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Stepping up Support Vector Machine Algorithm for Flood Prediction

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Abstract

Flooding is one of the natural disasters that requires an accurate prediction system is needed to detect the potential for flooding. This research aims to apply the machine learning method *Support Vector Machine* (SVM) as a flood prediction model in Rabalaju River. The data used in this research includes historical data on rainfall, water level, soil moisture, and river flow discharge. The research stages include data collection, data preprocessing, SVM model building, and model performance evaluation using accuracy, precision, *recall*, and F1-score metrics. The results showed that the SVM method was able to provide accurate predictions with an accuracy rate of 92%. The implementation of this method is expected to help related parties, such as local governments and local communities, in mitigating flood disasters more effectively. This research also provides further development recommendations, such as model integration with Python programming language technology for *real-time* data monitoring.

Keywords:
Flood, SVM, Machine Learning

1. Introduction

Indonesia is a country prone to flood disasters such as earthquakes, mountain eruptions, tsunamis that occur outside of human influence. Flooding is one of the events as well as the disaster of stagnant water and the flow of water on people's land that should not flow in that place so that it can damage anything in its path. Such as houses, trees, land, roads so that it affects community activities [1].

In recent years, flooding is a frequent disaster in Indonesia in terms of the frequency of rain discharge and the duration of the rainfall. Based on data from the National Disaster Management Agency (BNPB), flooding is the most frequent disaster in Indonesia with 464 flood events each year. in Indonesia with 32 events each year. There are several main factors that make flooding unavoidable today, including the reduction of tree cover, extreme weather, and the topographical conditions of the watershed [2].

Detecting flood natural disasters is important because the information obtained is very helpful to minimize the impact of losses experienced by victims. A big focus of Machine Learning research is how to automatically recognize complex patterns and make intelligent decisions based on data. Machine learning can learn existing historical data patterns to predict rainfall and flooding over the next few days [2].

Research in the field of Machine Learning also makes an important contribution to flood risk mitigation. The main focus in Machine Learning research is how to automatically recognize complex patterns and make intelligent decisions based on data. There are many

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algorithms used in flood detection systems, namely the Fuzzy Logic algorithm implemented to predict potential flood disasters. In the process, rainfall and water level data are processed using the Particle Swarm Optimization (PSO) algorithm. However, this research has not involved the development of flood predictions for programming-based, so information about flood predictions cannot be accessed by the public quickly [3] [4] [5].

Based on this description, researchers are interested in using the Support Vector Machine (SVM) algorithm because in previous studies, the Support Vector Machine (SVM) algorithm only determines the truth of flood information on twitter. In this research, the Support Vector Machine (SVM) algorithm is the main focus. The superiority of SVM in recognizing complex patterns in data and being able to apply linear separation to high-dimensional non-linear data input makes it an attractive choice. Therefore, the research entitled "Implementation of Support Vector Machine (SVM) Algorithm for Flood Detection" aims to design and analyze a flood detection system by implementing the Support Vector Machine (SVM) Algorithm based on python programming, making it easier to monitor or monitor floods. This research will focus on focusing on the implementation of SVM to detect floods in artificial simulations, without considering geographical and climatic variations [6][7].

2. Related Works

Flood detection and prediction have been widely studied using various techniques ranging from traditional statistical methods to machine learning (ML) and deep learning (DL) algorithms. Traditional methods such as logistic regression have served as baseline models in flood prediction. Although simple and interpretable, their limited ability to model non-linear relationships restricts their predictive accuracy, especially when applied to dynamic and complex datasets. In general, these models tend to underperform when compared to more adaptive approaches, with accuracy often falling below 80% in real-time flood forecasting scenarios [8].

In recent years, Support Vector Machine (SVM) has gained popularity due to its capacity to handle high-dimensional data and create optimal hyperplanes for classification. A study that utilized SVM for flood detection based on meteorological indicators such as surface pressure and precipitable water vapor demonstrated strong classification performance, achieving accuracy above 90%.The study revealed that SVM was particularly effective in detecting the onset of flood-prone conditions in real-time scenarios. However, the model performance was found to be sensitive to the quality and preprocessing of input data, indicating a need for careful feature selection [9].

In addition to SVM, classical machine learning methods like Random Forest (RF) have also shown promising results. In one comparative study, RF outperformed other classifiers by reaching an accuracy of 99% in binary flood detection tasks using historical rainfall and hydrological data. The ensemble nature of Random Forest allowed it to capture complex interactions between variables, leading to better generalization performance. However, despite its high accuracy, RF requires substantial computational resources and may suffer from overfitting if not properly regularized or tuned [10].

