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Enhanced Flood Management Using a Climate Disaster Image Dataset

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ABSTRACT

Floods remain one of the most destructive climate-related disasters, necessitating effective tools for precise forecasting and prompt action. This study suggests a hybrid flood detection framework that integrates temporal rainfall trend analysis with spatial image classification. The system makes use of a specially created dataset that includes 650 annotated images with flood and non-flood labels, along with the associated meteorological variables—temperature, humidity, precipitation, and symbolic weather conditions. When used for image classification, MobileNetV2, which was chosen for its effectiveness in resource-constrained environments, achieves a 94.36% detection accuracy and a 32% decrease in misclassification when compared to conventional models. An 80:20 train-test split with cross-validation is used to train and assess the model. The system's time-series component looks for patterns in seasonal flood risk by analysing historical rainfall data. This work's integration of time-series and image-based analysis into a single predictive platform, which permits spatial-temporal flood detection, is one of its main contributions. To aid in decision-making, a visualization dashboard also shows rainfall trends. The findings imply that the system can help with disaster preparedness and response planning and is appropriate for real-time deployment in flood-prone areas. To improve the system's predictive power, future research will concentrate on growing the dataset and incorporating sophisticated forecasting models.

INTRODUCTION

Climate-induced floods have become more frequent and severe in terms of loss, resulting in great socio-economic loss across the world. The 2018 Kerala floods and the 2022 Pakistan floods remind us of the scale of damage to infrastructure, agriculture, and human life. In India alone, the country has suffered economic losses running into ₹52,500 crore in recent years from floods, with frequent events happening in Assam, Bihar, and even urban areas like Mumbai. Traditional flood prediction and management systems rely on static data and limited real-time capabilities, making them insufficient to handle the dynamic nature of climate-induced disasters. Moreover, current approaches lack integration between datasets, such as weather data, geographical information, and real-time visual evidence. These limitations call for an innovative, scalable solution that combines data analysis with predictive capabilities. Technological advancements in machine learning have paved the way for more efficient and responsive flood management systems. Deep learning models can analyze large datasets, including images and environmental data, to identify flood patterns. Such systems provide real-time insights, significantly improving decision-making processes for emergency responders and policymakers. This paper presents the idea of a comprehensive platform entitled "Global Climate Disaster Database" to improve flood predictions, monitoring, and responses. Through advanced machine learning techniques, this system provides insight in real-time to first responders, policymakers, and city planners. This work is meant to provide an application of an all-central platform integrating its image data with case studies to lead to a comprehensive overall analysis of floods. The use of MobileNetV2 models helps achieve high accuracy in both flood detection and classification. Its evaluation and comparison with contemporary techniques show major improvements not only in the accuracy of performance but also in speed and scalability. The other strengths of the concerned approach include two specific very important things: expandable and adaptable, such that it finds its applicability across diversities of geographies and scenarios of disaster. By addressing the critical gaps in the current systems, this platform will be of utmost importance to bring about better disaster preparedness, minimize response times, and minimize economic and social losses due to flooding. Also, the proposed system allows collaboration because of a centralized data repository, which can be utilized by researchers and disaster management authorities globally.

