

A Lightweight SVM-Based Framework for Smart Urban Flood Prediction and Response

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ABSTRACT

Urban flooding poses significant risks to human life, urban systems, and the economies of affected communities. Recent flood-prediction studies increasingly employ deep learning, hybrid modelling, and IoT-based systems; however, their computational complexity, data requirements, and deployment constraints can limit their suitability for resource-constrained edge and IoT environments. This highlights the need for lightweight frameworks that can provide accurate multiclass flood-severity classification with low computational overhead. To address this need, this study proposes UFNet, a lightweight Support Vector Machine (SVM)-based framework for six-class urban flood-severity classification. UFNet uses hydrometeorological variables, including rainfall, temperature, humidity, and water-level measurements, to classify flood conditions into six severity levels. The model was evaluated on historical hydrometeorological data and achieved high class-wise classification performance, with precision ranging from 95.18% to 98.72%, recall from 92.50% to 100%, F1-score from 94.27% to 97.56%, and ROC-AUC values of 0.98 to 1.00, thus demonstrating strong class separability. Additionally, the Critical Success Index (CSI) and Composite Performance Index (CPI) further support the reliability of the obtained Classification results by having CSI values from 0.892 to 0.952 and CPI values from 0.966 to 0.985. Computational evaluation shows an inference time of 5 ms and memory consumption of 10 MB, hence providing low computational cost compared to tested machine-learning models. The obtained results indicate that the UFNet framework allows achieving high Classification performance with low computational cost and has potential to be applied to flood-severity classification in IoT and edge computing.

1. Introduction

Flooding is one of the most frequent natural disasters worldwide, endangering millions of people and causing substantial economic losses each year [1]. In many places, this issue has been made worse by fast metropolitan expansion, poor construction of drainage systems, and climate change. In 2015, the UN unveiled the 2030 Agenda for Sustainable Development, which has 17 Sustainable Development Goals (SDGs). Among these is Goal 11, which demands the construction of “Sustainable Cities and Communities” [2]. A major foundation of this objective is the strengthening of city resilience to natural disasters and the mitigation of their effects on people. Improving resilience to climate-related flooding therefore remains an important objective of global sustainability policies. During the monsoon season,

major floods frequently occur across Pakistan’s Indus River basin, particularly around Sukkur, Guddu, and Kotri. Fig. 1 shows the regions affected in the 2022 flood events in the lower Indus basin as well as the river system [3,4].

The use of traditional physics-based and hydrologic models is common practice in flood prediction, although such models may experience limitations in highly dynamic conditions due to complex spatial-temporal processes, data availability, and the need for model calibration and parameterization [5]. Modern research has witnessed an increasing trend to include sensor monitoring and ML algorithms coupled with IoT communications into flood prediction and early warning tasks [6,7]. ML methods can identify nonlinear relationships among hydrometeorological variables and

support rapid decision-making in flood-warning applications [8, 9]. This makes data-based methodologies attractive for tasks that require continual evaluation and quick assessments.

Most recently, there have been efforts to incorporate machine learning techniques into flood forecasting models. Deep learning and hybrid models can be used but may require a lot of computation and data, which may limit their deployment in resource-constrained fields, IoT, and edge-computing environments [10–14]. Moreover, the complexity of the model together with the requirement for extensive training data may be problematic for low-power and embedded devices. Therefore, there is still a need for flood prediction models that would enable multiclass severity classification while ensuring low computational complexity.

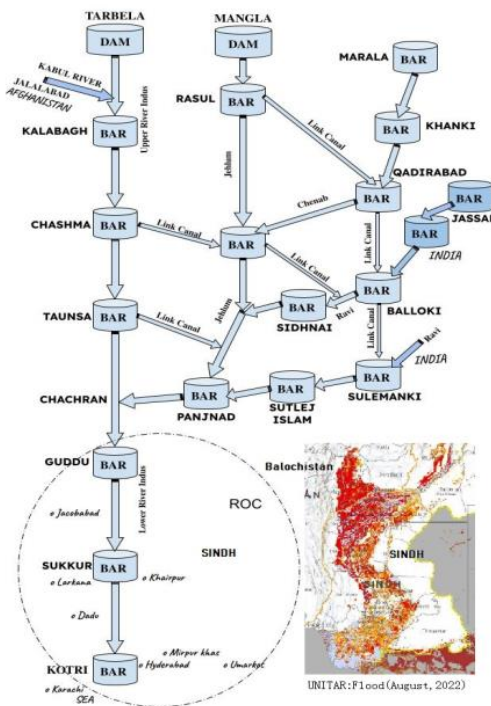


Fig. 1. Route guide of Pakistan river flow including flood prone area of river Indus.

SVMs provide an alternative lightweight ML approach that can perform nonlinear classification using an appropriate kernel and can be effective in relatively small-data settings [15–17]. The fact that they require relatively low computing power and memory makes them suitable for constrained resource environments. Existing studies have explored deep-learning-based flood forecasting, uncertainty modelling, and sensor-based flood-warning systems [18–20]. However, relatively less attention has been paid to lightweight multi-class flood severity classification models for IoT and edge computing platforms.

To address this gap, this study introduces UFNet, which is a lightweight framework based on SVM classification that classifies six levels of urban flooding using hydrometeorological attributes such as rain, temperature, humidity, water level, and discharge. These classes include flood conditions into six severity levels: No Flood, Low, Medium, High, Very High, and Extreme

High flood severities. The framework is designed to provide accurate flood severity classification with low memory requirements and rapid inference, making it potentially suitable for resource-constrained IoT and edge-computing environments. Unlike conventional binary or coarse-grained flood prediction approaches, the proposed six-class severity scale provides finer differentiation of flood conditions for operational assessment.

