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Enhanced Flood Management Using a Climate Disaster Image Dataset

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ABSTRACT

Floods are among the most destructive climate-related disasters, necessitating the development of effective tools for precise forecasting and prompt action. This study proposes a hybrid flood detection framework that integrates temporal rainfall trend analysis with spatial image classification. The system uses 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, achieved a 94.36% detection accuracy and a 32% decrease in misclassification compared to conventional models. An 80:20 train-test split with cross-validation was used to train and assess the model. The time-series component of the system looks for patterns in seasonal flood risk by analyzing historical rainfall data. The integration of time-series and image-based analyses into a single predictive platform, which permits spatiotemporal flood detection, is one of the main contributions of this study. To aid decision-making, a visualization dashboard shows rainfall trends. These findings imply that the system can assist with disaster preparedness and response planning and is appropriate for real-time deployment in flood-prone areas. To improve the predictive power of the system, future research should focus on expanding the dataset and incorporating sophisticated forecasting models.

INTRODUCTION

Climate-induced floods have become more frequent and severe in terms of loss, resulting in significant socioeconomic losses worldwide. The 2018 Kerala floods and the 2022 Pakistan floods remind us of the scale of damage to infrastructure, agriculture, and human life caused by such events. In India alone, the country has suffered economic losses of ₹52,500 crore in recent years from floods, with frequent events occurring in Assam, Bihar, and even urban areas like Mumbai. Traditional flood prediction and management systems rely on static data and have limited real-time capabilities, making them insufficient for handling the dynamic nature of climate-induced disasters. Moreover, current approaches lack integration between datasets, such as weather data, geographical information, and real-time video evidence. These limitations call for an innovative and 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. These systems provide real-time insights, significantly improving the decision-making processes of emergency responders and policymakers. This study presents the idea of a comprehensive platform, the Global Climate Disaster Database," to improve flood predictions, monitoring, and responses. Through advanced machine learning techniques, this system provides real-time insights to first responders, policymakers, and city planners. This study aims to provide an application of an all-inclusive platform by 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 in the accuracy of performance, speed, and scalability. Other strengths of the concerned approach include two specific, very important things: it is 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 in improving disaster preparedness, minimizing response times, and minimizing economic and social losses due to flooding. In addition, the proposed system allows collaboration because of a centralized data repository that can be utilized by researchers and disaster management authorities globally.