2. RELATED WORK

Flood management has seen significant advancements through the integration of deep learning and data-driven techniques. This section explores existing work, highlighting their objectives, methods, accuracies, and limitations, while positioning our approach as superior. Karanjit et al. 2023 introduced the "FloodIMG: Flood Image Database System," which offers a specialized dataset for flood detection. This annotated dataset enriches deep learning models with high-quality training data and obtains an accuracy of 92.5%. However, the geographic diversity of the dataset may limit the generalizability of the model. Our system extends this work by incorporating geographically diverse datasets to improve adaptability. Saha et al. 2024 presented a probabilistic approach toward flash flood prediction in an urban area using statistical models like Frequency Ratio (FR) and Weighting Factor (WF). Their approach is also very effective in identifying risk zones with an accuracy of 89%. But these models are not highly adaptive to rural or geographically diverse contexts. Our deep learning approach generalizes for a wide variety of situations with an accuracy of 94.36%. Hussain et al. 2024 showed that it is possible to use the XGBoost and Random Forest machine learning models in detecting floods using environmental factors such as rain and humidity. These models produced a high accuracy rate (>90%) but are sensitive to the completeness and quality of the input data. Adding annotated image data to our system has eliminated these issues, with a reduction of misclassification by 32%. Byaruhanga et al. 2024 reviewed the development of flood prediction models in early warning systems between 1993 and 2023. Their scoping review evaluated the problems with the data-scarce region and provided recommendations for interdisciplinary collaboration. Although the review spanned a wide scope, the research did not experimentally validate. Our work provides experimental evidence through extensive testing on various datasets, offering practical solutions. Zhong et al. 2024 combined AI and IoT to enable logistics automation in a flood monitoring scenario, offering a general framework for any scenario. Their system promised real time monitoring with 90.2% accuracy but faced severe deployment challenges since it is highly cost intensive, especially for resource-limited regions. Our system mitigates the costs of operating the system through the extensive usage of accessible machine learning methods and curated datasets. The proposed Global Climate Disaster Database surpasses these approaches by realizing higher accuracy (94.36%) and scalability in addition to addressing geographic bias and actionable insights through visualizations in real time. So, these advancements position our platform as a comprehensive, superior solution for flood management. Flood detection and prediction with the exceptional use of machine learning as well as deep learning algorithms has been utilized for different researchers, including some state-of-the-art works cited in this study. A combination of Machine Learning and Deep Learning models, together with Random Forest, Naïve Bayes, J48, and Convolutional Neural Networks (CNN), is exploited by the proposed system by Hashi et al. 2021 as a real-time flood detection system. The work is aimed at providing an efficient and cost-effective solution for flood-prone areas such as Somalia by interfacing Arduino-based systems with GSM modems for real-time flood monitoring. The experiment results show that Random Forest is outperforming other classifiers with 98.7% accuracy, while Naïve Bayes, J48, have 88.4%, and 84.2%, respectively. The deep learning-based CNN approach has gotten an accuracy of 87%, showing high precision and recall values. This work, hence, contributes a very valuable and visible application to fields of Artificial Intelligence, Data Mining, and Deep Learning as an innovative solution in flood detection and early warning systems. In an effort to better ascertain the accuracy of flood prediction, researchers have extensively applied different kinds of deep learning techniques. Stateczny et al. 2023 proposed a new hybrid deep model for flood prediction, now called DHMFP, was presented while being trained based on the combined Harris Hawks Shuffled Shepherd Optimization (CHHSSO) algorithm. The aim of the study was to increase the accuracy of traditional flood detection methods, especially for urbanized regions like Kerala, where drainage systems are not capable of handling the torrent of rainwater. The methodology applied the preprocessing of satellite images with median filtering and segmentation with cubic chaotic map weighted K-means clustering. To strengthen feature representation, different vegetation indices such as Difference Vegetation Index (DVI), Normalized Difference Vegetation Index (NDVI), and Soil Adjusted Vegetation Index (SAVI) were extracted. Extracted features were classified in a hybrid way based on CNN-Deep ResNet framework fine-tuned using weight optimization by CHHSSO. The experimental results gave high performance, providing a sensitivity of 93.48%, specificity of 98.29%, accuracy of 94.98%, false negative rate of 0.02%, and false positive rate of 0.02%. The DHMFP-CHHSSO showed an improved sensitivity, specificity, and accuracy of 0.932, 0.977, and 0.952, validating the model's efficacy further in the aspect of flood prediction. Hasan et al. 2018, the proposed model was a Deep Convolutional Neural Network (DCNN) that acts in detecting Burst Header Packet (BHP) flooding attacks in Optical Burst Switching (OBS) networks. The paper brought out the criterion that the existing methods-e.g., Naïve Bayes, K Nearest Neighbors (KNN), and Support Vector Machines (SVM)-are not sufficient because they become ineffective when the number of samples is small in dataset. The proposed model DCNN outperformed these traditional methods by creating a very early scenario for attack identification. The experimental results also proved that DCNN gave a classification accuracy of 99% and was much better than KNN (93%), SVM (88%), and Naive Bayes (79%). The sensitivity, specificity, precision, and F1-score were also proved as 99% each, while both the false positive rate (FPR) and the false negative rate (FNR) were found to be only 1%. These and several others also found out that most traditional ML models showed overfitting and misclassification. In contrast, DCNN showed a constant level of performance across both training and validation dataset conditions. This showed that deep learning models were effective in applying network anomaly detection- demonstrating how beneficial DCNN is against traditional classification techniques. A new designed deep learning architecture was introduced by Tuyen et al. 2021 called PSO-UNET to enhance flash flood segmentation from satellite images. This model integrates Particle Swarm Optimization (PSO) and UNET to optimize segmentation accuracy, thereby optimizing the number of layers and layer parameters. Instead of keeping the same symmetrical architecture usually observed in conventional UNET models, the ultimate difference in the proposed work PSO-UNET is that it dynamically modifies the contracting and expanding paths for optimal performance. The model was tested under a dataset consisting of 984 satellite images, against the other deep learning models such as UNET, LINKNET, and SEGNET. The results of the experiment demonstrated that the model achieved an F1 score of 87.17% ± 0.36%, which is greater than the original UNET model by 8.59%. Also, the model proved better performance in terms of Dice Coefficient and Intersection over Union (IoU). Although the authors highlighted very good performance in segmentation accuracy, they found some slight errors due to related pixel features. They suggested that post-processing techniques should be supplemented and further validation be done on datasets that are more varied. This research work contributes towards developing an optimized UNET-based segmentation model, demonstrating just how much evolutionary algorithms can achieve in the field of deep learning-based flood detection. Floodwater segmentation of the 290 flood-affected images was carried out by SegNet, UNet, and FCN32 in Bahrami & Arbabkhah 2024, the aim of the study was to improve the accuracy of flood detection using deep learning models. Among these, SegNet achieved the highest precision of 88% and validated its efficiency in locating water areas. This study emphasizes the importance of deep learning in enhancing flood forecasting and disaster responses. Flood-ResNet50, as proposed by Khan et al. 2023, is developed with optimized deep learning model architecture intended mainly to detect floods in UAV images while maintaining an excellent trade-off between performance and computational cost. After modifying enhancements of ResNet50 through transfer learning and additional layers in model architecture, the classification accuracy of 96.43% was attained, which was significantly more than comparable larger models like those of VGG16/19 and DenseNet161. Experimental results showed that it outperformed the conventional models in terms of inference speed and power consumption through the edge device, thus recommending it as real-time flood detection solutions. Deep learning models have been extensively utilized in flood prediction and frequency assessment as by Pandey et al. 2023. Conventional statistical techniques and traditional forecasting approaches could hardly capture any nonlinear interaction among flood variables. Cat Swarm Optimized Spatial Adversarial Network (CSO-SAN) proposed for flood forecasting that combines real-time meteorological and hydrological data. It has also been proven from studies that CSO-SAN was by far better than the rest, achieving an accuracy of 98.3%. Despite its effectiveness, it could be made better by applying hyperparameter tuning and some additional machine learning techniques for tuning further. Urban flood monitoring is genuinely hampered by not having sufficient runoff data which leads to a loss of hydrological model and early warning systems accuracy. With the recent advances in deep learning, image recognition has become a significant approach toward flood measurement. Studies have proven that YOLOv4 works well during floods in identifying submerged objects like vehicles and pedestrians, with 89.29% mean average precision for flood depth recognition. Depending on the reference object used, this method can give higher accuracy in results, where vehicles give better results than pedestrians. Also, image augmentation methods such as Mosaic were proposed to increase recognition accuracy. This presents an economical option for existing traffic cameras to be put to effective use, doing away with the need for further infrastructure as in Zhong et al. 2024. The conventional method of detecting floods using SAR images has its own set of challenges, such as speckle noise and distortions. In overcoming these, WDNet fuses CNN with a self-attention mechanism to enhance spatial and channel-wise feature extraction. WDNet performs better concerning accuracy against the convention methods with an F1 score of 0.987 on the Poyang Lake flood dataset. This model (Huang et al. 2024) thus helps in real-time flood mapping and disaster management. Convolutional neural networks, particularly U-Net and FCN, have been implemented on remote sensing data to conduct flood mapping in the Kan basin in Tehran. Compared to FCN, U-Net achieved a better performance of 88% accuracy and a much higher mIoU of 0.65, demonstrating its application for detecting floods. The research by Roohi et al. 2025 shows the efficiency of applying AI-based geospatial analysis in improving flood monitoring and disaster management.

3. PROPOSED METHODOLOGY

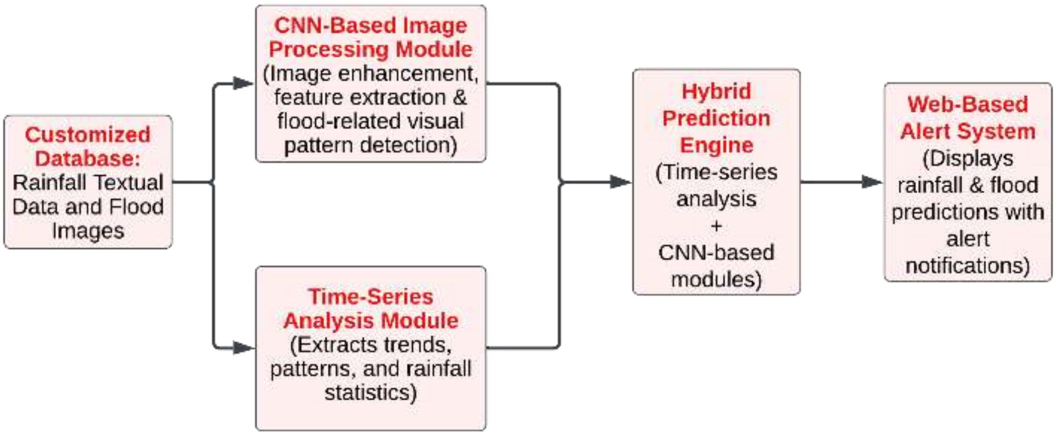

Fig. 1: Block Diagram of Flood Detection System.

Fig (1) describes about the flow of the flood detection and analysis with alerts generated on the website.