The primary contributions of this study are as follows:

1. The development of a lightweight SVM-based framework for multiclass flood-severity classification with six severity levels.
2. The integration of hydrometeorological variables with an operational six-class flood-severity scale to provide finer differentiation of flood conditions.
3. A comprehensive evaluation of classification performance using precision, recall, F1-score, ROC-AUC, Critical Success Index (CSI), and Composite Performance Index (CPI).
4. An assessment of computational efficiency in terms of inference latency and memory usage to evaluate the potential suitability of UFNet for resource-constrained IoT and edge-computing applications.

2. Related Work

Recent developments in flood prediction demonstrate how smart, data-driven methods incorporating IoT-based monitoring systems are supplanting conventional hydrological modeling approaches. The following sections will present major trends in IoT for remote sensing, machine learning, deep learning, hybrid modeling, and integrated systems for sustainable flood forecasting.

2.1 IoT and Remote-Sensing Developments

Recent IoT-based flood-monitoring systems enable continuous observation of environmental conditions through distributed sensors measuring rainfall, humidity, and river stage. These sensor networks improve the temporal resolution and spatial range of flood forecasting models when used in conjunction with satellite information. Lyu and Yin [9] used tree-based learning methods to evaluate flood vulnerability in difficult landscapes. Liu et al. [18] incorporated runoff-process vectorization into a deep-learning framework to improve hydrological representation. Wang and Xu [19] examined the Bayesian deep learning approach. Similarly, Langhammer [15] demonstrated the integration of SVM with IoT sensor networks for continuous flood simulation. Collectively, these studies demonstrate the increasing role of sensor-supported and data-driven approaches in developing timely and adaptive flood-monitoring systems.

2.2 Machine-Learning-Based Forecasting

Machine-learning algorithms have been widely applied to flood prediction, discharge prediction, and related hydrological forecasting tasks. Among these methods,

SVMs are particularly useful for nonlinear classification and can perform effectively when the available training data are limited. Abdullah and Abdulazeez [16] verified the dependability of SVMs and classifiers in data-scarce, non-linear contexts. Shi and Zhang [17] improved the computational efficiency of classifiers with imbalanced data distributions. These studies indicate that SVMs provide a flexible classification framework across datasets with different sizes, distributions, and computational requirements.

2.3 Deep Learning and Hybrid Approaches

Rapid developments in deep learning approaches have also enabled spatiotemporal modelling of the rainfall-runoff processes in complex urban environments. Zeng et al. [11] reviewed the transition from traditional numerical models to deep-learning approaches for urban flood simulation and highlighted their potential for improving predictive performance. Hu et al. [12] and Polson and Sokolov [13] examined model complexity and computational requirements associated with deep-learning architectures. Along with these modelling analyses, Mamat et al. [20] created IoT-based flood alerting systems by combining on-device analytics and sensing. At a broader scale, Mansida and Bancong [21] examined rainfall-runoff modelling trends, while Islam et al. [22] reviewed the use of remote sensing and machine learning for flood-susceptibility assessment. Anik et al. [14] further examined the transition from conventional physics-based models toward hybrid machine-learning approaches. Overall, these studies demonstrate the growing capability of deep and hybrid models for flood-related applications, while also indicating practical challenges associated with data availability and computational requirements.

2.4 Comparative Reviews and Modelling Trends

Several new studies have noted the most recent advancements in both machine learning-based flood simulation and hydrodynamic modeling. Karim et al. [23] compared physics-based and machine-learning methods for flood-inundation modelling, highlighting their respective strengths and limitations. Snikitha et al. [24] reviewed emerging flood-modelling approaches with particular emphasis on urban flood resilience and sustainability. Collectively, these studies indicate that current research is moving toward flood-modelling frameworks that consider not only predictive performance but also computational efficiency and practical deployment requirements.

2.5 Urban Adaptation and Policy Linkage

Flood modelling is increasingly being considered within urban planning and climate-adaptation strategies to strengthen the resilience of flood-prone communities. Yu et al. [25] evaluated flood risk in relation to building use, providing practical information for disaster-risk reduction and urban planning. Zhang et al. [26] developed deep-learning approaches for rapid spatiotemporal

flood prediction in coastal urban areas, demonstrating the potential of data-driven models for timely flood assessment. Bhusal et al. [27] evaluated management practices for adapting to climate-change-induced urban flooding, while Kumar et al. [28] provided a broader review of recent developments in flood-modelling approaches. Together, these studies demonstrate that effective urban flood management increasingly requires the integration of predictive modelling with risk assessment, adaptation planning, and timely decision support.

2.6 Physics-Guided and Hybridized Forecasting Models

Physics-guided and hybrid learning models have gained increasing attention because they combine data-driven learning with physical knowledge of hydrological processes. The research conducted by Liu et al. [29] used a physics-guided LSTM model in the simulation of river basin flow and floods by using physical constraints in the learning phase. Similarly, Wang et al. [30] used an artificial bee colony algorithm and a backpropagation neural network to optimize the precipitation forecast. Collectively, these studies indicate that physical knowledge and learning-based optimization algorithms can contribute to hydrological simulation when used together with data-driven models.