Deep learning approaches, particularly those involving Long Short-Term Memory (LSTM) networks, have brought significant advances in flood prediction. LSTM models, known for their ability to learn temporal dependencies, achieved a mean relative error of only 9.5% in multi-step flood forecasting tasks. The results indicate that LSTM excels in handling sequential weather data, such as rainfall over time, making it well-suited for early warning systems. Furthermore, its robustness in handling noisy and incomplete data provides an edge over traditional models, although the training process can be computationally intensive [11].

Overall, the body of research highlights that while traditional methods serve as foundational tools, machine learning and deep learning models—particularly SVM, RF, and LSTM—consistently deliver higher accuracy and lower error rates in flood detection and prediction. Each technique has its own strengths: SVM in high-dimensional space separation, RF in robust ensemble modeling, and LSTM in capturing temporal dynamics. These results reinforce the importance of selecting appropriate algorithms and preprocessing techniques tailored to the characteristics of the dataset and the specific goals of the flood prediction task [11].

3. Proposed Method

This research conducts long-term flood prediction (6 and 30 days ahead) using historical data for the last 1 month in 2024.

3.1 Dataset

Flood prediction datasets usually include weather and climate data obtained from BMKG (Badan Meteorologi, Klimatologi dan Geofisika). This data includes daily rainfall, humidity levels. This information is analyzed using statistical-based predictive models or machine learning SVM models to map the potential for flooding in an area. BMKG also provides historical data on flood events that can be accessed for research purposes or the development of flood early warning systems. This complete and accurate data source is important for risk mitigation and better spatial planning.

3.2 Research Flow

Based on the research flow shown, this research is entitled "Application of Machine Learning SVM Method for Flood Prediction. The research begins with the collection of weather and hydrological data from BMKG as the main source. The data was then processed to ensure the feasibility of the analysis. The next step was to divide the dataset into two parts: training data and testing data. The training data is used to train the model using the Support Vector Machine (SVM) method, while the testing data is used to evaluate the performance of the model. After the training process is complete, the resulting SVM model is used to perform flood prediction in the Rabalaju River area.

3.3 Proposed Algorithm

This research uses the SVM algorithm. In this case, the main focus is on the advantages of SVM regarding complex patterns in data and being able to design and analyze flood detection systems by implementing the SVM, making it easier to monitor or monitor floods. This research will focus on the implementation of SVM to detect floods in artificial simulations, without considering geography and climate. The SVM is a supervised learning algorithm primarily used for classification tasks, although it can also be adapted for regression. Mathematically, SVM aims to find the optimal hyperplane that best separates two classes of data points with the maximum possible margin. Given a training dataset $\{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$ where each x_i is a feature vector in $\mathbb{R}^d$and each y_i is a label in $\{-1, +1\}$, the linear SVM formulation seeks to minimize the norm of the weight vector w,

$$\min_{w,b} \frac{1}{2}\|w\|^2 \quad \text{Eq. (1)}$$

Subject to constraint $y_i(w^T x_i + b) \geq 1$. This ensures that each data point is correctly classified and lies on the correct side of the margin. However, real-world data is often not perfectly separable. To accommodate this, SVM introduces slack variables $\xi_i \geq 0$and modifies the optimization to allow for some misclassifications. The soft margin SVM objective becomes equation 2:

$$\min_{w,b,\xi} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \xi_i \quad \text{Eq. (2)}$$

subject to $y_i(w^T x_i + b) \geq 1 - \xi_i$. The parameter C controls the trade-off between maximizing the margin and minimizing classification errors. For data that is not linearly separable even with slack variables, SVM employs the "kernel trick" to implicitly map data into a higher-dimensional feature space where linear separation is possible. Instead of computing dot products directly in high-dimensional space, a kernel function K $K(x_i,x_j) = \phi(x_i)^T\phi(x_j)$ is used to compute inner products efficiently. In the dual form of the optimization, this leads to the objective in Equation 3:

$$\max_{\alpha} \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i\alpha_j y_i y_j K(x_i, x_j) \quad \text{Eq. (3)}$$

with constraints $\sum_{i=1}^{n} \alpha_i y_i = 0$ and $0 \leq \alpha_i \leq C$. The final decision function for classifying a new data point x is then in Equation 4:

$$f(x) = \text{sign}\left(\sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b\right) \quad \text{Eq. (4)}$$

which uses only a subset of the training data called support vectors. SVMs are powerful classifiers that maximize the margin between classes and can be extended to non-linear problems using kernel functions.