RELATED WORK

Flood management has significantly advanced through the integration of deep learning and data-driven techniques. This section explores existing studies, 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 enriched deep learning models with high-quality training data and achieved an accuracy of 92.5%. However, the geographic diversity of the dataset may limit the generalizability of this model. Our system extends this work by incorporating geographically diverse datasets to improve the 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 was also very effective in identifying risk zones with an accuracy of 89%. However, these models are not highly adaptive to rural or geographically diverse contexts. Our deep learning approach generalizes to a wide variety of situations with an accuracy of 94.36%. Hussain et al. (2024) showed that it is possible to use XGBoost and Random Forest machine learning models to detect floods using environmental factors such as rain and humidity. These models produced a high accuracy rate (>90%) but were sensitive to the completeness and quality of the input data. Adding annotated image data to our system eliminated these issues, with a 32% reduction in misclassification. 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 data-scarce regions and provided recommendations for interdisciplinary collaboration. Although the review spanned a wide scope, the research was not experimentally validated. Our work provides experimental evidence through extensive testing on various datasets and offers 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 because it is highly cost-intensive, especially for resource-limited regions. Our system mitigates the costs of operating the system through the extensive use of accessible machine learning methods and curated datasets. The proposed Global Climate Disaster Database surpasses these approaches by achieving higher accuracy (94.36%) and scalability, in addition to addressing geographic bias and providing actionable insights through real-time visualizations. These advancements position our platform as a comprehensive and 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 by 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), was exploited by the proposed system by Hashi et al. (2021) as a real-time flood detection system. This study aimed to provide 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 experimental results show that Random Forest outperforms the other classifiers with an accuracy of 98.7%, whereas Naïve Bayes and J48 have 88.4% and 84.2% accuracy, respectively. The deep learning-based CNN approach achieved an accuracy of 87%, showing high precision and recall values. Hence, this study contributes a valuable and visible application to the fields of Artificial Intelligence, Data Mining, and Deep Learning as an innovative solution in flood detection and early warning systems. To better ascertain the accuracy of flood prediction, researchers have extensively applied different types of deep learning techniques. Stateczny et al. (2023) proposed a new hybrid deep model for flood prediction, called the DHMFP, which was presented while being trained based on the combined Harris Hawks Shuffled Shepherd Optimization (CHHSSO) algorithm. This study aimed to increase the accuracy of traditional flood detection methods, especially for urbanized regions such as Kerala, where drainage systems are not capable of handling the torrent of rainwater. The methodology involved the preprocessing of satellite images using median filtering and segmentation with cubic chaotic map-weighted K-means clustering. To strengthen feature representation, different vegetation indices, such as the Difference Vegetation Index (DVI), Normalized Difference Vegetation Index (NDVI), and soil-adjusted vegetation index (SAVI), were extracted. The extracted features were classified in a hybrid manner based on a CNN-Deep ResNet framework fine-tuned using weight optimization by CHHSSO. The experimental results showed high performance, with 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 improved sensitivity, specificity, and accuracy of 0.932, 0.977, and 0.952, respectively, further validating the model's efficacy in terms of flood prediction. Hasan et al. (2018) proposed a Deep Convolutional Neural Network (DCNN) that detects Burst Header Packet (BHP) flooding attacks in Optical Burst Switching (OBS) networks. This study presents the criterion that the existing methods, such as 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 the dataset. The proposed DCNN model outperformed these traditional methods by creating a very early scenario for attack identification. The experimental results also proved that DCNN provided a classification accuracy of 99%, which was much better than KNN (93%), SVM (88%), and Naive Bayes (79%). The sensitivity, specificity, precision, and F1-score were also 99%, while both the false positive rate (FPR) and the false negative rate (FNR) were only 1%. These studies and several others have found that most traditional ML models exhibit overfitting and misclassification. In contrast, the DCNN showed a constant level of performance across both the training and validation dataset conditions. This showed that deep learning models were effective in applying network anomaly detection, demonstrating the benefits of DCNN over traditional classification techniques. Tuyen et al. (2021) introduced a newly designed deep learning architecture called PSO-UNET to enhance flash flood segmentation from satellite images. This model integrates Particle Swarm Optimization (PSO) and UNET to optimize the segmentation accuracy, thereby optimizing the number of layers and layer parameters. Instead of maintaining the same symmetrical architecture usually observed in conventional UNET models, the ultimate difference in the proposed PSO-UNET is that it dynamically modifies the contracting and expanding paths for optimal performance. The model was tested on a dataset consisting of 984 satellite images and compared with 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 8.59% greater than that of the original UNET model. In addition, the model exhibited better performance in terms of the Dice Coefficient and Intersection over Union (IoU). Although the authors highlighted a very good performance in terms of segmentation accuracy, they found some slight errors owing to related pixel features. They suggested that post-processing techniques should be supplemented, and further validation should be performed on datasets that are more varied. This study contributes to the development of an optimized UNET-based segmentation model, demonstrating the extent to which evolutionary algorithms can achieve in the field of deep learning-based flood detection. SegNet, UNet, and FCN32 carried out floodwater segmentation of 290 flood-affected images in Bahrami & Arbabkhah (2024), and the study aimed 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 in the images. This study emphasizes the importance of deep learning in enhancing flood forecasting and disaster response. Flood-ResNet50, as proposed by Khan et al. (2023), was developed with an 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 the enhancements of ResNet50 through transfer learning and additional layers in the model architecture, a classification accuracy of 96.43% was attained, which was significantly higher than comparable larger models such as VGG16/19 and DenseNet161. Experimental results showed that it outperformed conventional models in terms of inference speed and power consumption through the edge device, thus recommending it as a real-time flood detection solution. Deep learning models have been extensively utilized in flood prediction and frequency assessment, as shown by Pandey et al. (2023). Conventional statistical techniques and traditional forecasting approaches can hardly capture any nonlinear interactions among flood variables. A Cat Swarm Optimized Spatial Adversarial Network (CSO-SAN) was proposed for flood forecasting that combines real-time meteorological and hydrological data. Studies have also proven that CSO-SAN is by far better than the rest, achieving an accuracy of 98.3%. Despite its effectiveness, it could be improved by applying hyperparameter tuning and additional machine learning techniques for further tuning. Urban flood monitoring is hampered by insufficient runoff data, which leads to a loss of hydrological model and early warning system accuracy. With recent advances in deep learning, image recognition has become a significant approach for flood measurement. Studies have proven that YOLOv4 works well during floods in identifying submerged objects, such as vehicles and pedestrians, with a mean average precision of 89.29% % for flood depth recognition. Depending on the reference object used, this method can provide higher accuracy in the results, where vehicles provide better results than pedestrians. In addition, image augmentation methods, such as Mosaic, have been proposed to increase recognition accuracy. This presents an economical option for existing traffic cameras to be put to effective use, eliminating 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 image distortions. To overcome these limitations, WDNet fuses CNN with a self-attention mechanism to enhance spatial and channel-wise feature extraction. WDNet performs better than conventional methods in terms of accuracy, with an F1 score of 0.987 on the Poyang Lake flood dataset. This model (Huang et al. 2024) thus aids 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 the FCN, the U-Net achieved a better performance with an accuracy of 88% and a much higher mIoU of 0.65, demonstrating its application for flood detection. The research by Roohi et al. (2025) shows the efficiency of applying AI-based geospatial analysis in improving flood monitoring and disaster management.