The literature review demonstrates a gradual trend from physics-driven modeling approaches to machine learning (ML), deep learning, hybrid learning, and Internet of Things (IoT)-based flood monitoring techniques. Fig. 2 summarizes these developments through four broad categories: (i) hydrological models that are mostly driven by physical aspects and calibration; (ii) ML models that are trained to capture non-linear patterns within hydrometeorological datasets; (iii) deep and hybrid learning models combining complex learning algorithms with physical, statistical, and optimization methods; and (iv) Lightweight IoT-oriented approaches that emphasize timely prediction under computational and resource constraints. Despite these advances, comparatively limited attention has been given to lightweight multi-class flood-severity classification that jointly considers predictive reliability and computational efficiency for potential IoT and edge deployment. The UFNet falls under the fourth class, using an SVM-based multiclass approach that aims to achieve fine-grained flood severity classification while being fast and memory-efficient.

3. Dataset Overview and Acquisition

Reliable hydrometeorological data are essential for accurate flood-severity assessment. The datasets used in this study integrate past hydrological data, meteorological data, and IoT-based data to facilitate model development and validation.

3.1 Data Sources

Data for flood risk areas inside the lower Indus Basin, particularly the Sukkur area, have been obtained from

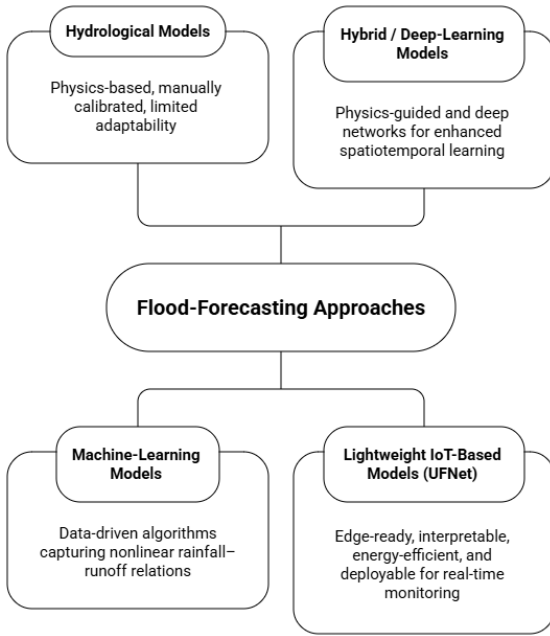


Fig. 2. Taxonomy of existing flood forecasting approaches.

the Pakistan Meteorological Department (PMD) and the Flood Forecast Division (FFD). Including only 4-month durations of the monsoon season, the datasets given span 2015 to 2022. Data on rainfall (mm), temperature (°C), relative humidity (%), wind speed (Knots), upstream and downstream flow (m³/s), and river stage elevation (m) are among the datasets. These variables characterize the atmospheric and hydrological conditions associated with flood development. Prototype sensor nodes (such as tipping-bucket rain gauges, DHT22 temperature and humidity sensors, and ultrasonic level sensors) have been tested for performance on LoRa-based wireless networks to allow low-power, long-range wireless data transmission in preparation for future integration of Internet of Things (IoT) systems.

3.2 Static Basin Parameters

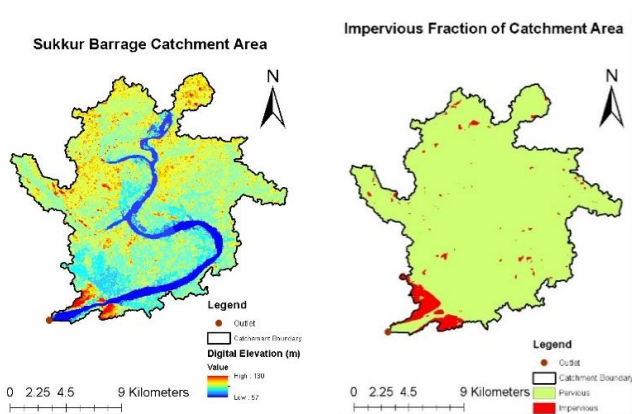


Fig. 3. Study area of the Indus River near Sukkur Barrage: (a) discharge stations and (b) impervious-surface fraction.

Found in Sindh's lower Indus region (Pakistan), the Sukkur Basin has a semi-arid climate with occasional monsoon runoff. The static parameters directly affect runoff, infiltration, and discharge by describing the basin's physical features that stay constant throughout the study period. Fig. 3 shows the arrangement of discharge stations and an impervious-surface fraction. Although these characteristics are not used as predictors

in UFNet, they provide physical context for the study area. Furthermore, Table 1 summarizes the major static characteristics of the Sukkur catchment.

3.3 Dynamic Variables

Dynamic factors change over time and reflect climatic and hydrological changes that cause floods. They incorporate both atmospheric inputs and river-system outputs utilized to train the UFNet model. Table 2 summarizes the key dynamic variables.

3.4 Sample Gauge Observations

To ensure data integrity, Table 3 contains a small sample of gauge readings from the PMD station recorded during the 2022 monsoon season.

Table 4 presents hydrological observations collected from the FFD station over the same period. These records show the temporal structure and numerical diversity of the dataset used for UFNet training and validation.

3.5 Data Pre-Processing and Class Balancing

The data pre-processing consisted of four sequential steps:

1. Noise reduction using moving-average filtering.
2. Outlier identification using z-score thresholding.
3. Missing-value imputation using linear interpolation.
4. Normalize numerical variables to the [0, 1] range.

SMOTE was applied only to the training set in order to make the six classes of flood severity data balanced. Initially, there were 2,400 observations in the dataset, out of which 1,920 (80%) were kept for training and 480 (20%) for testing, as shown in Table 5.

The training data for each class were augmented to 500 through SMOTE, leading to a total of 3,000 balanced training observations. The independent test set was not altered and still had 80 original samples per class, ensuring there was no data leakage in order to provide an unbiased assessment of the model's performance. The final class-wise distribution is shown in Table 6.

