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ARTIFICIAL INTELLIGENCE-POWERED LANDSCAPE VISION TRANSFORMATION TECHNIQUE FOR EARLY FLOOD RISK DETECTION THROUGH SATELLITE MAPPING SYSTEM USING DEEP FEATURE ENGINEERING

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ABSTRACT

Environmental development depends entirely on natural resources, such as covering landscapes based on human lives and technological improvement. Specifically, the sloping mountain regions of land and their nature depend on sliding partitions; due to large floods, human lives are affected mainly by sudden causes of disasters. This paper addresses the critical issue of early flood risk detection in sloping mountain regions, where human lives and technological infrastructure are heavily reliant on natural resources. Satellite images and AI techniques are crucial developments to make analysis effective. Still, traditional methods fail to analyze the feature mapping and presence in feature variability due to increasing time frames, resulting in a high recall, which means that fables are unable to detect the flood quantity from regions where rainfall occurred, regions, and landscape regions. To resolve this problem, we propose an AI-powered landscape Vision Transformation Technique (LVTT) For Early Flood Risk Detection through a Satellite Mapping System Using Deep Feature Engineering. Initially, the landscape region images are collected from the satellite monitoring system. An adaptive Gaussian filter carries out the preprocessing. The historic color difference-based Slice Window Canny Edge Detection (SWCES) is used to segment the two-layer flooding and water flow region with dependable features. Then, Region Scaled Ant Colony Optimization (RSACO) for selecting the variability region features mutually depends on detecting the flooding variation region. Finally, the Hyper Capsuled LSTM Gated Convolution Neural Network (LSTMG-CNN) predicts that the flood region will cover the risk region of landscapes for early detection of floods to safeguard human lives. The proposed system produces high performance by predicting in the early stage of flooding variation limits depending on the flood flow through the image, progressing to achieve a high precision rate and recall rate with improved detection accuracy than any conventional methods.

Keywords: *Risk Detection, Satellite Imagery, Deep Learning, Feature Engineering, Landscape Analysis, Artificial Intelligence, Convolutional Neural Networks, LSTM.*

1. INTRODUCTION

The rising rates and intensity of floods propelled by climate change and extreme weather condition have increased the necessity of efficient early floods risk sensing frameworks, especially in hilly and sloppy areas. These locations are extremely susceptible because of the dear nature of the topography, high dynamics of water circulation and minimal response time, which pose a profound risk to human lives and facilities. Recent developments in remote sensing systems, particularly the high-resolution satellite systems like Sentinel-1, have now made flood-scale monitoring possible due to the constant scanning process of the earth.

With all this, the traditional methods of flood detection and mapping are still greatly challenged when it comes to properly capturing spatial-temporal changes in flood dynamics. Classical image processing and machine learning rule-of-thumb approaches are not always capable of dealing with dynamic variability of features, distortions in terrain, and noise in multisource satellite images.

Consequently, these techniques are characterized by slow response, poor estimation of flood boundary, and false alarm, which restricts their application in early warning.

Even with the development of satellite imagery and AI-controlled flood-detection frameworks, there are areas that are not complex to predict the risk of early flooding. Behaviour in floods is naturally nonlinear and spatially heterogeneous, especially in sloping and mountainous areas, where terrain topography, variability of water-flow, and heterogeneity of land-cover all interact in unforeseeable manner. Traditional methods- CNNs, LSTMs and XGBoost models have difficulty in modelling such spatial-temporal dynamics and they frequently make delayed or inaccurate predictions.

The inadequacy of the modeling of variability of features, time development, and the combination of multi-source satellite data point to a general gap between existing practices and the realities of flood monitoring. This unsolved issue contributes to the creation of a theoretically based, feature-adaptable, and spatially-temporally-conscious model, e.g., the offered LVTT, to translate raw satellite measurements into practical flood hazards forecasts.

Deep learning and computer vision approaches to interpret multifaceted satellite images have become an effective option to address the previously discussed limitations, due to the emergence of Artificial Intelligence (AI). Nevertheless, the current AI-based flood detection frameworks mainly concentrate on a one-stage forecasting or separately distinguishing features and do not entail a unified framework that includes noise reduction, accurate boundary divisions, optimal selection of features, and spatial-temporal forecasting of floods. This realization underscores the necessity to have an effective, elucidate, and scalable AI-powered pipeline that is specifically intended to detect early flood risks.

To overcome all these issues, this paper will suggest an AI Powered LVTT which, based on satellite mapping systems and deep feature engineering, should identify the early flood risk. The suggested framework converts raw satellite imagery into useful flood risk indicators in a multi-stage processing pipeline in a systematic way. The first step is called adaptive Gaussian filtering which removes noise at the expense of important landscape features. This is followed by SWCES which is used to automatically mark boundaries of floods and water-flow. It is then followed by the introduction of RSACO that isolates critical features of flood-varying features by identifying areas of spatial variability. Lastly, a LSTMGCNN is a predictor of early flood-prone areas by learning spatial and temporal patterns of flood-flows.

