoring Detection System Using IoT Application , ” in Emerging Advances in Integrated Technology VOL.3 NO.2 (2022)27-36 .
[7] Pavithraa Senthilkumar, Menaka Pushpa Arthur,”A review of intelligent models for mapping city development and urban flooding ” in Land Degradation Development(LDD) Volume 34, Issue 13 , 15 August 2023.
[8] Kumar, V.; Azamathulla, H.M.; Sharma, K.V.; Mehta, D.J.; Maharaj, K.T. “The State of the Art in Deep Learning Applications, Challenges, and Future Prospects: A Comprehensive Review of Flood Forecasting and Management. Sustainability 2023”
[9] Yashon O. Ouma, Lawrence Omai, ”Flood Susceptibility Mapping Using Image-Based 2D-CNN Deep Learning: Overview and Case Study Application Using Multiparametric Spatial Data in Data-Scarce Urban Environments”, International Journal of Intelligent Systems, vol. 2023, Article ID 5672401, 23 pages, 2023.

[10] Zhang, Y., Zhang, Z., Zhang, L., Chen, J. (2019). Flood detection and mapping using deep learning from synthetic aperture radar images. Remote Sensing, 11(6), 660.
[11] Zhang, J., Zheng, Y., Li, H. (2018). Flood monitoring and damage assessment using unmanned aerial vehicle imagery and deep learning. Water, 10(11), 1601.
[12] Liu, Y., Li, Y., Tang, H., Lin, J. (2017). Flood inundation mapping using high-resolution UAV images and deep learning. Water, 9(9), 688.
[13] Chen, L., Xu, X., Chen, L., Hong, Y. (2020). Urban flood monitoring using crowd-sourced social media data and machine learning algorithms. Journal of Hydrology, 586, 124891.
[14] Jia, K., Huang, L., Cai, H. (2019). Real-time flood monitoring and early warning system based on Internet of Things (IoT) and machine learning. Water, 11(1), 184.
[15] Zhang, J., Liu, Q., Zhang, L., Song, X. (2018). Flood detection and monitoring using satellite remote sensing data: A review. Remote Sensing, 10(10), 1642.
[16] Wang, Z., Hu, J., Zhang, Y., Li, W. (2017). A novel approach to flood inundation mapping using unmanned aerial vehicle remote sensing imagery and machine learning algorithms. Water, 9(11), 835.
[17] Huang, Q., He, J., Zhang, J., Wu, J. (2019). Flood forecasting and warning system based on machine learning and ensemble methods: A case study in the Huaihe River Basin, China. Water, 11(2), 381.
[18] Zhao, H., Zhu, J., Liu, C., Li, X. (2018). Flood risk assessment using machine learning algorithms and GIS-based spatial analysis. Journal of Hydrology, 561, 822-833.
[19] Liu, P., Li, X., Chen, L., Zhang, X. (2019). Real-time flood monitoring and early warning system using Internet of Things technology and cloud computing. Journal of Hydrology, 572, 76-84.
[20] Wang, J., Lin, J., Li, J., Li, R. (2017). A novel approach to flood monitoring and early warning based on wireless sensor networks and machine learning. Water, 9(4), 243.



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