3.6 Statistical Analysis

Statistical significance of Pearson correlation was employed in analyzing the relationship between each input variable in terms of hydrometeorology and the ordinal level of flooding. All nine UFNet input variables were evaluated, i.e., rainfall, wind speed, minimum and maximum temperatures, humidity, upstream water level, downstream water level, upstream discharge, and downstream discharge. The Pearson correlation coefficient is given by:

$$r = \frac{n \sum xy - \sum x \sum y}{\sqrt{[n \sum x^2 - (\sum x)^2] [n \sum y^2 - (\sum y)^2]}} \quad (1)$$

In this equation, the variables x and y are paired, and n represents the number of observations. The correlation

Table 1

Static basin parameters of the Sukkur region.

Parameter	Symbol	Unit	Description	Sukkur Region
Catchment Area	A	sq-km	Total contribution area	204
Stream length	L	km	Indus channel length at Sukkur	249.31
Average Slope	S	%	Vertical / horizontal ratio	1.59
Impervious Fraction	ϕ	%	Manmade structure	4.26
Curve Number (Soil Group)	CN	-	Soil composition	50 to 65
Drainage density	D_d	km/km ²	$\frac{\text{Stream length}}{\text{Basin area}}$	1.22

Table 2

Dynamic parameters used for UFNet training

Parameter	Symbol	Unit	Type	Description
Rainfall	RF	mm	Input	Precipitation intensity per time step
Temperature Max.	Tmax	°C	Input	Maximum air temperature
Temperature Min.	Tmin	°C	Input	Minimum air temperature
Humidity	H	%	Input	Relative humidity
Wind Speed	WS	Knots	Input	At 1200 UTC
Upstream water level	HU	Feet	Input	Stage height at upstream gauge
Downstream water level	HD	Feet	Input	Stage height at the Sukkur barrage outlet
Upstream discharge	QU	Cusecs	Input	Flow entering the basin
Downstream discharge	QD	Cusecs	Input	Flow leaving the basin
Flood severity class	FS	—	Output	Target class (No Flood, Low, Medium, High, Very High, and Extreme High)

Table 3

Sample gauge readings from PMD (Sukkur Region, 2022)

Date	Rainfall	Wind Speed	Tmin	Tmax	Humidity
20220814	27	6	25	36.5	69
20220815	0	6	26.5	32.5	60
20220816	0.5	12	27.5	35	65
20220817	9	8	26	36	92
20220818	54	10	26	34.5	96
20220819	75	10	25.5	29	96
20220820	49	10	25	26.5	92
20220821	22	10	25	27.5	96
20220822	69	4	25	27.5	92
20220823	1	10	24.5	29.5	79
20220824	24	10	24	32.5	96
20220825	39	8	24.5	28.5	92

analysis was used to examine the statistical relationships between the hydrometeorological input variables and the ordinal flood-severity levels. For the analysis, the ordinal levels of flood severity were coded as no flood = 0, low = 1, medium = 2, high = 3, very high = 4, and extreme high = 5. As shown in Table 7, rainfall exhibited a very strong positive and statistically significant correlation with flood severity ($r = 0.948$, $p < 0.001$). At the same time, downstream discharge also showed a very strong positive and significant relationship ($r = 0.814$, $p < 0.001$). Humidity ($r = 0.714$, $p = 0.009$) and upstream water level ($r = 0.653$, $p = 0.0107$) showed strong positive and significant correlations. In con-

trast, wind speed ($r = -0.157$, $p = 0.626$), minimum temperature ($r = -0.411$, $p = 0.185$), maximum temperature ($r = -0.402$, $p = 0.195$), downstream water level ($r = -0.256$, $p = 0.323$), and upstream discharge ($r = -0.531$, $p = 0.127$) showed negative relationships that were reported as non-significant. Overall, the results indicate that rainfall, downstream discharge, humidity, and upstream water level have the strongest statistically significant associations with the assigned flood-severity levels.

Table 4

Sample gauge readings from FFD (Sukkur Region, 2022)

Date	HU	QU	HD	QD	FS
20220814	200.8	143124	195.475	108474	No Flood
20220815	200.65	190752.5	196.55	160625	No Flood
20220816	199.9	251833.8	197.875	231691.3	Low
20220817	199.725	284389.8	199	277714.8	Low
20220818	200.15	320666	199.875	318916	Low
20220819	200.375	339790	200.175	339790	Low
20220820	200.4375	349336.5	200.2375	349336.5	Low
20220821	200.6	374670.8	200.4	374670.8	Medium
20220822	200.95	426415.5	200.75	426415.5	Medium
20220823	201.375	488185.5	201.175	488185.5	Medium
20220824	202.05	554271.5	201.85	554271.5	High
20220825	202.675	575732.5	202.55	575732.5	High

Table 5

Dataset partitioning and SMOTE-based augmentation.

Dataset Stage	Number of Classes	Original Samples	Percentage	SMOTE Applied	Samples After SMOTE	Purpose
Original Dataset	6	2,400	100%	No	2,400	Complete dataset before splitting
Training Set	6	1,920	80%	Yes	3,000	Model training and optimization
Testing Set	6	480	20%	No	480	Independent model performance evaluation
Final Experimental Dataset	6	2,400 before augmentation	—	Training set only	3,480	3,000 training + 480 testing samples

Table 6

Class-wise distribution of training and test samples.

Class No.	Flood-Severity Class	Training Samples After SMOTE	Testing Samples
1	No Flood	500	80
2	Low	500	80
3	Medium	500	80
4	High	500	80
5	Very High	500	80
6	Extreme High	500	80
Total	6 Classes	3,000	480

Table 7

Pearson correlation between hydrometeorological variables and flood severity.