Hypothesis The AI-based LVTT that incorporates adaptive processing, optimized region-based feature selection, and spatial-temporal deep learning will be more effective at capturing the patterns of flood variability using satellite imagery and the detection of early risks of floods will be significantly more accurate than traditional image processing and the use of standalone deep learning techniques.

The research design applied in the study is an experimental, model-based research, which is often used in disaster prediction research and artificial intelligence research that require satellites to gather and examine data. The suggested framework is constructed, deployed, and tested on an empirical basis with the help of satellite imaging to determine its suitability in detecting early flood risk. Other uses of similar experimental designs have been successful in studies involving flood monitoring using SAR data, wildfire detection using deep learning in remote sensing and spatiotemporal risk prediction in environmental monitoring systems. Adhering to this time-tested research paradigm, the current work will guarantee the consistency of its methodology and allow comparing the performance of the results with the existing studies in various geographic and application settings.

CONTRIBUTION OF THE WORK

- This paper presents the Landscape Vision Transformation Technique (LVTT), a combined deep neural network (DNN) based flood monitoring system to identify early flood risks in sloping mountains due to the inability of conventional approaches to manage complexity and fluctuations in the landscape.
- This system contains an Adaptive Gaussian Filtering, SWCES, and RSACO to improve noise reduction, the boundary segmentation in the flooding, and the selection of critical flood or satellite features.
- The new model, the Hyper Capsuled LSTM Gated Convolutional Neural Network, is developed as a hybrid deep neural model that can accurately predict the occurrence of floods in the identified flood-prone area, utilizing the extracted

features, and can significantly compare the performance of early detection to the existing methods using a higher precision and recall.

The suggested LVTT model will enhance the accuracy and reliability of the early floods detection with the help of advanced preprocessing, feature engineering technologies, and hybrid deep learning networks. It is a measure that encourages early management of disasters, enables quick evacuation measures, and reduces the threats, resulting into reduced loss due to floods and increased resilience to water-related disasters due to climate change.

The remaining portion of the document is divided into significant sections, which are described as follows: Section II examines the current research efforts in Artificial Intelligence Powered Landscape Vision Transformation Technique for Early Flood Risk Detection Through Satellite Mapping System Using Deep Feature Engineering, used by different authors. The workflow of the suggested approach is explained in Section III and consists of the proposed methodology. Section IV presents the findings, analysis, and performance data. Section V presents the conclusion.

2. LITERATURE SURVEY

Monitoring floods with Synthetic Aperture Radar (SAR) and cloud-based services has undergone significant improvement. The methodology presented in **Hamidi et al. (2023)** utilizes Google Earth Engine to enhance the efficiency of change detection, enabling the rapid identification of flooding extent. The procedure enables the provision of near-real-time disaster response, based on the analysis of pre- and post-event SAR images. The study is more accurate compared to optical-based methodologies because it is able to map areas covered by floodwater even when there is cloud cover. In addition, automation enhances the handling of manual processes, and related processes facilitate timely decision-making during emergency management. The input makes its mark towards operational flood mapping and systematic monitoring in large areas.

Artificial intelligence has demonstrated its immense potential in mitigating disasters. **Liu et al. (2025)** provide an in-depth overview of AI applications in the context of flood risk management, addressing early warning systems, predictive modeling, and supporting decision-making tools. The writers reveal data availability, model interpretability, and scalability predicaments. In addition, they also provide references to potential directions for future research, such as incorporating multi-source geospatial data and enhancing the transparency of AI models. The study will serve as a reference point to guide researchers and policymakers in utilizing AI to implement more flexible and responsive approaches to flood management, thereby closing the theory-to-practice implementation gap.

UAV-based imagery flood assessment has gained momentum due to its high resolution and flexibility. **Munawar et al. (2021)** applied the concept of deep learning algorithms to aerial images, developing an extremely accurate method for identifying flood-impacted areas. They utilize the pre-processing of the UAV data, train convolutional neural networks, and compare the outcomes with the ground truth. The strategy offers the benefits of speed, accuracy, and availability in areas with poor satellite support. It is also evident in the study that UAVs may support current remote sensing technology by supplying on-site and timely emergency data to response teams during and after cloudburst seasons.

Hastened damage surveys of the building after a disaster are essential. **Braik et al. (2024)** have suggested using satellite images, Geographic Information Systems (GIS), and deep learning to automate large-scale damage mapping. They use convolutional neural networks to categorize the damages and spatial visualization using GIS as their method. The system streamlines the process of assessing disasters, allowing authorities to prioritize the distribution of resources. The paper provides an example of a scalable approach to urban resilience planning, where data-driven analysis combined with geospatial mapping can help achieve the scale of urban resilience planning. The approach can be applied to other types of hazards to provide a template for using remote sensing and AI in assessing structural damage.