MATERIALS AND METHODS

Fig. 1 describes the flow of the flood detection and analysis, with alerts generated on the website. The architecture consists of the following key components:

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 the 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 suggested by Karanjit et al. (2023). 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 to guarantee label accuracy. Only images with unambiguous visual proof and reviewers’ agreement were included after labeling by the authors. A combination of street-level and aerial views is included in the dataset, along with a variety of environmental features such as lighting, weather, and scene complexity. The visual context shows coverage from various urban and semi-urban regions, mainly from India and Southeast Asia,

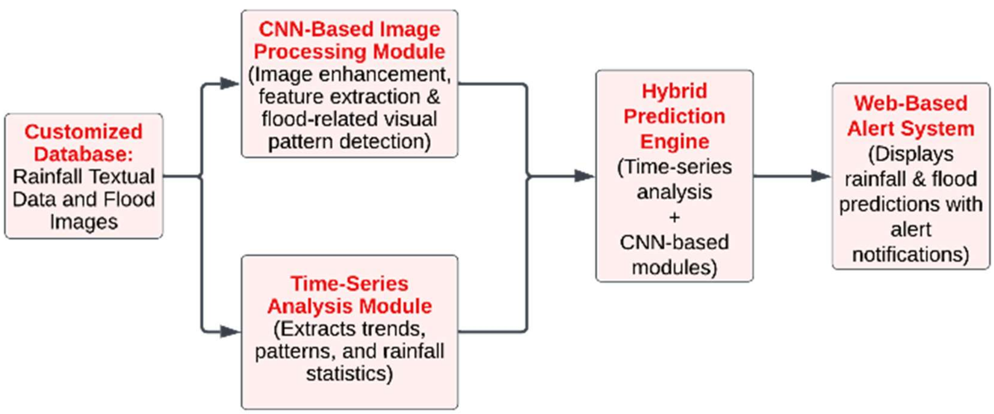

Fig. 1: Block diagram of flood detection system.

Table 1: Overview of dataset.

Dataset Type	Source(s)	Size/Duration	Key Features	Purpose
Image Dataset	Google Images, Kaggle, FloodIMG (Karanjit et al. 2023)	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

with a smaller number from Europe, even though precise geolocation metadata were 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, was 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 such as conditions, icons, and descriptions. Preprocessing included classifying weather conditions into four symbolic types: clear, cloudy, partly cloudy, and rainy; handling missing values through interpolation; and eliminating outliers using interquartile range-based filtering. Seasonal decomposition and long-term trend analyses 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 rainfall trends as a temporal input, which improved the system's capacity to identify floods by utilizing both historical climate context and visual features. An overview of the dataset is presented in Table 1.

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." Deep learning models were applied to a dataset of 650 flood images that were marked using TensorFlow and Keras. Four classic deep learning networks, EfficientNetB0, ResNet50, InceptionV3, and MobileNetV2, were initially tested, and InceptionV3 and MobileNetV2 were chosen for their high performance. The 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. The model was designed to provide smooth gradients during the course of backpropagation with the help of shortcut connections, and thus, effective convergence. The application of ResNet50 for flood detection yielded a fairly moderate accuracy of 64.7%, primarily attributed to its stickiness towards overfitting on a very small dataset. However, it was capable of adequately capturing the hierarchical features of flood imagery; its high computational complexity hindered its adoption in streaming, as extensive GPU resources were required. There is room for improving the performance of this model using data augmentation techniques and larger and more diverse datasets.