Variable	Pearson r	p -value	Direction	Strength	Statistical Significance
Rainfall	0.948	< 0.001	Positive	Very strong	Significant
Wind Speed	-0.157	0.626	Negative	Very weak	Not significant
Tmin	-0.411	0.185	Negative	Moderate	Not significant
Tmax	-0.402	0.195	Negative	Moderate	Not significant
Humidity	0.714	0.009	Positive	Strong	Significant
Upstream water level	0.653	0.0107	Positive	Strong	Significant
Downstream water level	-0.256	0.323	Negative	Moderate	Not significant
Upstream discharge	-0.531	0.127	Negative	Moderate	Not significant
Downstream discharge	0.814	< 0.001	Positive	Very strong	Significant

3.7 Real-Time Acquisition Framework

Although this study used historical hydrometeorological data to train UFNet, a conceptual framework for future real-time deployment is proposed. Field nodes with level, temperature, relative humidity, and rain sensors can be linked to lightweight microsystems like ESP32. Through GSM or Wi-Fi, these nodes can send data to a central cloud dashboard. With low latency, this architecture enables real-time monitoring of the system and is suitable for embedded systems operating on UFNet. Although this conceptual model was not applied in the dataset of the research, it demonstrates how UFNet interacts with smart city technologies for flood warning.

4. Proposed UFNet Framework

UFNet is a lightweight machine-learning framework designed for six-class flood-severity classification. Hydrometeorological observations are divided into six severity levels: No Flood, Low, Medium, High, Very High, and Extreme High using SVM with a Radial Basis Function (RBF) kernel. The framework prioritizes low computational cost and rapid inference to support potential deployment in resource-constrained IoT and edge-computing environments.

4.1 Framework Architecture

In Fig. 4, UFNet is built as a modular system integrating data acquisition, feature selection, model training, and IoT-based deployment. The data layer preprocesses and normalizes incoming hydrometeorological factors, including rainfall, temperature, humidity, and discharge. The learning layer receives the processed features, where SVM constructs an optimal separating hyperplane for flood severity levels. In the proposed deployment architecture, the predicted severity output could be forwarded to the IoT visualization and alerting layer.

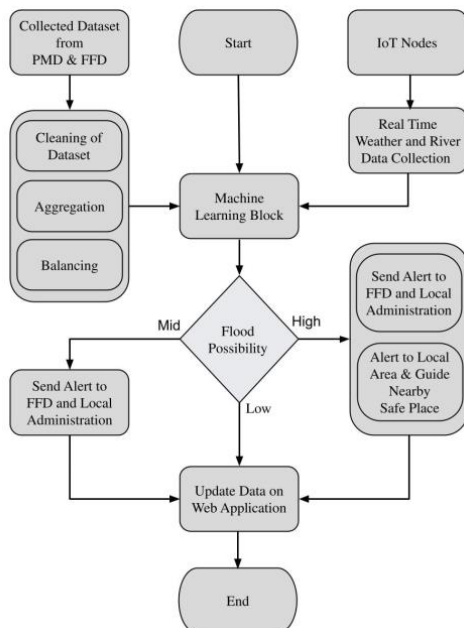


Fig. 4. Conceptual architecture of the UFNet framework showing machine learning-based flood prediction and future integration with IoT sensor data.

4.2 Mathematical Formulation

UFNet's core uses SVM for multi-class flood-severity classification. Given input vectors $x_i = [x_{i1}, x_{i2}, \dots, x_{in}]$ and target labels $y_i \in \{-1, +1\}$, the optimal separating hyperplane is defined as:

$$w \cdot x + b = 0 \quad (2)$$

where w is the weight vector and b is the bias term. The optimization minimizes the structural risk function:

$$\min_{w, b, \xi_i} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^N \xi_i \quad (3)$$

subject to

$$y_i(w \cdot x_i + b) \geq 1 - \xi_i, \quad \xi_i \geq 0 \quad (4)$$

where C is the penalty parameter balancing margin width and misclassification error, and ξ_i denotes slack variables. For nonlinear separation, UFNet applies the Radial Basis Function (RBF) kernel:

$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2) \quad (5)$$

where γ controls the width of the RBF kernel and therefore determines the influence of individual training samples on the decision boundary. The decision function for new observations becomes:

$$f(x) = \text{sign} \left(\sum_{i=1}^N \alpha_i y_i K(x_i, x) + b \right) \quad (6)$$

where α_i are Lagrange multipliers obtained through quadratic programming. The key hyperparameters for RBF-SVM were tuned through five-fold stratified grid search on the training dataset. Kernel function choices and values of the penalty parameter C and kernel coefficient γ were tested on the cross-validation stage, and the combination of the settings that yielded the best cross-validation results was chosen as the optimal one. Table 8 summarizes the search space and the selected hyperparameters used for UFNet training.

Table 8

Search ranges and selected hyperparameters for the UFNet RBF-SVM model.