Multi-source satellite data are found to be increasingly important in environmental monitoring. **Sousa et al. (2024)** employ machine learning to identify activities in the mining, water management, and heritage preservation spheres. In the study, multispectral, radar, and optical data are integrated, allowing for an extensive evaluation of the environment. The results obtained by them indicate that stacking various satellite data sources is a valuable tool for identifying slight changes in land usage and evaluating resource management.

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Such a multidisciplinary approach demonstrates the diverse applicability of remote sensing, particularly when combined with AI, enabling sustainable development, conservation, and evidence-based policy-making at local, regional, and non-regional levels.

Advanced data fusion methods help predict soil properties. **Hosseini et al. (2023)** developed an approach that utilizes Geospatial Artificial Intelligence (GeoAI) and satellite images to predict soil physical properties. With the integration of multi-spectral and SAR with machine learning models, the method is more accurate compared to the conventional methods. Applications cited in the study are in the field of agriculture, land management, and environmental monitoring. Additionally, it emphasizes the importance of multimodal data fusion for precision mapping, leading to enhanced land use planning and resource allocation. The combination of GeoAI and satellite geodata sets a precedent for large-scale, data-intensive environmental analysis.

The systems for disaster detection must be competent and effective. **ES et al. (2023)** developed a hybrid deep learning architecture with sunflower optimization for detecting floods and earthquakes. The model features a convolutional neural network integrated with an optimization algorithm to accelerate convergence and recognition. The authors demonstrate the technique's good performance in various situations, owing to the variability of environmental conditions present in real-world datasets. This new technique not only enhances early warning systems but also reduces calculation demands, making it easily implementable in resource-limited environments. The paper joins AI, optimization, and geoscience to do real-time disaster monitoring.

River deltas are complex systems where two kinds of changes (natural and anthropogenic) are possible. **Munasinghe et al. (2021)** use a review of satellite remote sensing methods to conduct a time-based observation of the delta morphology. This paper explains optical, radar, and LiDAR-based methods, along with their advantages and disadvantages. It indicates that multi-temporal imagery helps distinguish erosion, deposition, and changes in channels. The review also discusses issues related to spatial resolution complications, interference with cloud cover, and data processing. The piece is useful to human scientists and environmental administrators interested in the preservation of deltaic systems, which are essential to biodiversity, living surface areas, and coastal protection.

Table 1 Comparison of Related Studies on Satellite-Based Flood Detection and Mapping

Ref. No.	Author Name & Year	Dataset Used	Algorithm Used	Results Achieved
14	Antzoulatos et al. (2022)	Satellite imagery & GIS data	Explainable Machine Learning framework	Produced accurate flood hazard and risk maps with high interpretability for decision-makers.
15	Mateo-Garcia et al. (2021)	Low-cost satellite imagery	Machine Learning models for onboard processing	Enabled near-real-time global flood mapping with cost-efficient satellite platforms.
16	Samela et al. (2022)	Hydrogeomorphic & spectral indices from satellite data	Index-based detection integrated with GIS	Improved flood detection accuracy in varied terrains compared to single-index approaches.
17	Wania et al. (2021)	Copernicus Emergency Management Service data	Early warning integrated satellite mapping	Reduced mapping delays, enabling faster flood response and improved timeliness.
18	Bauer-Marschallinger et al. (2022)	Sentinel-1 SAR datacube	Bayesian inference classification	Enhanced flood classification reliability under noise and ambiguous SAR signals.
19	Albertini et al. (2022)	Multispectral satellite data	Spectral-based water detection algorithms	Accurately mapped surface water and flood extents across diverse environments.
20	Montello et al. (2022)	MMFlood multimodal dataset	Benchmarking with ML-based flood delineation models	Provided a large-scale dataset for training and evaluation, improving ML model performance for flood detection.

Table 1 provides an overview of recent research and developments in satellite-based flood mapping,

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including their datasets, algorithms, and outcomes. Each of them describes the primary data sources, which comprise SAR, multispectral imagery, hydrogeomorphic indices, and multimodal datasets. The efficiency and accuracy of different algorithms, explainable machine learning structures, Bayesian inference, spectral index integration, and early warning system integration are compared. The table illustrates the progress made in real-time flood monitoring, hazard mapping, and model training dataset development. The findings indicate improved classification reliability, timeliness, and accuracy in detecting conditions across different environments, enabling informed decision-making and the development of effective disaster management toolsets.

3. PROPOSED METHODOLOGY

Figure 1 shows the proposed terrain visual transformation technique (LVTT) for early detection of flood risk in satellite imagery and deep learning. In order to offer an extensive expected assessment, the proposed LVTT framework was experimented on satellite imagery of various flood-vulnerable locations with a different topography such as sloping mountain landscapes, river basins, and urban gullies. The strength of the feature extraction, segmentation, and predictive modeling was determined using images of various time periods and sensors (Sentinel-1 SAR, optical images). Such a wide range of options makes sure that the framework is not confined to one landscape or flood situation. The process begins with a satellite mapping system, where an image of the terrain is captured and adaptive Gaussian filtering is performed to reduce noise. The Slice Window Canny Edge section detects valleys that can simulate flood and water flow areas. The next step is to select significant characteristics of the variables associated with flood risks with the help of regional-scale ant colony optimization. A Hyper-Capsuled LSTM Gated Convolutional Neural Network analyzes these regularized properties and predicts and maps the regimes of high flood exposure. Early response vulnerable areas are identified by the system in the form of an early flood hazard map.