Architecture InceptionV3 is another model in the competition for multi-scale feature extraction based on a factorized convolution design with asymmetric kernel designs. 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 improved computational effectiveness in reducing the number of parameters while maintaining very high accuracy. In flood classification, InceptionV3 achieved a high rate of 93%, marking it as one of the standout models in this study. Its strengths include the excellent capture of both local and global flood patterns. However, owing to its deep and complex architecture, the inference time was higher than that of MobileNetV2, making it less favorable for real-time applications where deciding in the moment was essential. EfficientNetB0 was established to maximize accuracy while maintaining efficiency by scaling its dimensions (i.e., depth, width, and resolution) with compound scaling factors. The compound scaling formula is as follows:

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

Where α, β, γ are constants determined through grid search, and 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 high accuracy with a small number of parameters. Although EfficientNetB0 performed poorly in our flood detection study, with an accuracy of only %39, primarily due to the non-availability of high-quality, large-scale datasets for appropriate feature extraction, low-light conditions caused performance issues with flood classification, suggesting that extreme tuning and transfer learning adjustments are required. Nonetheless, despite its inefficiency, EfficientNetB0 remains a promising model for lightweight work, where power consumption is a constraint. Among all the trained models, MobileNetV2 showed the best performance in terms of flood detection, achieving an accuracy of %94.36. Designed for mobile and edge devices, it uses depth-wise separable convolutions to reduce computation while maintaining a 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:

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

This architectural choice allows MobileNetV2 to perform well in real-time applications while maintaining low computational costs. It is also designed with an inverted residual structure and linear bottlenecks, allowing for feature propagation and reducing redundancy. This aspect enables the architecture to easily process flood imagery for real-time detection with minimal resource consumption. It optimally balances accuracy, speed, and computational efficiency; hence, it is ideal for deployment in flood monitoring applications. The comparative analysis showed that deeper models, such as InceptionV3 and ResNet50, could extract complex flood-related features; however, 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 the classification performance in this domain. Finally, MobileNetV2 was identified as the most suitable model because of its high accuracy with low computational 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 the complete monitoring of floods as part of a larger predictive and alert system. In addition, by deploying a deep learning mechanism, the system can continue to improve the analysis of new flood imagery, indicating that the system is efficient and expandable in disaster scrutiny and handling.

Time-Series Analysis Module

To complement the image processing module, the Time-Series Analysis Module focuses on textual rainfall data, which extracts trends and patterns to understand seasonal variations. The analysis revealed 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 for identifying regions prone to floods and periods of increased risk, which aid in the predictive capabilities of the system.

Hybrid Prediction Engine

At the heart of the architecture is the Hybrid Prediction Engine, which combines the outputs from the CNN-based image processing and time-series analysis modules. This engine combines spatial and temporal data using 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 of the prediction.

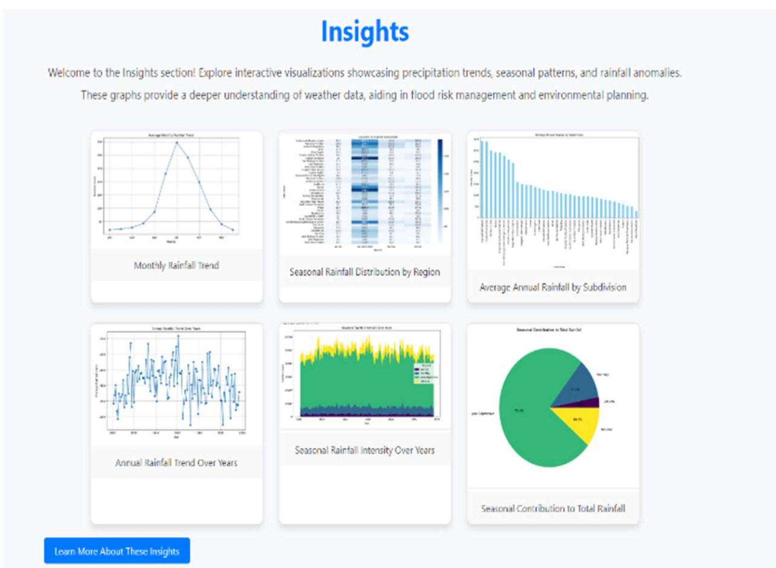

Fig. 2: Insight's page.