Configuration	Search/setting	Selected value
Kernel	Linear, Polynomial, RBF	RBF
C	0.1, 1, 10, 100	10
γ	0.001, 0.01, 0.1, 1	0.01
Cross-validation	Stratified k-fold	5 folds
SMOTE neighbors (k)	Fixed	5
Random state	Fixed seed	42
Feature scaling	Min-max normalization	[0,1]

4.3 Flood Severity Classification

UFNet performs six-class flood-severity classification based on hydrological discharge and meteorological

thresholds derived from PMD and FFD standards. Each record in the dataset is labeled according to river stage and discharge intensity as one of the following categories:

- Class 0 – No Flood: The river stage is normal, with no risk of overflows and no surrounding areas susceptible to inundation.
- Class 1 – Low Flood: There is a slight increase in river stage, and minor surface water accumulation is possible in the surrounding low-lying areas.
- Class 2 – Medium Flood: Water level increase is observable at vulnerable locations, and minor localized overflows may affect agro fields and/or nearby houses.
- Class 3 – High Flood: There is a drastic increase in river stage, which causes wide-scale flooding, with possible inundation of the transport and other infrastructural facilities, which may be disrupted.
- Class 4 – Very High Flood: The warning threshold for river level is crossed and flooding is likely to inundate; major impacts on the residential and commercial set ups are expected.
- Class 5 – Extreme High Flood: There is serious flooding with threatened lives and destruction of infrastructures; Emergency Response is required as severely and widely affected multiple areas are at risk.

The classification thresholds are computed from historical hydrographs using the following rule:

$$Class = \begin{cases} 0, & WL < T_1 \\ 1, & \text{if } T_1 \leq WL < T_2 \\ 2, & \text{if } T_2 \leq WL < T_3 \\ 3, & \text{if } T_3 \leq WL < T_4 \\ 4, & \text{if } T_4 \leq WL < T_5 \\ 5, & WL \geq T_5 \end{cases} \quad (7)$$

where WL is the normalized water level observation at time t . The discharge rates specified by FFD criteria for Sukkur Basin are represented by the threshold values $T_1 - T_5$. Ensuring consistency with the dynamic parameters given in Table 3 and 4, these categorical levels are used as the target variable of flood severity classes in UFNet's SVM classifier. UFNet learns the nonlinear links between normalized meteorological factors (rainfall, temperature, humidity) and hydrological outputs (discharge, water level) to classify each new observation to its appropriate flood category during training.

4.4 Algorithmic Workflow

UFNet follows the workflow outlined below.

Algorithm 1: UFNet Multiclass Flood Severity Classification Input: Hydrometeorological dataset $D = \{X, Y\}$, where $X = \{RF, H, T_{min}, T_{max}, WS, HU, HD, QU, QD\}$ represents the predictor variables, and Y denotes the six-class flood-severity label.

Output: Predicted Flood-severity class $\in \{0, 1, 2, 3, 4, 5\}$

1. Load dataset D and clean noise, inconsistencies, and missing values.
2. Normalize all features to $[0,1]$
3. Split dataset into Training (80%) and Testing (20%)
4. Fit preprocessing on training data
5. Apply SMOTE only on the training subset
6. Select hyperparameters (C, γ) using grid search
7. Train RBF-SVM classifier on balanced training data
8. Evaluate performance using: Precision, Recall, F1-score, ROC-AUC, CSI, CPI
9. For each new input x : Predict class using the trained SVM model
10. Output severity label

4.5 Conceptual Extension: Online and Incremental UFNet

Although the present study evaluates UFNet using a standard batch-trained RBF-SVM, the framework is designed to support future enhancements through incremental learning. Flood data in operational monitoring environments often arrives continuously from field sensors, making online adaptation desirable. To accommodate this, we outline a conceptual extension of UFNet that enables the model to update its decision boundary as new observations become available.

4.5.1 Incremental update of support vector weights

The adaptive update of support-vector coefficients can be expressed as:

$$SV = \left\{ x_i \mid \min_j \|x_i - x_j\|^2 > \epsilon \right\}, \quad 0 < \epsilon < 1 \quad (8)$$

where ϵ defines the minimal margin tolerance in normalized feature space. This rule conceptually filters redundant vectors when data streams evolve.

4.5.2 Incremental weight update

$$w_{t+1} = w_t + \eta_t y_t K(x_t, \cdot) \quad (9)$$

where w_t is the current weight vector and $K(\cdot)$ is the kernel function. The η_t is the adaptive step size governed by

$$\eta_t = \frac{1}{\lambda + \|w_t\|_2^2} \quad (10)$$

and λ is the regularization factor controlling stability. These update rules illustrate how UFNet could incorporate real-time sensor data streams in future implementations. However, the current experiments in Section 5 use only a standard offline SVM, and incremental learning was reserved for future work.

4.6 Evaluation Metrics and Hydrological Performance Indices

Conventional accuracy metrics were extended with hydrological reliability indicators to evaluate operational performance. Beyond Precision and Recall, UFNet

incorporates the CSI that combines hits and errors into one index.

$$CSI = \frac{TP}{TP + FP + FN} \quad (11)$$

whereas CPI is calculated by summing up F1-score and AUC with weights of 0.6 and 0.4.

$$CPI = 0.6 \times F1 + 0.4 \times AUC \quad (12)$$

5. Results and Discussion

The section evaluates the proposed UFNNet lightweight flood-severity classification model by conducting experiments using Python and the PMD/FFD dataset. The following parameters are considered in the experiment: multiclass accuracy, reliability of classification, separation of classes, and efficiency. Only the metrics obtained from the experiments are presented.

5.1 Classification Accuracy and Reliability

UFNNet demonstrates high multiclass classification accuracy across all six severity categories (Extreme High, Very High, High, Medium, Low, and No Flood). Fig. 5 shows the multiclass confusion matrix of UFNNet for the 480-sample independent test dataset with 80 observations in each flood severity level. The strong diagonal distribution dominance indicates strong classification reliability, with 464 out of 480 samples being correctly classified, which represents an accuracy rate of 96.67%. The Low class achieved 100% recall, with all 80 test samples correctly identified; its one-versus-rest class-wise accuracy was 99.17%. Extreme High, Medium, and No Flood levels of floods were correctly classified in 77/80 samples each, while Very High had the highest error among all levels, with 74/80 samples correctly identified. Most misclassifications occurred between neighboring or closely related severity categories, indicating greater difficulty in distinguishing hydrologically similar conditions.