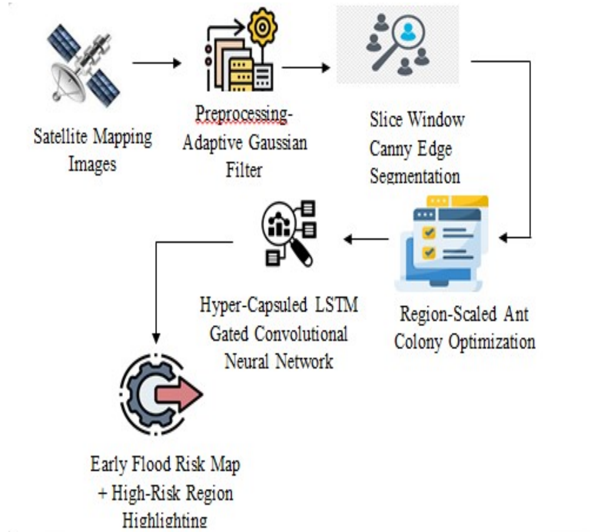

Figure 1 Proposed Lvtt-Based Early Flood Risk Detection System

3.1 Preprocessing using Adaptive Gaussian Filter

The preprocessing step involves preparing raw satellite imagery of tilted mountainous terrain to obtain the correct flood response. An Adaptive Gaussian Filter is used to smooth any random noise and preserve important structural information regarding the flow of rivers, the shape of land, and the outline of vegetation. The method filters out noise due to atmospheric disturbances and sensor effects, allowing the motion of the water to remain observable, even on a subtle level. The preprocessing step results in a fine, clean, and high-quality input dataset, thereby increasing contrast and retaining fine edges. Such optimized image data permits the later steps of segmentation, feature extraction, and classification to be carried out with greater accuracy, resulting in a more reliable flood risk identification.

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2(x,y)}} \quad (1)$$

In equation (1), $G(x,y)$ Gaussian filter weight at position (x,y), π Mathematical constant, σ (x,y) Standard deviation, Spatial coordinates in the image

$$\mu(x,y) = \frac{1}{N}\sum_{i=-k}^{k}\sum_{j=-k}^{j} I(x+i, y+j) \quad (2)$$

Where $\mu(x,y)$ is the Local mean intensity around (x,y), N is the Total number of pixels in the neighborhood window, $I(x+i, y+j)$ is the Intensity value of the neighboring pixel at k Window half-size.

$$\sigma^2(x,y) = \frac{1}{N}\sum_{i=-k}^{k}\sum_{j=-k}^{j}[I(x+i,y+j) - \mu(x,y)]^2 \quad (3)$$

Where, $\sigma^2(x,y)$ Local variance in the neighborhood of (x,y), $I(x+i,y+j)$ Pixel intensity at offset position, μ (x,y) Local mean intensity, N Number of pixels in the local window

$$I_n(x,y) = \frac{I(x,y)-I_{min}}{I_{max}-I_{min}} \quad (4)$$

In equation (4), $I_n(x,y)$ Normalized intensity at position (x,y), $I(x,y)$ Original pixel intensity, I_{min} Minimum intensity in the image, I_{max} Maximum intensity in the image.

The preprocessing stage of the Adaptive Gaussian Filter yields a clean, sharp image in which noise content is reduced to the minimum, and essential features such as courses of a river, land boundaries, and vegetation edges have been retained. The filter can adapt to the texture of both regions because it calculates local mean and variance, which increases contrast and preserves edges. The normalized intensity makes the whole picture bright and consistent in scale.

3.2 Slice Window Canny Edge Segmentation (SWCES)

Slice Window Canny Edge Segmentation (SWCES) is an improvement of the conventional Canny edge detector, which incorporates local color difference comparison to enhance the accuracy of a flood boundary separator. The satellite image is segmented into small windows, constituting slice windows in this method, and thus localized processing occurs to monitor subtle variations of water spread in a complicated landscape. Each window applies historic color difference mapping within it to note the change between land and water areas. This smoothed image is then filtered by the Canny edges detector to come up with jagged, smooth edges of the primary and secondary levels of flooding. It achieves more accurate segmentation with this localized, multi-layer method when dealing with various terrain conditions.