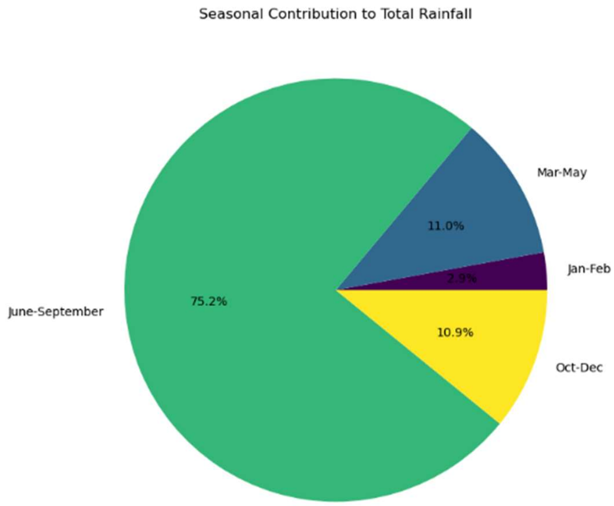

Fig. 3: Seasonal contribution to total rainfall.

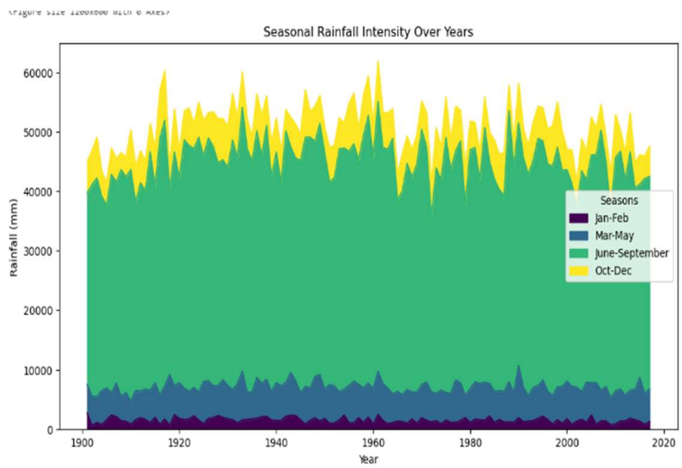

Fig. 4: Seasonal rainfall intensity over years.

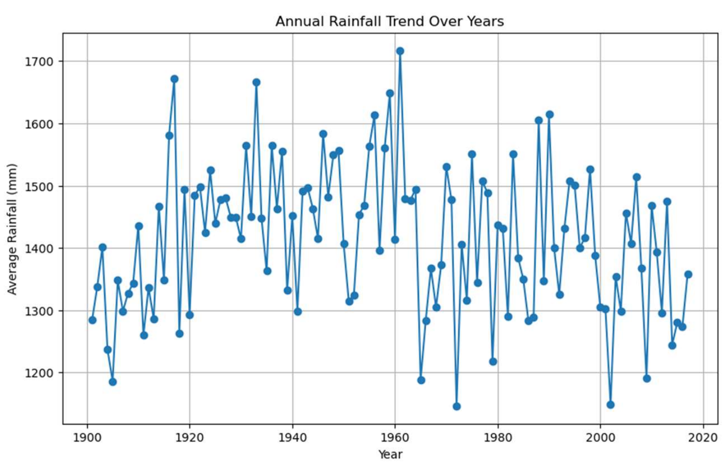

Fig. 5: Annual rainfall trend over years.

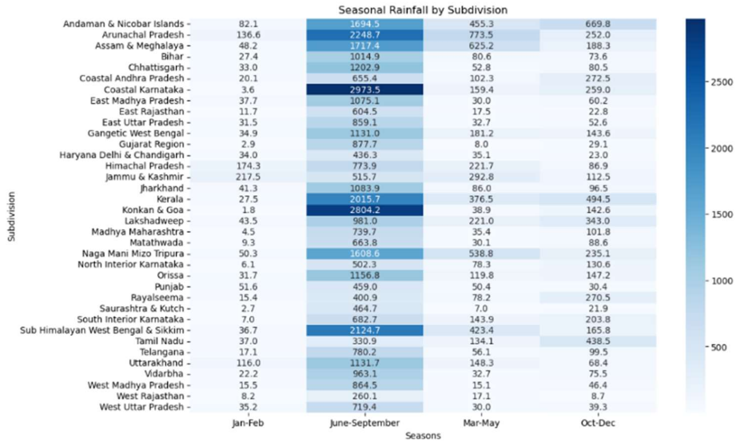

Fig. 6: Seasonal rainfall by subdivision.