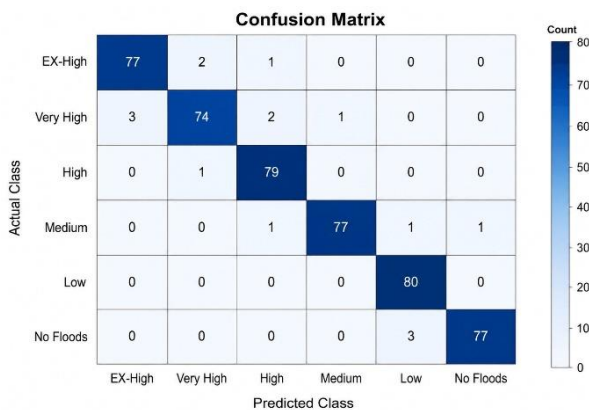


Fig. 5. Multiclass confusion matrix for UFNNet flood-severity classification.

The confusion matrix for the one-versus-rest binary classification of the six categories is illustrated in Fig. 6, showing the detailed results of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). In the case of the Low category, a sensitivity of 100 percent was observed due to the presence of 80 TP and zero FN, while the High class classified 79 out

of 80 samples correctly. The Very High class showed the largest number of missed detections, with six false negatives and 74 true positives. All three classes, i.e., Extreme High, Medium, and No Flood, had 77 true positives, while there were only three false negatives. The small numbers of false positives and false negatives across all six classes indicate high class-wise reliability and complement the multiclass confusion matrix by identifying where the remaining classification errors occur.

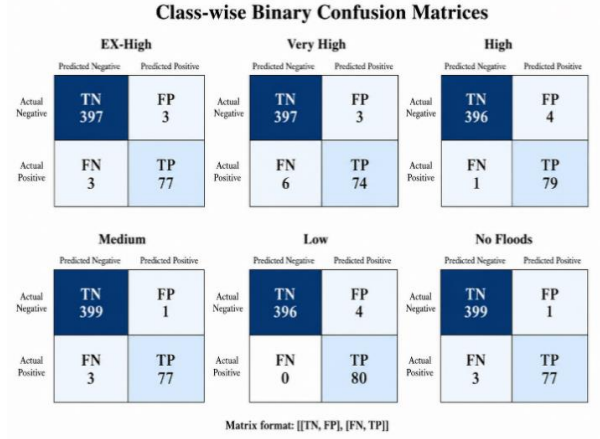


Fig. 6. Class-wise binary confusion matrices for UFNNet.

To further quantify class-wise reliability, the Critical Success Index (CSI) was computed directly from the confusion matrices, yielding values from 0.892 to 0.952. The Composite Performance Index (CPI), calculated by assigning weights of 0.6 and 0.4 to the F1-score and AUC, respectively, ranged from 0.966 to 0.985, indicating consistently strong predictive performance across the six classes. Table 9 summarizes the overall UFNNet performance on the 480-sample test set, with 464 correct predictions, corresponding to an accuracy of 96.67% and an error rate of 3.33%. UFNNet achieved class-wise precision of 95.18%–98.72%, recall of 92.50%–100%, and F1-scores of 94.27%–97.56%, with a mean specificity value of 99.33%.

Table 10 presents the class-wise performance of UFNNet and shows consistently high predictive capability across all six flood-severity levels. The Low class achieved 100% recall, with all 80 test samples correctly identified, while 79 of 80 High-class samples were correctly classified. Extreme High, Medium, and No Flood each had 77 of 80 samples correctly identified, whereas Very High showed the largest number of missed classifications, with 74 of 80 samples correctly identified. The High class achieved a recall of 98.75%, while the Extreme High class maintained balanced precision and recall of 96.25%. The Very High class showed the lowest recall of 92.50% and F1-score of 94.27%, suggesting greater overlap with neighboring severity categories. Despite this variation, class-wise accuracy remained between 98.12% and 99.17%, demonstrating robust performance across both moderate and severe flood conditions.

Taken together, Tables 9 and 10 show that UFNNet combines high overall accuracy with stable class-wise performance. The close agreement between macro and

Table 9

Overall classification performance of UFNet on the test set.

Performance Parameter	Result
Total Test Samples	480
Correct Predictions	464
Incorrect Predictions	16
Overall Accuracy	96.67%
Error Rate	3.33%
Macro Precision	96.70%
Macro Recall / Sensitivity	96.67%
Macro F1-Score	96.66%
Weighted Precision	96.70%
Weighted Recall	96.67%
Weighted F1-Score	96.66%
Balanced Accuracy	96.67%
Average Specificity	99.33%
Average NPV	99.34%
Cohen's Kappa	0.9600
Matthews Correlation Coefficient (MCC)	0.9601

weighted metrics indicates that no individual severity class dominates the overall evaluation. Most remaining errors occur between neighbouring flood categories, which is expected because adjacent severity levels may share similar hydrometeorological characteristics. These results support the use of the proposed six-class formulation for fine-grained flood-severity assessment.

5.2 ROC–AUC Class Separability

The ROC-AUC curves in Fig. 7 show that there is strong separation among classes at all six flood severity levels. The AUC values ranged from 0.98 to 1.00, indicating that UFNet maintains high discriminatory capability across different classification thresholds. This performance is particularly relevant to early-warning applications, where reliable discrimination between severity levels is required under varying decision thresholds.