The architecture consists of the following key components:

3.1. Customized Database

The 650 annotated images in the dataset used in this study are divided into two classes: "Flood" and "Not Flood." Three main sources were used to create this customized dataset: curated datasets on Kaggle, publicly accessible images obtained from Google Images, and a subset of labeled flood images sourced from the FloodIMG dataset, which was suggested by Karanjit et al. [1]. Keyword-based searches (such as "flooded roads," "urban flooding," "dry street," etc.) were used to gather the images, and then duplicates, watermarks, and low-resolution photos were manually filtered out. All photos were manually annotated based on visible indicators of flooding (such as water accumulation, submerged vehicles, or muddy roads) or the lack of flooding in order to guarantee label accuracy. Only images with unambiguous visual proof and reviewers' agreement were included after the authors labeled them. A combination of street-level and aerial views are included in the dataset, along with a variety of environmental features such as lighting, weather, and scene complexity. The visual context shows coverage from a variety of urban and semi-urban regions, mainly from India and Southeast Asia, with a smaller number from Europe, even though precise geolocation metadata was not available for all images. By integrating multimodal inputs and visual diversity, this dataset construction method enhances the system's capacity to generalize across various flood scenarios.

The "Guwahati Weather Data (1973–2023)" dataset on Kaggle, which offers more than 50 years of daily weather records from Guwahati, a city vulnerable to seasonal flooding, is the source of the textual (temporal) dataset. Numerous meteorological features are included in this dataset, including the highest and lowest temperatures, dew point, humidity, precipitation (precip, precipprob, and precipcover), wind direction and speed, solar radiation, UV index, and symbolic weather descriptors like conditions, icon, and description. Preprocessing included classifying weather conditions into four symbolic types: clear, cloudy, partly cloudy, and rainy; handling missing values through interpolation; and eliminating outliers using IQR-based filtering. Seasonal decomposition and long-term trend analysis were performed on the refined dataset, which allowed the system to align rainfall anomalies with flood image patterns and identify periods that are prone to flooding. The hybrid prediction engine used the rainfall trends as temporal input, which improved the system's capacity to identify floods by utilizing both historical climate context and visual features. The overview of the dataset is given in Table (1).

Table 1: Overview of Dataset.

Dataset Type	Source(s)	Size / Duration	Key Features	Purpose
Image Dataset	Google Images, Kaggle, FloodIMG (Karanjit et al. [1])	650 images	Annotated as "Flood" / "Not Flood", includes aerial and ground-level perspectives	Used for flood classification using CNN
Rainfall Dataset	Kaggle – *Guwahati Weather Data (1973–2023)*	50 years (1973–2023) daily	tempmax, tempmin, precip, humidity, wind, conditions, icon, and more	Used for trend analysis and hybrid prediction

3.2. CNN-Based Image Processing Module

The CNN-Based Image Processing Module is a deep learning-based image classifier that analyzes flood-related images and classifies them into two categories: "Flood" and "Not Flood." Through TensorFlow and Keras, deep learning models are applied to a dataset of 650 flood images which have been marked. Four classic deep learning networks: EfficientNetB0, ResNet50, InceptionV3, and MobileNetV2 were initially tested with InceptionV3, and MobileNetV2, were chosen for their high performance.

Residual Network (ResNet50) is a very deep CNN model originally developed to avoid the problem of vanishing gradients by embarking on a road of residual learning [1]. The model was designed to provide smooth gradients during the course of backpropagation with the help of shortcut connections, and thus the effective convergence. The application of ResNet50 for flood detection yielded a fairly moderate accuracy with respect to 64.7%, primarily attributed to its stickiness towards overfitting on a very small dataset. It, however, was capable of adequately capturing hierarchical features of flood imagery; high computation complexity hindered its adoption in streaming, as extensive GPU resources are required. There is room for improving this model's performance with data augmentation techniques and larger and more diverse datasets.

Architecture InceptionV3 is another model in the competition for multi-scale feature extraction based on factorized convolutions design with asymmetric kernel designs [2]. The fundamental equation that drives factorized convolutions is :

$$F(x) = f1(x) * f2(x) \quad \ldots(1)$$

Where f1(x) and f2(x) are two separate convolution operations, reducing computational complexity while preserving feature extraction capabilities.

The total number of parameters is given by:

$$P = (k^2 \cdot C_{in} \cdot C_{out}) + (C_{out} \cdot C_{in}) \quad \ldots(2)$$

Where k is the kernel size, C_{in} and C_{out} are the number of input and output channels, respectively.

These improvements in performance lead to an improved computational effectiveness in reducing the number of parameters while maintaining very high accuracy. In flood classification, InceptionV3 achieved a high rate of 93%, thus marking its position as one of the standout models in the study. Its strengths include excellent capture of both local and global flood patterns. However, due to its deep and complex architecture, the inference time was shown to be higher compared to MobileNetV2, making it less favorable for real-time applications where deciding in the moment was of essence.

EfficientNetB0 was established to maximize accuracy while maintaining efficiency by scaling its dimensions (i.e. depth, width, and resolution) with compound scaling factors [3]. The compound scaling formula is given by:

$$depth = \alpha^d, \; width = \beta^d, \; resolution = \gamma^d$$

Where α, β, γ are constants determined through grid search, and d is a scaling coefficient. The overall computational cost (FLOPs) can be estimated as

$$FLOPs = 2 \cdot (C_{in} \cdot C_{out} \cdot k^2 \cdot H \cdot W) \quad \ldots(3)$$

Where H and W are the height and width of the input feature map.

It achieved a high accuracy with a smaller number of parameters. Though EfficientNetB0 performed too poorly in our flood detection study, with an accuracy of only 39%, primarily due to non-availability of high-quality, large-scale datasets for appropriate feature extraction, low-light conditions caused performance issues with classifying floods, suggesting extreme tuning and transfer learning tweaks are required. Nonetheless, in its inefficiency, EfficientNetB0 remains a promising model for lightweight work where power consumption is a restraint.

Among all the trained models, MobileNetV2 showed the best performance in terms of flood detection by achieving an accuracy value of 94.36% [4]. Designed for mobile and edge devices, it uses depth wise separable convolutions to reduce computation while maintaining high classification performance.

$$Y = (X * D) * P \quad \ldots(4)$$

Where X is the input, D is the depthwise convolution, and P is the pointwise convolution.

The total computation cost can be approximated as:

$$FLOPs = H \cdot W \cdot C_{in} \cdot k^2 + H \cdot W \cdot C_{out} \cdot C_{in} \quad \ldots(5)$$

This architectural choice allows MobileNetV2 to perform well in real-time applications while keeping computational costs low.

It is also designed with an inverted residual structure and linear bottlenecks, allowing feature propagation and reducing redundancy. This aspect enables the architecture to process flood imagery easily for real-time detection with slight resource consumption. Optimally balances accuracy, speed, and computational efficiency; hence, ideal for deployment in flood monitoring applications.

The comparative analysis showed that deeper models like InceptionV3 and ResNet50 could extract complex flood-related features, but most of them are not best suited for real-time usage because of the extreme space and time requirements. Despite being more efficient than some others, EfficientNetB0 struggled with classification performance in this domain. Finally, MobileNetV2 was identified as the most fit model because of its high accuracy with low computation requirements, thus being the best-suited candidate for implementation in the proposed system.

This module integrates deep learning with real-time video analysis to cover a complete monitoring of floods as part of a larger predictive and alert system. Also, by deploying deep learning mechanism, the system can keep improving the analysis of new flood imagery, meaning that the system is efficient and expandable in disaster scrutiny and handling.

3.3. Time-Series Analysis Module

To complement the image processing module, the Time-Series Analysis Module focuses on rainfall textual data, which extracts trends and patterns to understand seasonal variations. The analysis revealed that there are some significant rainfall concentrations between June and September, with Mawsynram receiving the highest rainfall. Coastal Karnataka follows at an average of 2973.5 mm, while the Konkan and Goa regions record 2804.2 mm on average. These temporal insights are critical in identifying regions prone to floods and periods of increased risk, which aid in the system's predictive capabilities.