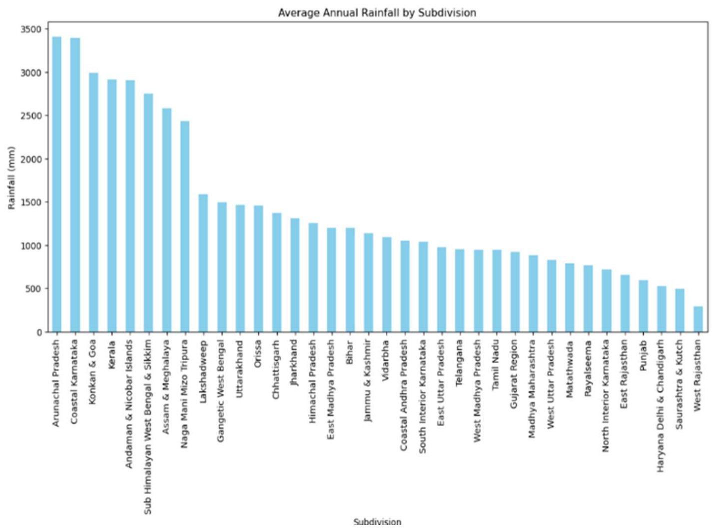

Fig. 7: Average annual rainfall by subdivision.

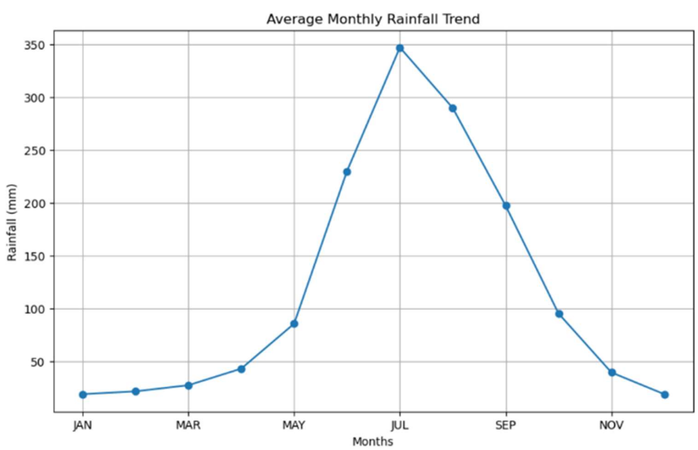

Fig. 8: Average annual rainfall by subdivision.

Analytical Insights and Decision-Support Integration

An analytical module called the Insights Page combines the flood prediction architecture of the system 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 analyzing flood risk across time and space. Annual trends (Fig. 5) show evidence of long-term variability possibly related to climate change, and 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 regions. 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 usefulness of the system 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, thereby 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 and 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.

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

RESULTS AND DISCUSSION

The proposed flood detection methodology was tested using four of the most widely developed deep convolutional neural network (CNN) models. It is evident that the performance metrics, specifically the accuracy characteristics, significantly differ from model to model, indicating different strengths and weaknesses. The performance of the models was compared in the context of each city, and Table 2 provides a summary. The authors used 5-fold cross-validation on the training data to guarantee robustness and reduce the impact of variance caused by dataset split or model initialization. Five separate runs, each with retrained models and shuffled data, were averaged to produce the reported results (Accuracy, Precision, and Recall). The model's behavior was consistent and generalizable, as evidenced by the standard deviation of the performance metrics 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 and recall, which were calculated using macro-averaging across both classes, ensuring equal weights to both classes. All reported values represent the means across five validation folds.