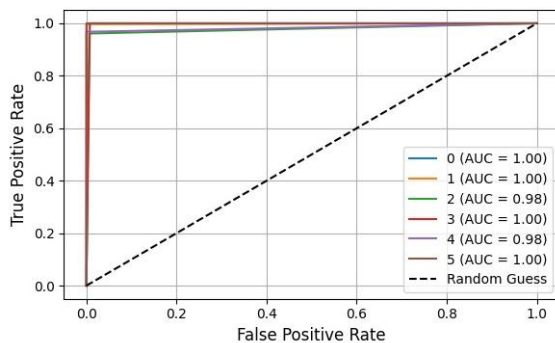


Fig. 7. ROC-AUC curves for the six UFNet flood-severity classes.

5.3 Computational Performance and Lightweight Efficiency

UFNet's computational performance was benchmarked against traditional machine-learning models (KNN, Random Forest, Neural Network, Logistic Regression). All experiments were conducted on a CPU-based system

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equipped with an Intel Core i5 processor and 8 GB RAM, running 64-bit Windows 11. UFNet was implemented in Python 3.11 using scikit-learn 1.5 and imbalanced-learn 0.12 libraries, without GPU acceleration. Model hyperparameter tuning was optimized using five-fold stratified grid search. Inference latency was measured through repeated post-training predictions using `time.perf_counter()`, while process-level memory consumption during inference was monitored using `psutil`. As shown in Fig. 8, the SVM-based UFNet achieved the lowest measured inference latency (~5 ms per prediction) and memory footprint (~10 MB) among the evaluated models. KNN and Neural Networks exhibited significantly higher resource requirements, while Random Forest and Logistic Regression showed moderate performance. The findings show that UFNet has strong classification performance with lower computing requirements, suggesting the possible suitability of UFNet for IoT, edge computing, and embedded flood monitoring applications.

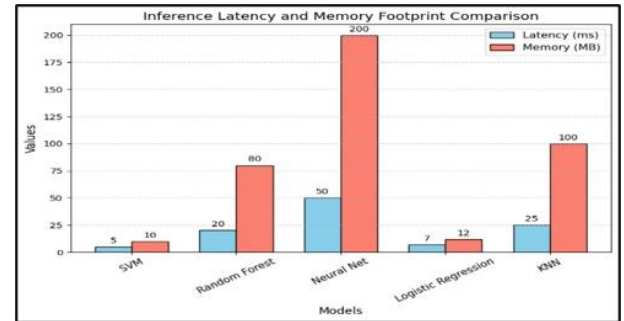


Fig. 8. Inference latency and memory-footprint comparison of UFNet and baseline models.

5.4 Overall Discussion

Overall, the results show that UFNet achieves a favourable balance between multiclass classification accuracy and computational efficiency. The residual errors of classification are mostly made in terms of neighbouring severity classes, which suggests that the main problem is to recognize the hydrologically similar floods. The consistently high class-based metrics and ROC-AUC values support the reliability of classification within six severity classes. The fact that the inference latency and memory requirement are relatively low implies that this level of performance can be attained without deep models or the need for GPUs. The major strength of UFNet lies in its accurate classification capability, but the ability to preserve strong discrimination even through six levels of severity without increasing its computational load. This is highly significant in edge-based flood monitoring systems where computational capabilities may be limited.

6. Conclusion and Future Work

The work introduced UFNet, a lightweight and computationally efficient SVM-based approach for multiclass urban flood severity prediction. The model is appropriate for deployment in resource-constrained, IoT-enabled settings since it combines hydrometeorological charac-

Table 10

Class-wise classification performance of UFNet.

Class	Precision	Recall / Sensitivity	Specificity	F1-Score	NPV	Accuracy
Extreme High	96.25%	96.25%	99.25%	96.25%	99.25%	98.75%
Very High	96.10%	92.50%	99.25%	94.27%	98.51%	98.12%
High	95.18%	98.75%	99.00%	96.93%	99.75%	98.96%
Medium	98.72%	96.25%	99.75%	97.47%	99.25%	99.17%
Low	95.24%	100.00%	99.00%	97.56%	100.00%	99.17%
No Flood	98.72%	96.25%	99.75%	97.47%	99.25%	99.17%

teristics and runs with low memory and latency needs. Class-wise precision ranged from 95.18% to 98.72%, recall from 92.50% to 100%, and F1-score from 94.27% to 97.56%, achieving strong predictive reliability over six severity levels. Strong class separability is confirmed by the ROC–AUC curves (0.98–1.00); the CSI and CPI indices emphasize the robustness of UFNet in differentiating both mild and severe flood situations. Computational profiling demonstrates the low inference latency and memory footprint of UFNet, supporting its potential suitability for future resource-constrained and edge-based implementations. Beyond its predictive ability, UFNet offers practical advantages for systems used for operational flood monitoring. The structure offers a scalable architecture for field deployment as well as consolidates meteorological and hydrological parameters inside an IoT-ready data pipeline. While this research centered on batch-trained SVM categorization, a conceptual incremental-learning extension was suggested to enable future real-time adaptation. The results show that UFNet meets the potential requirements of a future early-warning decision-support system, including classification reliability and rapid inference. Still, there are some constraints. Only static SVM-based categorization was investigated; the present model neither includes temporal dependencies nor rainfall-runoff development. Future research will incorporate temporal learning elements, assess spatial generalization by way of UFNet over various basins, and validate real-time streaming performance on edge computing platforms. These extensions could support the future development of UFNet as a deployable decision-support framework for smart-city flood management.

7. Acknowledgment

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