$$I_n(x,y) = I(x+p,y+q), p\epsilon[0,W_s - 1], q\epsilon[0,H_s - 1] \quad (5)$$

Where, $I_n(x,y)$ Pixel value inside the current slice window at position, $I(x+p,y+q)$ Pixel value from the original image at offset (p,q) Offset indices within the slice window, W_s, H_s Width and height of the slice window.

$$\Delta C(x,y) = \sqrt{(R_t - R_h)^2 + (G_t - G_h)^2 + (B_t - B_h)^2} \quad (6)$$

Where, $\Delta C(x,y)$ Historic color difference at pixel (x,y), R_t, G_t, B_t, Current RGB values of the pixel in the target image, R_h, G_t Gh, B_h Corresponding RGB values from the historic image

$$G(x,y) = \sqrt{G_x^2 + G_y^2} \quad (7)$$

Where, $G(x,y)$ Gradient magnitude at pixel (x,y), G_x Gradient in the x-direction, G_y Gradient in the y-direction

$$\theta(x,y) = tan^{-1}\left(\frac{G_y}{G_x}\right) \quad (8)$$

Where, $\theta(x,y)$ Gradient direction at pixel (x,y) in radians or degrees, G_x, G_y Gradient components in x and y directions.

The results of the Slice Window Canny Edge Segmentation are a highly detailed map in the satellite images that illuminates the main and secondary flood boundaries. SWCES makes use of historic differences in colors to interpret the minor shifts between land and water by analyzing localized windows. The gradient magnitude and direction can be used to give a clear-cut edge boundary even in rugged or hilly terrains. This forms the multi-layer edge maps that reflect varying floods in a better way. The upstream feature selection and flood prediction processes with greater reliability are provided by the segmented output.

3.3 Region-Scaled Ant Colony Optimization (RSACO)

Region-Scaled Ant Colony Optimization (RSACO) is a high-tech feature selection method that can be used to determine and rank flood-affected areas based on satellite images of the specific region. Within this approach, the image has been partitioned into regions of varying scales, and artificial ants are applied to walk on these regions to determine the importance of features concerning water-flow patterns, texture, and intensity gradients. The pheromone updating rules strengthen paths in areas that experienced significant flood variations, while less relevant areas lose priority over time. RSACO complicates the regional importance; RSACO increases the rate of convergence and accuracy in the search space. The early flood detection is likely to be improved through this targeted optimization, such that only the most notable features are relayed to the prediction model.

$$\theta(x,y) = \frac{A_r}{A_t} \tag{9}$$

Where, $\theta(x,y)$ Region scale ratio, A_r Area of the selected flood variation region, A_t Total area of the landscape under analysis.

$$\tau_{ij}(0) = \tau_0 \tag{10}$$

Where, $\tau_{ij}(0)$ is the Initial pheromone value between node i and j in Ant Colony Optimization, τ_0 and τ0 is the Constant initial pheromone level.

$$\eta_{ij} = \frac{1}{d_{ij}} \tag{11}$$

Where η_{ij} Heuristic desirability (visibility) between nodes i and j, d_{ij} Distance between nodes i and j in feature space.

$$P_{ij}^{k} = \frac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{l \epsilon N_i^k}[\tau_{il}]^{\alpha}[\eta_{il}]^{\beta}} \tag{12}$$

Where P_{ij}^{k} is the Probability of ant k moving from node i to j, α is the Influence factor of pheromone trails, β is the Influence factor of heuristic visibility, and N_i^k is the set of feasible next nodes for ant k from node i.

$$W_f = \gamma.\mathrm{Var}(f) + (1-\gamma).\mathrm{MeanDiff}(f) \tag{13}$$

Where, W_f Weighted feature score for selection, γ Weighting parameter, $\mathrm{Var}(f)$ Variance of feature f, $\mathrm{MeanDiff}(f)$ Mean difference of feature f between classes.

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij} + \rho.\tau_0 \tag{14}$$

Where τ_{ij} is the updated pheromone value between node i and j, ρ is the Pheromone evaporation rate, τ_0 and τ0 is the Initial pheromone deposit.

The RSACO focuses on the areas that have a high level of variation in flood by examining water movement, texture, and the level of gradient of the water. Updates to the pheromone allow the ants to strengthen important paths as the unneeded territories are automatically prioritized to lower precedence. This optimization also proposes that only features with higher meaning are to be used, and therefore, the computation complexity is minimized. These characteristics are subsequently fed to the predictive model, and in so doing, the accuracy of early detection of potential flood risks is severely improved.