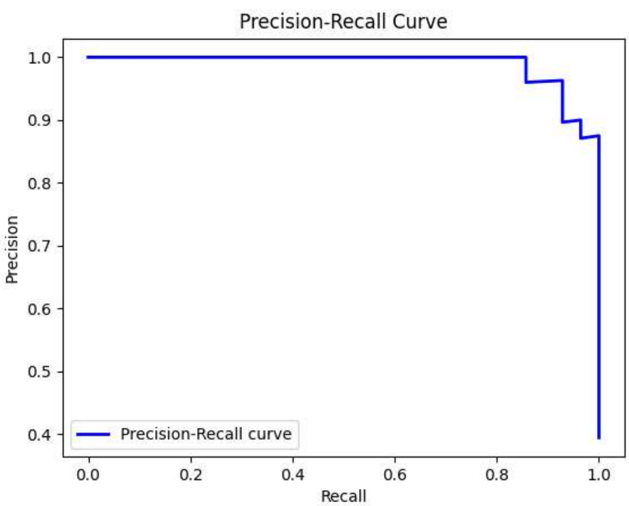

Fig. 9: Precision and recall curve.

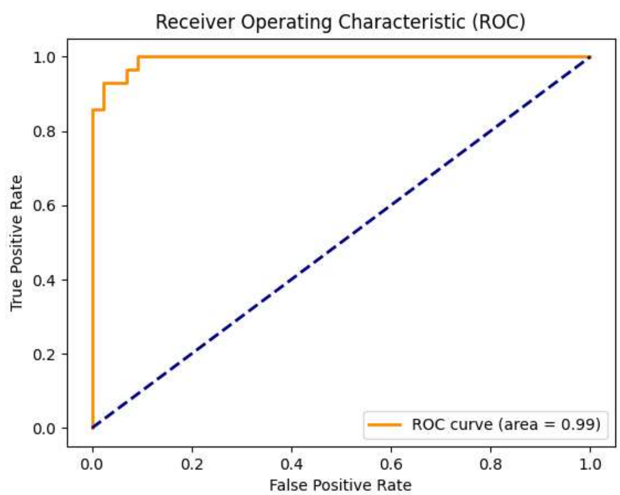

Fig. 10: Receiver operating characteristic (ROC) curve for the flood detection system.

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

Fig. 10 shows that the high AUC of 0.99 indicates the reliability of identifying flood occurrences with minimal false alarms. Of the four trained models discussed in Table 3, MobileNetV2 was the fastest and most accurate model for flood detection in practical applications when

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.

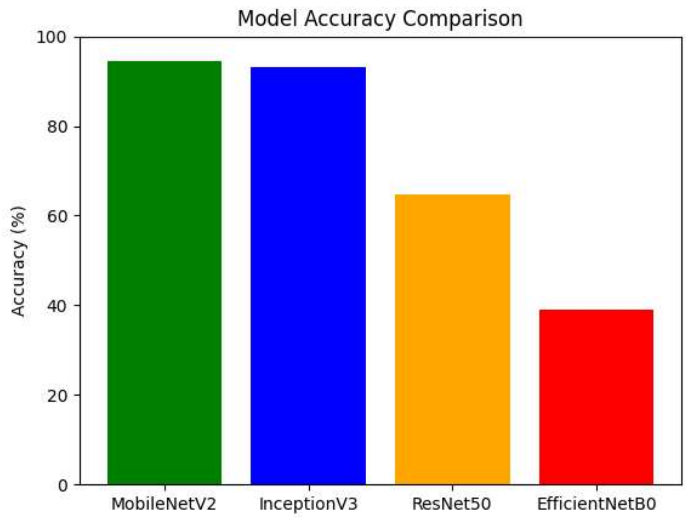

Fig. 11: Comparative performance metrics of different models.

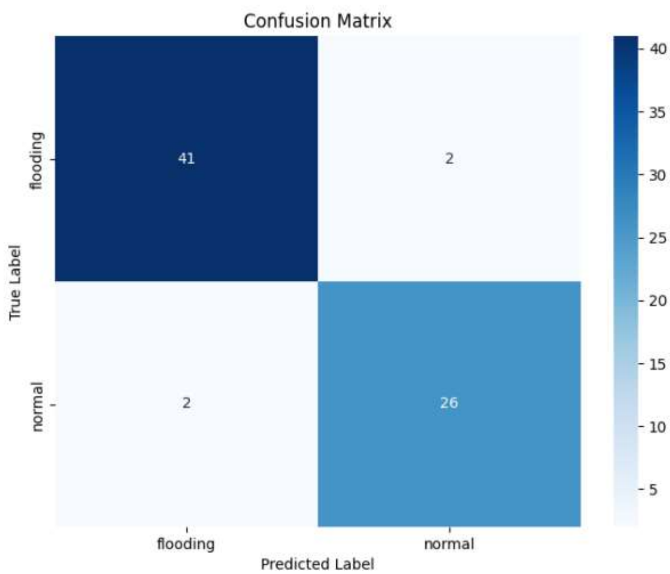

Fig. 12: Depicting the confusion matrix of the research.