5. Result and Analysis

Datasets are taken from 100 dataset predictions with a combination of 60% training and 40% testing. Flood prediction using SVM is 100% accurate and precise which can state future flood predictions. The data is taken from BMKG Sultan Muhammad Salahuddin Meteorological Station online. In this study, flooding can be defined based on rainfall 0-3.5 mm, humidity 60-70%. There are 3 conditions, namely safe, alert, and danger.

No.	DATE	RH_AVG	RR
1	01-01-2023	72	0
2	02-01-2023	86	0

3	03-01-2023	84	2.2
4	04-01-2023	77	2
5	05-01-2023	77	0
6	06-01-2023	82	0
7	07-01-2023	75	8888
8	08-01-2023	83	0
9	09-01-2023	98	0
10	10-01-2023	84	0

Notes
8888 : Data
9999 : No data (no measurements taken)
RH_AVG : Average humidity (%)
RR : Rainfall (mm)

The Support Vector Machine (SVM) kernel model that can evaluate the model well, can be seen from the results of accuracy, precision, recall, and F1-score and support. In the figure below. visualization is done between numerical variables to see how close the relationship between variables. Calculation. The correlation was done using the Pandas and numpy libraries.

```
              precision    recall  f1-score   support

           0       0.97      0.94      0.95        31
           1       0.94      0.97      0.95        31

    accuracy                           0.95        62
   macro avg       0.95      0.95      0.95        62
weighted avg       0.95      0.95      0.95        62
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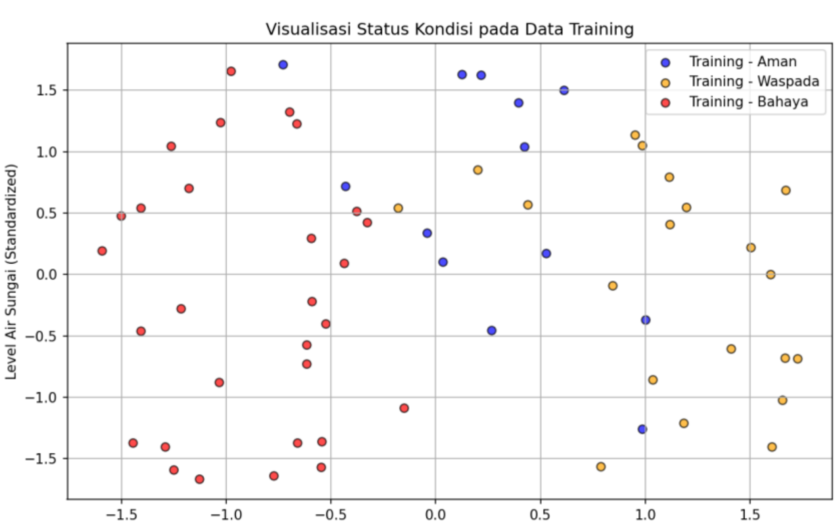


No.	Rainfall	Humidity	River Water Level	Risk Score	Flood Prediction	Condition Status

0	-1.179336	-0.686572	0.704359	-1.222154	1	Danger
1	1.196036	1.427757	0.549323	1.658711	0	Alert
2	0.392985	-0.034511	1.397872	0.377983	0	Safe
3	-0.731326	0.395131	1.71273	-0.295659	0	Safe
4	-0.663038	0.072336	1.22812	-0.422058	1	Danger
5	0.612358	-1.672326	1.500294	-0.215282	0	Safe
6	0.78659	1.314971	-1.565617	1.156242	0	Alert
7	-0.6984	-1.486897	1.324985	-1.181296	1	Danger
8	1.410328	-0.100894	-0.603578	1.03983	0	Alert
9	-0.592682	0.316166	-0.220715	-0.335271	1	Danger
10	0.26458	0.397894	-0.454687	0.372123	0	Safe
11	-1.265401	-1.322897	1.04426	-1.57152	1	Danger
12	-1.503855	-0.026953	0.47767	-1.182026	1	Danger
13	-1.028436	-0.832871	1.241148	-1.139877	1	Danger
14	-0.618337	0.990162	-0.574405	-0.057844	1	Danger
15	1.596018	-0.628115	0.000663	0.973747	0	Alert
16	0.985908	0.598717	1.052871	1.129066	0	Alert
17	0.526603	0.127401	0.173154	0.489483	0	Safe
18	-1.033416	1.225542	-0.87774	-0.294722	1	Danger
19	0.438308	1.003246	0.568771	0.856084	0	Alert
20	0.949891	1.32609	1.136508	1.448951	0	Alert
21	1.726553	0.251334	-0.683859	1.453306	0	Alert
22	-0.151485	1.573886	-1.084681	0.559861	1	Danger
23	-0.328302	-0.523364	0.422161	-0.484028	1	Danger
24	-1.592704	-0.794311	0.194108	-1.631852	1	Danger