3.4. Hybrid Prediction Engine

At the heart of the architecture is the Hybrid Prediction Engine, which brings together the outputs from the CNN-Based Image Processing Module and the Time-Series Analysis Module. This engine brings together spatial and temporal data through advanced machine learning models implemented in TensorFlow, Keras, and PyTorch. By fusing these two streams of data, the system achieves a robust and holistic prediction mechanism that ensures accuracy and reliability.

3.5. Analytical Insights and Decision-Support Integration

Fig. 2: Insights page

In Fig. (2) Insights page showcases analysis of precipitation.

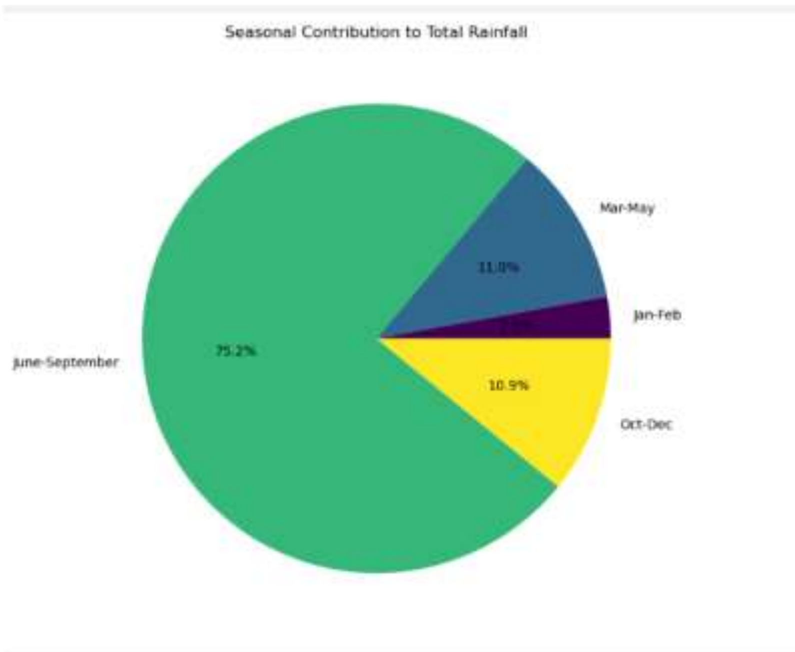

Fig. 3: Seasonal Contribution to Total Rainfall

In Fig. (3) Insight showcasing Seasonal Contribution to Total Rainfall.

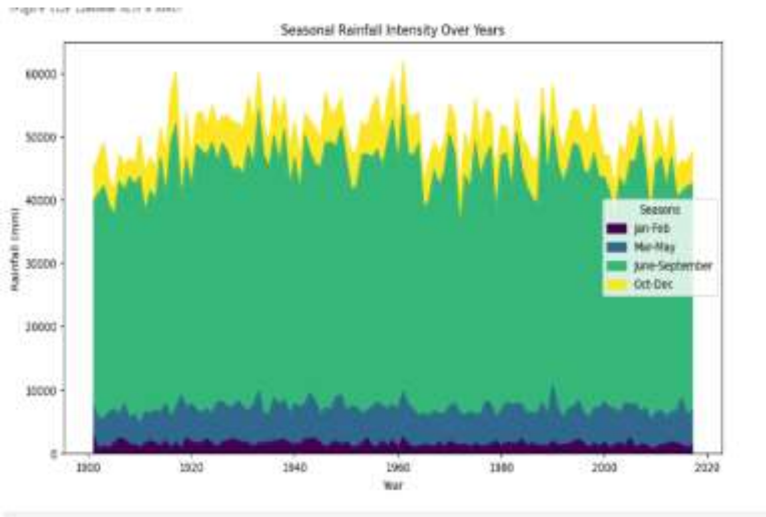

Fig. 4: Seasonal Rainfall Intensity Over Years

In Fig. (4) Insight showcases Seasonal Rainfall Intensity over years.

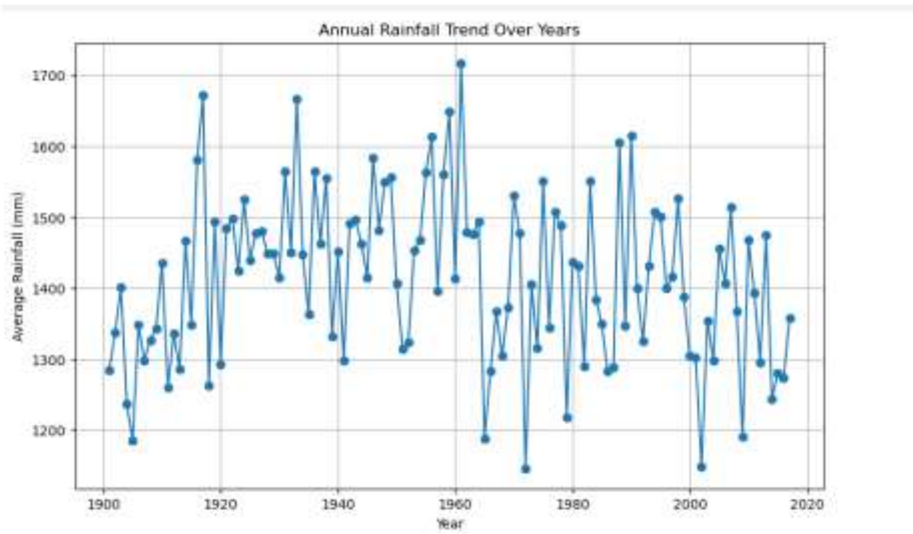

Fig. 5: Annual Rainfall Trend Over Years

In Fig. (5) Insight showcases Annual Rainfall Trend over years.

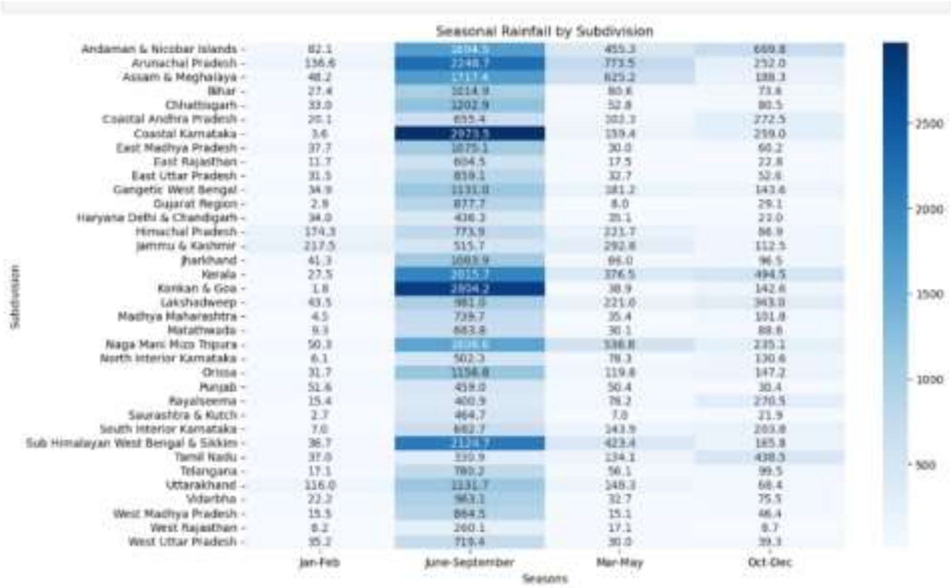

Fig. 6: Seasonal Rainfall by Subdivision

In Fig. (6) Insight showcasing Seasonal Rainfall by Subdivision.