both speed and accuracy were important. InceptionV3 also provided adequate results with a slight difference and excellent results in cases that required 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 to increase model accuracy. These findings call for lightweight but strong models, such as MobileNetV2, to be adopted in flood detection systems, particularly in real-time disaster surveillance and risk evaluation applications. The same train-test split (80:20) was used to train and assess every model listed 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. The authors applied the same early stopping criteria, input resolution (224×224), and preprocessing pipeline to all models. Using the validation set, a grid search was used to choose hyperparameters such as the 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.

Fig. 11 compares the classification accuracy across different models, while Fig. 12 shows the confusion matrix, which provides detailed insight into the classification accuracy for different classes. The matrix shows high true positive rates across categories, validating the effectiveness of the model in distinguishing between flood types with minimal misclassification.

Comparative Analysis

Table 4 provides a summary of the reported accuracy of current flood detection models from the 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%, whereas 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 proposed MobileNetV2-based model achieved 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 the internal covariate shift during training, resulting in more stable learning, shorter training times, and enhanced performance in a variety of environmental conditions that are frequently present in flood imagery (e.g., varying lighting, water reflections, and shadows). This is particularly advantageous when training on datasets of moderate size, such as those used in this study. To avoid overfitting, dropout was used concurrently at a rate of 0.5. By forcing the network to learn distributed and generalized representations during training instead of

Table 4: Comparative analysis of research.

Model	Accuracy	Reference
Hussain et al. (2024) – Deep learning on visual images	92.5%	Hussain et al. (2024)
Yede et al. – CNN-based flood detection (Original Paper)	82%	Yede et al. (2021)
Our Work (MobileNetV2, Custom Dataset)	94.36%	-

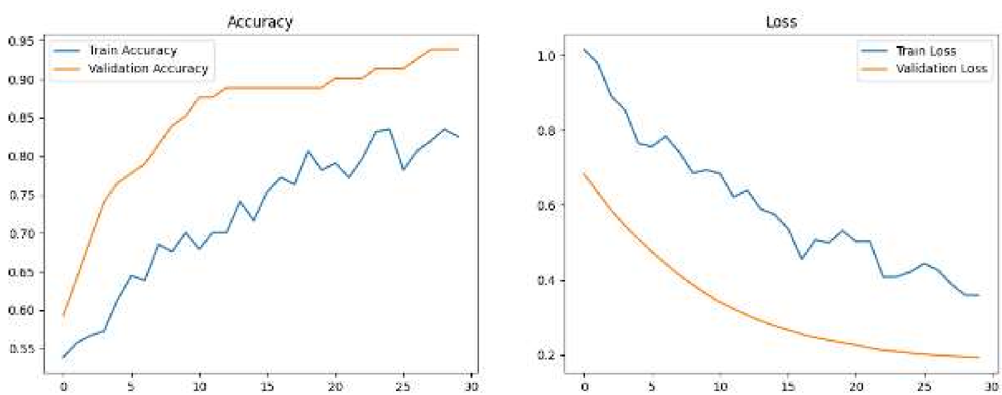

Fig. 13: Training and validation accuracy and loss curves over 30 epochs.

memorizing patterns, the 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 combining these methods in a lightweight architecture, such as MobileNetV2. To assess the model›s resilience on more extensive and geographically varied datasets and determine whether real-time deployment is feasible through field testing or edge computing simulations, further research is necessary.

CONCLUSIONS

This study proposed a hybrid flood detection system that combines long-term rainfall trend analysis with deep learning-based image classification. The system used 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 tests. The robustness of the model, with minimal variance across the folds, was validated using cross-validation. Because dropout and batch normalization were used, the learning curves showed minimal overfitting and good generalization performance. Learning curves, which plot the accuracy and loss of training and validation over 30 epochs, were used to further assess the training behavior of the system (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 a validation loss of approximately 0.2. This stability was facilitated by methods such as dropout regularization and batch normalization. The system's decision-support component incorporates 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 based on past climatic conditions. Overall, the findings support the viability and efficiency of integrating temporal and visual data for detecting floods. To improve predictive capabilities, future work will focus on expanding the dataset, adding multi-region weather data, and enhancing model performance using sophisticated temporal models.

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