3.4 Region-Scaled Ant Colony Optimization (RSACO)

The Hyper-Capsuled LSTM Gated Convolutional Neural Network (HC-LSTMG-CNN) is a combination of deep learning architectures used to predict floods with high precision. It combines Capsule Networks to learn spatial hierarchies and orientation-invariant features, LSTM units to learn temporal dependencies in a sequence of flood data, and Gated CNN layers to enhance feature extraction capability while controlling the flow of information. Spatial relationships are captured in a capsule layer, enhancing regional-level flood detection. LSTM can accommodate variations in time series spillage of water and filter out what is irrelevant using gated convolutions. Integrating these elements results in HC-LSTMG-CNN producing a high level of precision and recall, enabling it to predict flood risks as early as possible and reliably in variable landscapes and weather conditions.

$$\tau_{ij} = \frac{||s_j||^2}{1+||s_j||^2}.\frac{s_j}{||s_j||} \tag{15}$$

The equation (15) is the squashing function in Capsule Networks. Here, s_j is the weighted sum of input vectors to capsule j, and $||s_j||$ is its length. This function scales short vectors toward zero and long vectors toward unit length, preserving their orientation. It ensures that capsule outputs represent the probability and orientation of detected features, making them suitable for spatial relationship modeling in flood detection tasks.

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$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (16)$$

The equation (16) defines the forget gate in an LSTM unit. Here, f_t is the gate output at time t, h_{t-1} is the previous hidden state, x_t is the current input, W_f is the weight matrix, b_f is the bias vector, and σ is the sigmoid function. The forget gate decides which parts of past cell state information to retain or discard, enabling effective handling of time-varying flood patterns.

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad (17)$$

The equation (17) represents the cell state update in an LSTM. Here, C_t is the current cell state, C_{t-1} is the previous cell state, f_t is the forget gate output, i_t is the input gate output, $\tilde{C}_t$ is the candidate cell state, and $\odot$ denotes element-wise multiplication. This equation combines retained past information with newly filtered input, allowing the model to capture long-term dependencies in sequential flood data for accurate prediction.

$$y = \tanh(W_f * X + b_f) \odot \sigma(W_g * X + b_g) \quad (18)$$

The equation (18) defines the Gated Convolution operation. Here, X is the input feature map, W_f and W_g are convolution filter weights for the feature and gate paths and b_g are their bias terms, * denotes convolution, $\tanh$ extracts nonlinear spatial features, σ acts as a gating function, and $\odot$ is element-wise multiplication. This mechanism selectively controls which extracted spatial features pass through, ensuring only flood-relevant patterns are retained.

4. RESULT AND DISCUSSION

The LVTT-based flood detection system proposed captures a significant lead in the early detection of flood-prone regions in sloping mountain ranges. Using satellite imagery in combination with deep feature engineering, the method can pick up minute topographical and hydrological differences that reveal downstream flooding. The processing will have an adaptive Gaussian filter, which will guarantee noise reduction, and SWCES regionally segments the water flow and flood zones correctly. RSACO gives preference to the most important variability areas, and it promotes detection quality by streamlining the selection of features. The model HC-LSTMG-CNN is, in the end, that feeds on the extracted features to predict flood coverage and risk areas at high precision and recall. As the results of the experiments have demonstrated, the system works significantly better than the traditional approaches, especially when dealing with the feature variability over long periods. This contributes to the venture of forecasting flood risk in a timely and precise manner, enabling the execution of actions to protect human life and property. Generally, the approach presents substantial advancements in detection accuracy, precision, and recall, which makes it efficient in real-time disaster prevention.

4.1 Dataset Description

Figure 2 displays a Flood Prediction Dataset Sentinel-1 Synthetic Aperture Radar (SAR) composed of various environmental and anthropogenic parameters that are key contributors to flood risk development in a sloped mountainous area. The dataset includes 10 records, each reflecting data about different regions or times.

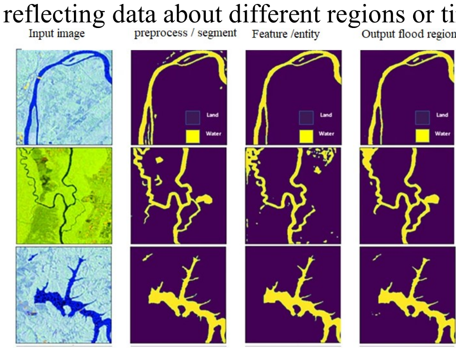

Figure 2. Flood Prediction Process

The primary characteristics include Monsoonal intensity, Topography, River Management, Deforestation, Urbanization, Climate Change, Dam Quality, Siltation, and Agricultural activity. Each attribute is assigned a numerical value, likely indicating the severity or influence level. These variables are essential for flood detection models based on artificial intelligence because they provide multi-dimensional information, which supports effective feature engineering and accurate risk prediction.