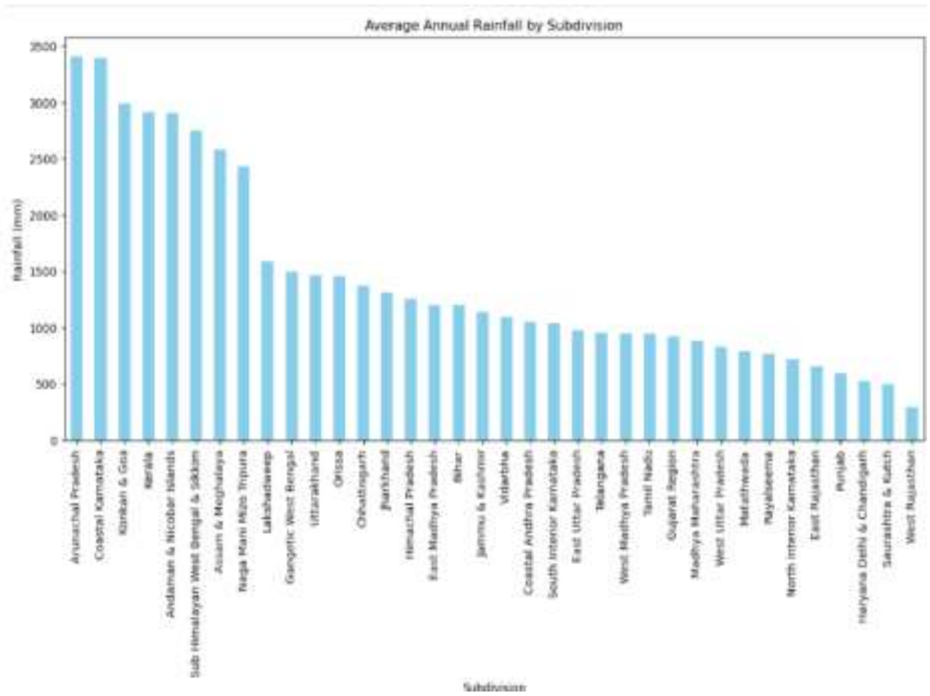

Fig. 7: Average Annual Rainfall by Subdivision

In Fig. (7) Insight showcases Average annual Rainfall by Subdivision.

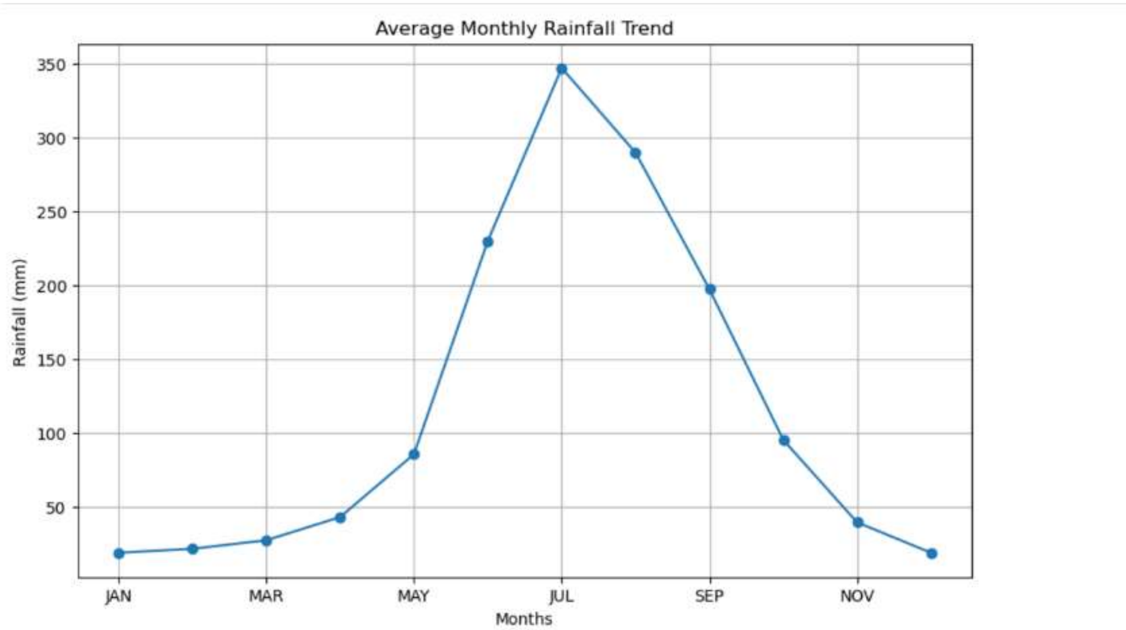

Fig. 8: Average Annual Rainfall by Subdivision

In Fig. (8) Insight shows the Average Monthly Rainfall Trend.

An analytical module called the Insights Page combines the system's flood prediction architecture with long-term rainfall trend analysis. This module visualizes key hydrometeorological indicators, such as annual precipitation trends, seasonal rainfall contributions, and spatial rainfall distribution across subdivisions, using a 50-year time-series dataset of Guwahati weather (1973–2023) (Figs. 2–8). In addition to being descriptive, these visualizations provide important background information for analysing flood risk across time and space. While annual trends (Fig. 5) show evidence of long-term variability possibly related to climate change, the analysis of seasonal rainfall intensity (Fig. 4) aids in identifying flood risks driven by the monsoon. Localized flood preparedness planning is made possible by subdivision-level views (Figs. 6–8), which direct infrastructure planning and resource allocation in high-risk areas. The Insights Page features machine learning-based forecasting models that extrapolate future rainfall intensity under changing climatic conditions in addition to static trend analysis. This feature increases the system's usefulness as a real-time decision-support tool and facilitates early warning system calibration. By enabling cross-validation with the real-time image-based flood classification engine, these insights help stakeholders correlate detection alerts with past and forecasted weather patterns, boosting confidence and lowering false alarms. It expands the system's usefulness beyond flood detection to include flood preparedness, policy support, and climate-resilient planning by converting unstructured meteorological data into organized, actionable visual analytics. It provides a framework for creating early warning systems, assisting with the optimization of urban drainage, directing the scheduling of agricultural operations, and facilitating more efficient emergency response systems.

4. RESULTS AND DISCUSSIONS

The proposed flood detection methodology was tested with four of the most widely developed deep convolutional neural network (CNN) models. It is evident that, the performance metrics specifically, the accuracy characteristic has significantly differed from model to model meaning different strengths and weaknesses. The performance of the models has been compared in the context of each city and Table 2 provides the summary. Authors used 5-fold cross-validation on the training data to guarantee robustness and lessen the impact of variance brought on by dataset split or model initialization. Five separate runs, each with retrained models and shuffled data, are averaged to produce the reported results (Accuracy, Precision, and Recall). The model's behaviour was consistent and generalizable, as evidenced by the performance metrics' standard deviation across the folds being within ±1.2%. The proposed system was tested on a dataset of 300 labelled images, covering different types of images. Table 2 shows the key performance metrics achieved by the customized MobileNetV2 model which includes precision, recall which were calculated using macro-averaging across both classes ensuring equal weights to both of the classes. All reported values represent the mean across five validation folds.