25	-0.659893	-0.696213	-1.371792	-0.934196	1	Danger
26	1.503234	-0.959926	0.221869	0.755998	0	Alert
27	-1.12757	-0.934797	-1.662488	-1.436155	1	Danger
28	-0.5459	0.728159	-1.359742	-0.16974	1	Danger
29	-0.376864	-1.691277	0.515154	-1.069101	1	Danger
30	-0.04135	-0.96063	0.338976	-0.467058	0	Safe
31	1.66712	1.35334	-0.68091	1.926861	0	Alert
32	0.984867	-0.623204	-1.256909	0.416286	0	Safe
33	-0.179677	1.298801	0.541311	0.502193	0	Alert
34	-0.432079	1.452175	0.721397	0.384235	0	Safe
35	0.42351	-0.351042	1.040883	0.231919	0	Safe
36	-0.617061	0.000975	-0.727972	-0.533164	1	Danger
37	0.842791	1.037211	-0.09197	1.155614	0	Alert
38	1.653542	1.473633	-1.022286	1.952998	0	Alert

39	-0.977531	1.039963	1.654083	-0.190384	1	Danger
40	-1.252605	-1.47713	-1.589181	-1.787666	1	Danger
41	-1.40733	-1.658825	-0.457094	-1.930714	1	Danger
42	-0.774501	-0.811364	-1.640948	-1.095522	1	Danger
43	1.033674	-0.317373	-0.854545	0.623089	0	Alert
44	-0.546405	0.491238	-1.570455	-0.294366	1	Danger
45	1.668237	-1.240603	0.686739	0.781817	0	Alert
46	-0.526775	1.410382	-0.40172	0.223659	1	Danger
47	1.183308	0.399381	-1.212094	1.060032	0	Alert
48	0.214542	-1.62166	1.621769	-0.50094	0	Safe
49	0.200754	1.099991	0.854917	0.729368	0	Alert
50	-0.437961	0.059949	0.089484	-0.315094	1	Danger
51	1.6023	0.409383	-1.404602	1.387074	0	Alert
52	-1.292804	0.907534	-1.400447	-0.681923	1	Danger
53	1.11344	-0.678159	0.791888	0.612058	0	Alert
54	0.03278	-0.587857	0.102951	-0.245667	0	Safe
55	-0.595185	-0.904764	0.295779	-0.884052	1	Danger
56	-1.445089	1.245955	-1.370735	-0.641513	1	Danger
57	0.123026	-0.054969	1.632212	0.167075	0	Safe
58	-1.409068	-0.457557	0.54245	-1.306256	1	Danger
59	0.999176	-0.968583	-0.368979	0.316228	0	Safe
60	-1.218307	-1.664778	-0.27875	-1.772664	1	Danger
61	1.118213	1.341716	0.40804	1.547874	0	Alert

The data in the table above is the output of training data that has been entered into the flood prediction python program, serving as training data to build a flood prediction model using Support Vector Machine (SVM). SVM is a machine learning method used for classification and regression. In this case, SVM can be used to predict flood status based on given weather attributes, such as rainfall, humidity, and river water levels. Through SVM, the model can separate data that is related to flood events or not by finding a hyperplane that separates two classes, namely "Safe" and "Danger/Wary," based on the input data.

For example, data with very low precipitation (-1.179336) and negative humidity (-0.686572) and high river levels (0.704359) indicates high flood potential, with a very negative risk score (-1.222154). Based on this pattern, the SVM will label this data as "Danger," as it indicates that the weather conditions are highly risky for flooding. Meanwhile, data with relatively moderate rainfall and humidity (e.g., rainfall 1.196036 and humidity 1.427757) with a lower river water level (0.549323) can be predicted as "Alert" or "Safe," depending on the risk score value and patterns found in the SVM model.