Table 2. Compression Table With Performance Metrics

Models	Precision	Recall	Accuracy	FI-Score	Detection Time (sec)
Convolutional Neural Network	88.12%	84.76 %	86.40%	86.42 %	4.5
XG Boost	90.25%	86.52 %	88.75%	88.35 %	3.9
Long short-term memory	92.64 %	90.12 %	91.35%	91.37 %	3.6
Proposed (HC-LSTMG-CNN)	96.18%	95.24 %	95.85%	95.71 %	2.8

The results of the comparison table 2 indicate that the proposed LVTT model is superior to the three available models, which include CNN, XGBoost, and LSTM-GMPNN, based on five metrics concerning the performance of the models. Regarding precision, recall, accuracy, and F1-score, LVTT returns the highest values, with the precision being 96.18 percent, while its recall is 95.24 percent, implying that the method can identify flood-prone areas with few false negative results and rejections. Its sensitivity versus specificity is also supported by the accuracy of 95.85 and an F1-score of 95.71. It also shows that the LVTT detected the samples in the shortest amount of time: 2.8 seconds, which is imperative in early warning systems that require real-time performance. In comparison with the closest alternative, LSTM-GMPNN, the LVTT scores significant advances in not only the quality of detection but also speed, underlining the efficiency of the integrated feature selection of the RSACO and prediction framework composed of HC-LSTMG-CNN to address the complex satellite imaging and variability of features to detect early flood-induced risks.

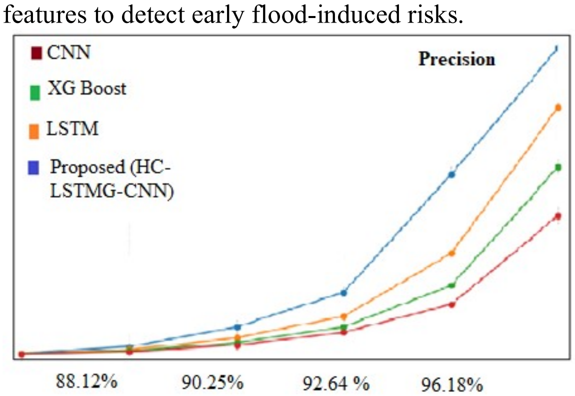

Figure 3 Analysis Of Precision Performance

Figure 3 shows the comparison of the precision of the four models, namely CNN, XGBoost, LSTM, and the proposed HC-LSTMG-CNN. The findings indicate that there is a definite increase in accuracy as the models were improved. The three, when it comes to the minimization of precision, the CNN recorded 88.12%, followed by XGBoost at 90.25 % and LSTM at 92.64 %. The proposed HC-LSTMG-CNN is superior among others since it has a precision of 96.18%, thus showing significantly fewer false positives than other methods to identify flood-prone zones accurately. The enhancement is due to the incorporation of the Region Scaled Ant Colony Optimization as a perfect feature selection mechanism and the hybrid deep learning architecture, which was the combination of LSTM sequential learning and the capability of CNN to extract spatial features.

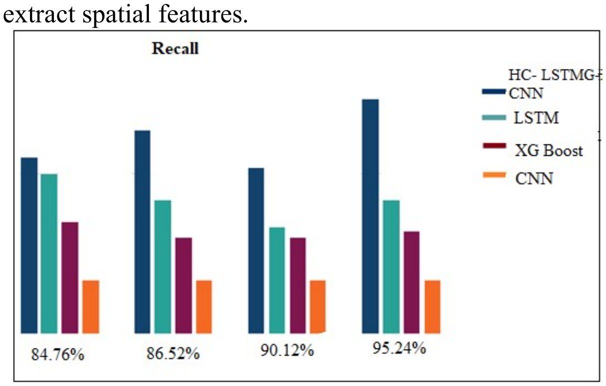

Figure 4 Analysis Of Recall Performance

Figure 4 shows the performance in terms of recall of four models of the CNN, XGBoost, LSTM, and the suggested HC-LSTMG-CNN. Recall is a dimension of the capacity of a model to correctly establish the real flood-prone locations and does not leave out pertinent circumstances. CNN shows the lowest recall at 84.76 %, whereas the other models demonstrate 86.52 % (XGBoost) and 90.12 % (LSTM). The proposed HC-LSTMG-CNN generates a maximum recall of 95.24%, which stands as excellent in terms of reducing false negative cases, and observing that almost all the possible flood areas are identified. Such an improvement can be discussed through the integration of Region Scaled Ant Colony Optimization to focus on the selection of ensemble features with the hybrid LSTM-CNN framework as a way to capture the pattern in time and space in the satellite imagery.