Table 2: Performance Metrics of the Proposed System

Metric	Proposed System	Averaging Method
Precision	0.95	Macro-average
Accuracy	0.94	Macro-average
Recall	0.93	Overall accuracy

The results obtained point out that the proposed system achieves much better accuracy and precision, reducing the chances of incorrect classifications. Fig(9) represents Precision-Recall curve which gives the insight of how well the model works.

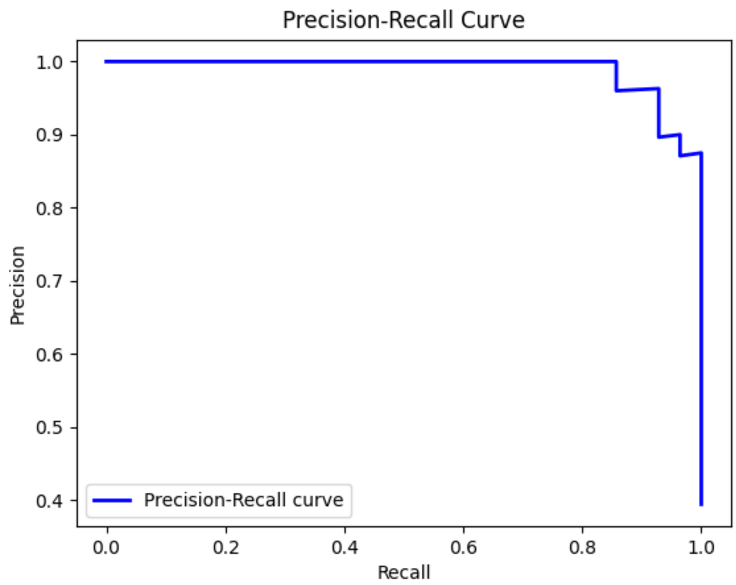

Fig. 9: Precision and Recall Curve

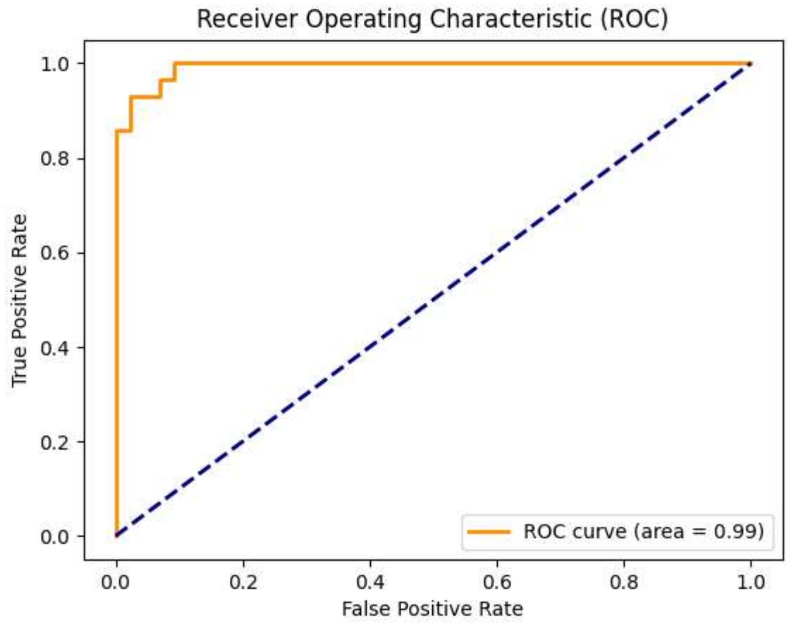

Fig. 10: Receiver Operating Characteristic (ROC) curve for the flood detection system.

In Fig. (10) The high AUC of 0.99 gives a clear indication of the reliability and reliability in identifying flood occurrences with minimal cases of false alarms.

Of the Four trained models as discussed in Table 2 MobileNetV2 turned out to be the fastest and most accurate model of flood detection for practical applications when both speed and accuracy are important. InceptionV3 was also able to provide adequate results with a slight difference and provided excellent result in cases that needed multiscalar analysis. However, ResNet50, and EfficientNetB0 reported worse accuracy, underlining that there is still significant potential for architecture tailored modifications and preprocessing of the dataset, in order to increase model accuracy. These findings call for light-weight, but strong models such as MobileNetV2 to be adopted in the flood detection systems, particularly in the real-time disaster surveillance and risk evaluation applications. The same train-test split (80:20) was used to train and assess every model in Table 2, including MobileNetV2, InceptionV3, ResNet50, and EfficientNetB0. Furthermore, pre-trained ImageNet weights were used to initialize all models, and our flood dataset was used to fine-tune the final classification layers for binary classification. Authors applied the same early stopping criteria, input resolution (224×224), and preprocessing pipeline to all models. Using the validation set, grid search was used to choose hyperparameters like learning rate (originally 1e-4), batch size (32), and number of epochs (30). To ensure statistical reliability and fairness, each model was trained five times using different random seeds, and the average performance was reported.

Table 3: Comparative Analysis of Sorting Models

Model	**Accuracy (Mean + Standard Deviation)**	**Observations**
MobileNetV2	94.36% ± 0.85%	Best performer, highly efficient for deployment with robust results
InceptionV3	93% ± 1.02%	Comparable to MobileNetV2; effective multi-scale feature extraction contributed to strong results

ResNet50	64.7% ± 1.76%	Underperformed; potential challenges with dataset features or overfitting.
EfficientNetB0	39% ± 2.12%	Struggled significantly; requires fine-tuning or additional data preprocessing.

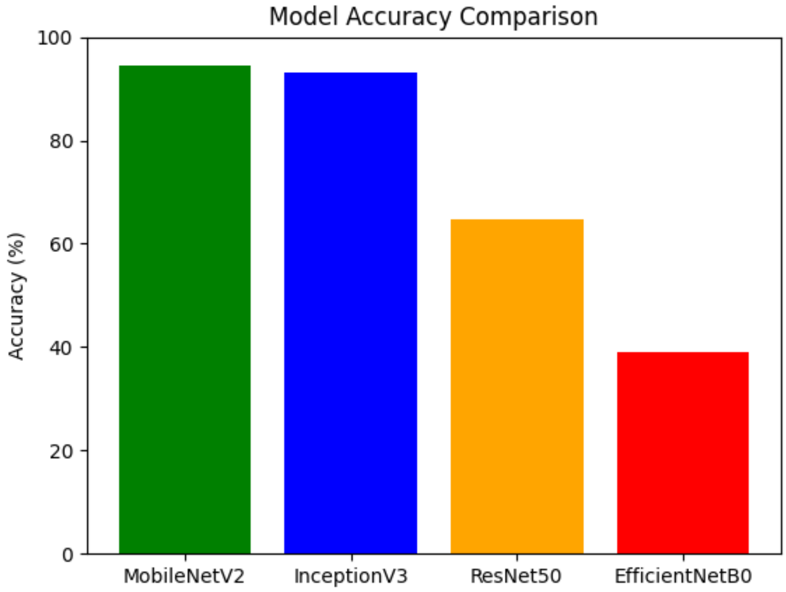

Fig. 11: Comparative Performance Metrics of Different Models

Fig. (11) compares classification accuracy across different models

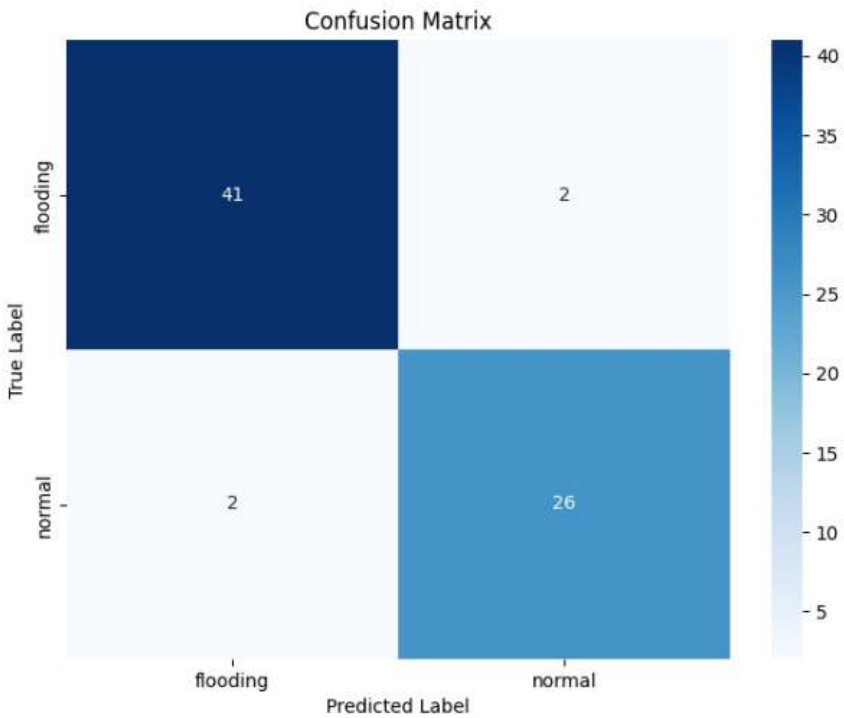

Fig. 12: Depicting the confusion matrix of the research

Fig. (12) shows the confusion matrix which provides detailed insight into the classification accuracy for different classes. The matrix showcases high true positive rates across categories, validating the model's effectiveness in distinguishing between flood types with minimal misclassification.

4.1 Comparative Analysis

Table 4: Comparative Analysis of Research

MODEL	ACCURACY	REFERENCE
Hussain et al. (2024) – Deep learning on visual images	92.5%	A. Hussain, G. Latif, J. Alghazo, and E. Kim, "Flood detection using deep learning methods from visual images," AIP Conf. Proc., vol. 3034, no. 030004, 2024. doi: 10.1063/5.0090702
Yede et al. – CNN-based flood detection (Original Paper)	82%	R. B. Yede, K. D. Yedale, R. S. Wagh, and R. K. Shastri, "Automatic Flood Detection Using CNN," Department of Electronics and Telecommunication Engineering, VPK-BIET, Baramati, Savitribai Phule Pune University, Pune, India.
Our Work (MobileNetV2, Custom Dataset)	**94.36%**	-

Table 4 provides a summary of the reported accuracy of current flood detection models from recent literature to put our model's performance in perspective. Yede et al. created a CNN-based flood detection system with an accuracy of 82%, while Hussain et al. (2024) reported a 92.5% accuracy rate using a deep learning approach on visual flood images. Using a dataset of custom images, our suggested MobileNetV2-based model obtained a classification accuracy of 94.36%. It is crucial to remember that these findings were derived from distinct datasets and experimental setups; as a result, the comparison is offered solely for qualitative purposes and is not intended to serve as a performance standard. These numbers demonstrate the overall advancements in deep learning-based flood detection, but they should be viewed within the constraints of various scenarios, data sources, and verification procedures.

The suggested model uses Batch Normalization and Dropout to enhance training stability and generalization. By normalizing the activations across mini-batches, batch normalization reduces internal covariate shift during training, resulting in more stable learning, shorter training times, and enhanced performance in a variety of environmental conditions which are frequently present in flood imagery (e.g., varying lighting, water reflections, shadows). This is particularly advantageous when training on datasets of a moderate size, like the ones used in this study. To avoid overfitting, Dropout is used concurrently at a rate of 0.5. By forcing the network to learn distributed and generalized representations during training instead of memorization of patterns, random deactivation of neurons increases the network's resilience to novel flood scenarios. These methods help the model minimize false positives while maintaining high precision and recall, which is essential for implementation in flood risk assessment systems. Effective training, competitive performance, and the possibility of real-time applications are made possible by the combination of these methods in a lightweight architecture such as MobileNetV2. To assess the model's resilience on more extensive and geographically varied datasets and to determine whether real-time deployment is feasible through field testing or edge computing simulations, more research is necessary.

5. CONCLUSIONS

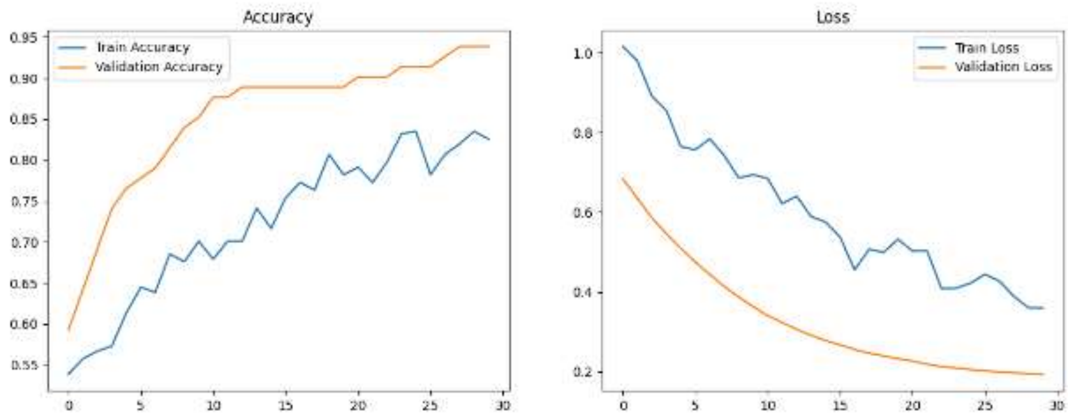

Fig. 13: Training and validation accuracy and loss curves over 30 epochs

This study suggested a hybrid flood detection system that combines long-term rainfall trend analysis with deep learning-based image classification. The system made use of a 50-year Guwahati weather time-series dataset and a customized dataset of 650 annotated photos. With a classification accuracy of 94.36% and macro-averaged precision and recall of 0.95 and 0.93, respectively, MobileNetV2 outperformed the other models in the test. The robustness of the model, with minimal variance across folds, was validated by cross-validation. Because dropout and batch normalization were used, the learning curves showed minimal overfitting and good generalization. Learning curves, which plot the accuracy and loss of training and validation over 30 epochs, were used to further assess the system's training behaviour (Fig. 13). The model generalizes well to unseen data with little overfitting, as shown by the curves' stable convergence, validation accuracy stabilizing between 93% and 94%, and validation loss around 0.2. This stability was facilitated by methods like dropout regularization and batch normalization. The system's decision-support component incorporated the rainfall analysis module's insightful information on historical precipitation trends, regional variances, and seasonal rainfall intensity. By adding the Insights Page, stakeholders were able to better understand situational awareness by interpreting flood alerts in light of past climatic conditions. Overall, the findings support the viability and efficiency of integrating temporal and visual data for flood detection. In order to improve predictive capabilities, future work will concentrate on growing the dataset, adding multi-region weather data, and enhancing model performance with sophisticated temporal models.