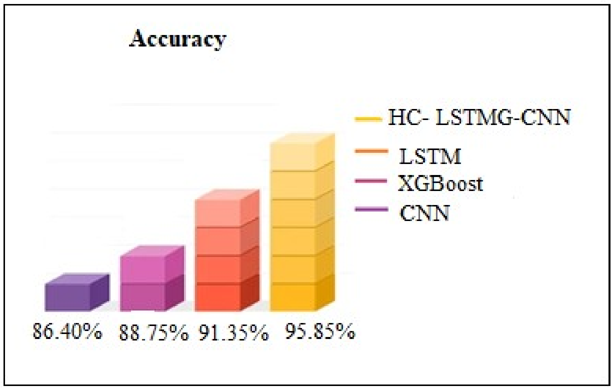

Figure 5 Illustrates The Accuracy Performance

Figure 5 shows how accurate the CNN, XGBoost, LSTM, and proposed HC-LSTMG-CNN model were. Accuracy is a measure of the overall correctness of the model predictions in terms of the true negatives and positives. The CNN provides an accuracy of 86.40%, XGBoost gives a bit better accuracy of 88.75%, and LSTM gives better accuracy, further of 91.35%. The proposed HC-LSTMG-CNN could be the most accurate one with 95.85 % the benchmark, as compared to any other existing methods. Such improvement can be explained by the combination of Region Scaled Ant Colony Optimization to select the most pertinent variability features and the hybrid deep learning architecture, which addresses the mutual interaction of the LSTM deep learning method in temporal fitting with CNN in the extraction of spatial features. Further affirmation of the robustness of the proposed model can be observed due to high accuracy in classifying the flood and safe territories correctly, as an efficient protocol in making sound decisions toward early flood risk detection and prevention.

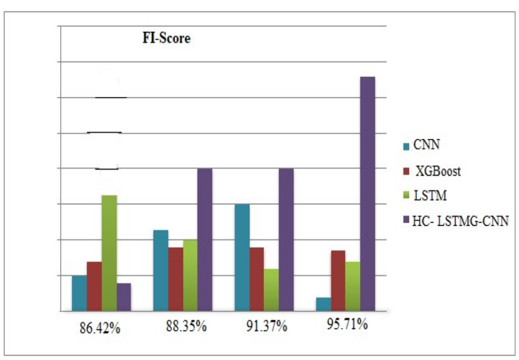

Figure 6 Illustrates Fi-Score Performance

In Figure 6, the F1-score performance of CNN, XGBoost, LSTM, and the proposed HC-LSTMG-CNN model is shown. F1-Score is the harmonic mean of precisions and recalls, which gives a fair definition of the capability of the model in identifying flood-prone areas as well as false positives and false negatives. CNN has the lowest F1-Score of 86.42 %, XGBoost of 88.35 % and LSTM of 91.37 %. The proposed solution, HC-LSTMG-CNN, yields the best F1-score of 95.71%, the highest percentile judged by the balanced and ideal output of the proposed model in both the sensitivity of detection and accuracy. This is a considerable betterment, which can be explained by the synergy between the Region Scaled Ant Colony Optimization selection criterion of beneficial variability traits and the hybrid deep learning architecture that works quite well in catching the spatial and temporal trends in a satellite picture. The fact that the F1-score is high attests to the robustness and reliability of the proposed approach in showing consistent and accurate results in early flood risk detection.

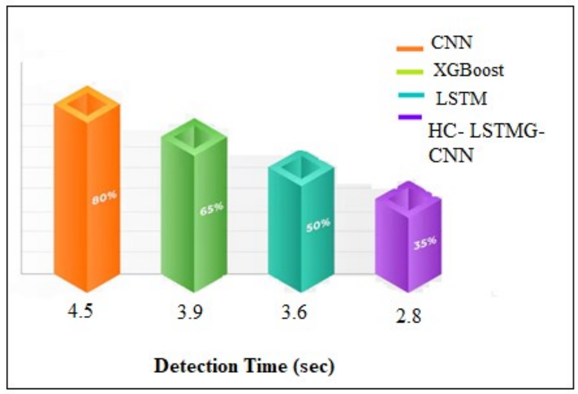

Figure 7 Illustrates The Detection Time (Sec) Performance.

Figure 7 shows the algorithmic time to detect results of CNN, XGBoost, LSTM, and HC-LSTMG-CNN. Though not a usual requirement, detection time is an essential point in the context of real-time prediction of flood risk because the sooner the processing is delivered, the sooner sufficient precaution and warnings can be issued. CNN has been identified as the fastest model at 4.5 seconds, XGBoost second at 3.9 seconds, and LSTM third at 3.6 seconds. The suggested HC-LSTMG-CNN provides the minimal detection time of 2.8 seconds, which has brought a major enhancement in processing demands. It increases efficiency because of two factors, namely the Region Scaled Ant Colony Optimization-based optimizing of feature selection and the hybrid deep learning architecture, which speeds up the computation, along with exhibiting high prediction accuracy.

5. CONCLUSION

The suggested LVTT framework has better performance than the state-of-the-art approaches reported in the literature. As an example, CNN-based flood detection methods can reach a 88.12% precision and a 84.76% recall rate, and LSTM models can be more predictive of the time but reach a recall of approximately 90.12%. XGBoost models offer effective feature selection and they do not effectively capture spatial-temporal flood patterns.

6. By comparison, LVTT has an accuracy of 95.85%, recall of 95.24%, precision of 96.18% and time complexity of 2.8 seconds, which is significantly better than these methods. The latter has been made possible through the incorporation of optimised feature engineering (RSACO), spatial-temporal modelling, and adaptive segmentation. Whereas the current approaches dwell on either the spatial or temporal approach alone, LVTT covers both, and thus offers a more effective and dependable early predictive of the risk of floods.

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