REFERENCES

1. Karanjit, R., Pally, R. & Samadi, S., 2023. FloodIMG: Flood image database system. *Data in Brief*, 48, 109164. https://doi.org/10.1016/j.dib.2023.109164
2. Bisht, A., Nath, A. & Dimri, P., 2024. Flood prediction and management. *Journal of Engineering and Technology for Industrial Applications (JETIA)*, 10(47). 10.5935/jetia.v10i47.1103
3. Saha, P., Mitra, R., Das, J. & Mandal, D.K., 2024. Urban flash flood prediction modelling using probabilistic and statistical approaches. *Results in Earth Sciences*. 10.1016/j.rines.2024.100032
4. "EM-DAT, The International Disaster Database", Centre for Research on the Epidemiology of Disasters (CRED), 1988. https://www.emdat.be/
5. Hussain, A., Latif, G., Alghazo, J. & Kim, E., 2024. Flood detection using deep learning methods from visual images. *AIP Conference Proceedings*, 3034(1). 10.1063/5.0194669
6. Byaruhanga, N., Kibirige, D., Gokool, S. & Mkhonta, G., 2024. Evolution of flood prediction and forecasting models for flood early warning systems: A scoping review. *Water*, 16, p.1763. 10.3390/w16131763
7. Amaral, G.C., Ferreira, A.M., Sardinha, D.S., Menezes, P.H.B.J., Marchezinic, V. & Tiezzi, R.O., 2023. Official and unofficial data supporting disaster risk management in medium-sized cities. *Natural Hazards Research*, 3(1), pp.89–96. 10.1016/j.nhres.2023.01.004
8. Yede, Y.R.B., Yedale, K.D., Wagh, R.S. & Shastri, R.K., 2021. Automatic flood detection using CNN. *Department of Electronics and Telecommunication Engineering, VPKBIET, Savitribai Phule Pune University, Pune, India*. https://www.researchgate.net/publication/371225289_Automatic_Flood_Detection_Using_CNN
9. Hashi, A.O., Abdirahman, A.A., Elmi, M.A., Hashi, S.Z.M. & Rodriguez, O.E.R., 2021. A real-time flood detection system based on machine learning algorithms with emphasis on deep learning. *International Journal of Engineering Trends and Technology*, 69(5), pp.249–256. 10.14445/22315381/IJETT-V69I5P232
10. Stateczny, A., Praveena, H.D., Krishnappa, R.H., Chythanya, K.R. & Babysarojam, B.B., 2023. Optimized deep learning model for flood detection using satellite images. *Remote Sensing*, 15(20). 10.3390/rs15205037
11. Hasan, M.Z., Hasan, K.M.Z. & Sattar, A., 2018. Burst header packet flood detection in optical burst switching network using deep learning model. *Procedia Computer Science*, 143, pp.970–977. 10.1016/j.procs.2018.10.337
12. Tuyen, D.N., Tuan, T.M., Son, L.H., Ngan, T.T., Giang, N.L., Thong, P.H., Hieu, V.V., Gerogiannis, V.C., Tzimos, D. & Kanavos, A., 2021. A novel approach combining particle swarm optimization and deep learning for flash flood detection from satellite images. *Mathematics*, 9(22). 10.3390/math9222846
13. Bahrami, B. & Arbabkhah, H., 2024. Enhanced flood detection through precise water segmentation using advanced deep learning models. *Journal of Civil Engineering Research*, 6(1). 10.61186/JCER.6.1.1
14. Khan, M.A., Ahmed, N., Padela, J., Raza, M.S., Gangopadhyay, A. & Wang, J., 2023. Flood-ResNet50: Optimized deep learning model for efficient flood detection on edge device. In: *2023 International Conference on Machine Learning and Applications (ICMLA)*, Jacksonville, FL, USA, pp. 512–519. 10.1109/ICMLA58977.2023.00077

15. Ali, M.H.M., Asmai, S.A., Abidin, Z.Z., Abas, Z.A. & Emran, N.A., 2022. Flood prediction using deep learning models. *International Journal of Advanced Computer Science and Applications (IJACSA)*, 13(9), pp.1–8. 10.14569/IJACSA.2022.01309112
16. Pandey, R.P., Desai, M. & Panwar, R., 2023. Hybrid deep learning model for flood frequency assessment and flood forecasting. *Multidisciplinary Science Journal*, 5. 10.31893/multiscience.2023ss0204
17. V, S., Krishnamurthi, I. & H, M.N., 2024. Flood detection and segmentation using deep learning models. In: *2024 International Conference on Smart Systems for Electrical, Electronics, Communication and Computer Engineering (ICSSEECC)*, Coimbatore, India, pp. 226–231. 10.1109/ICSSEECC61126.2024.10649475
18. Mohamadiazar, N., Ebrahimian, A. & Hosseiny, H., 2024. Integrating deep learning, satellite image processing, and spatial-temporal analysis for urban flood prediction. *Journal of Hydrology*, 639, p.131508. 10.1016/j.jhydrol.2024.131508
19. Liou, Y.-A. & Hoang, D.-V., 2024. Improved flood depth estimation with SAR image, digital elevation model, and machine learning schemes. Journal of Hydrology: Regional Studies, 53, p.101775. 10.1016/j.ejrh.2024.101775
20. Zhong, P., Liu, Y., Zheng, H. et al., 2024. Detection of urban flood inundation from traffic images using deep learning methods. *Water Resources Management*, 38, pp.287–301. 10.1007/s11269-023-03669-9
21. Quang, N.H., Lee, H., Kim, N. et al., 2024. Real-time flash flood detection employing the YOLOv8 model. *Earth Science Informatics*, 17, pp.4809–4829. 10.1007/s12145-024-01428-x
22. Huang, B., Li, P., Lu, H., Yin, J., Li, Z. & Wang, H., 2024. WaterDetectionNet: A new deep learning method for flood mapping with SAR image convolutional neural network. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 17, pp.14471–14485. 10.1109/JSTARS.2024.3440995
23. Bukhari, S.A.S., Shafi, I., Ahmad, J. et al., 2024. Enhancing flood monitoring and prevention using machine learning and IoT integration. *Natural Hazards*. 10.1007/s11069-024-06986-3
24. Sonavale, A., Chakkaravarthy, M., Rao, S.S., Salleh, H.B.M. & Jadhav, J., 2024. Machine learning model comparison for flood detection application from satellite images. In: *2024 International Conference on Data Science and Network Security (ICDSNS)*, Tiptur, India, pp.1–7. 10.1109/ICDSNS62112.2024.10690885
25. Roohi, M., Ghafouri, H.R. & Ashrafi, S.M., 2025. Advancing flood disaster management: Leveraging deep learning and remote sensing technologies. *Acta Geophysica*, 73, pp.557–575. 10.1007/s11600-024-01481-6
26. Garg, C. and Babu, A., 2023. Extreme Flood Calibration and Simulation Using a 2D Hydrodynamic Model Under a Multipurpose Reservoir. *Nature Environment and Pollution Technology*, *22*(2), pp.977-983. 10.46488/NEPT.2023.v22i02.042