For example, if we use the following data:

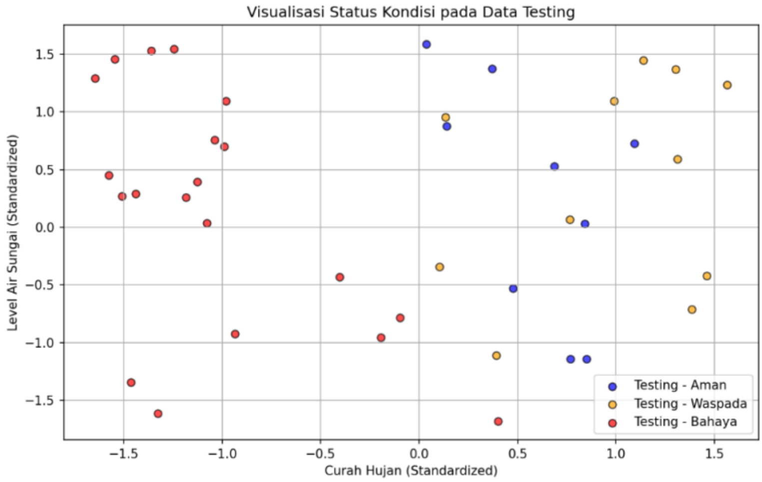
- Rainfall: 0.78659
- Humidity: 1.314971
- River Water Level: -1.565617
- Risk Score: 1.156242

The SVM model trained from the training data will classify the status of this condition as "Alert" based on the existing patterns in the previous data, indicating that this weather condition carries a potential flood risk that is not too high, but still needs to be alerted. The model will be continuously updated and tested using new data to improve the prediction accuracy in detecting potential flooding.

5.2 Flood Prediction

No.	Rainfall	Humidity	River Water Level	Risk Score	Flood Prediction	Condition Status
0	-1.24421	1.541473	1.542069	-0.172236	1	Danger
1	1.301356	-0.616132	1.368454	0.824552	0	Alert
2	-1.18425	1.311067	0.261466	-0.307996	1	Danger
3	0.371537	-1.776268	1.375478	-0.46337	0	Safe
4	-0.194805	1.314605	-0.951476	0.410629	1	Danger
5	-1.439959	-1.384202	0.291044	-1.783334	1	Danger
6	1.31191	0.823073	0.589035	1.467555	0	Alert
7	0.139131	-1.152585	0.87461	-0.382874	0	Safe
8	-1.508056	-0.975265	0.267497	-1.645692	1	Danger
9	-1.463895	-0.375446	-1.344963	-1.421088	1	Danger
10	0.401423	-1.005958	-1.676718	-0.253471	1	Danger
11	0.390379	1.622041	-1.110895	1.012431	0	Alert
12	-1.545287	-0.073825	1.453997	-1.180261	1	Danger
13	0.840734	-1.19496	0.031628	0.106484	0	Safe
14	-1.576097	1.279799	0.449288	-0.623751	1	Danger
15	1.137705	-1.013952	1.448409	0.51097	0	Alert
16	0.037525	-0.926151	1.58842	-0.31517	0	Safe
17	-1.07766	-1.029189	0.035485	-1.342079	1	Danger
18	0.989255	0.552281	1.09095	1.112009	0	Alert
19	-1.038842	0.398944	0.756538	-0.594372	1	Danger
20	1.092142	-1.152764	0.723176	0.36685	0	Safe
21	-0.980822	-1.74281	1.093539	-1.54052	1	Danger
22	1.460111	-0.755676	-0.420386	0.780753	0	Alert
23	0.686934	-0.537786	0.526994	0.323433	0	Safe
24	-1.327908	0.640667	-1.610462	-0.848198	1	Danger
25	1.384171	0.038684	-0.708121	1.078867	0	Alert
26	0.13218	0.720309	0.955483	0.501243	0	Alert
27	-0.934026	1.005607	-0.922404	-0.322125	1	Danger
28	-0.096808	-1.008955	-0.78155	-0.599334	1	Danger
29	-1.35944	0.533431	1.527259	-0.741123	1	Danger
30	-0.990209	0.844144	0.700967	-0.348541	1	Danger
31	-1.644444	-0.02228	1.28954	-1.244422	1	Danger
32	0.477622	-1.406397	-0.531063	-0.315259	0	Safe

33	0.850993	-0.708878	-1.137956	0.276169	0	Safe
34	-0.404956	-1.418277	-0.428792	-1.017479	1	Danger
35	0.102988	1.188285	-0.34145	0.623545	0	Alert
36	0.764649	0.439809	0.06544	0.820311	0	Alert
37	1.563775	-1.297293	1.234704	0.703807	0	Alert
38	-1.127487	1.350912	0.392642	-0.23634	1	Danger
39	0.768823	-1.533112	-1.14078	-0.178855	0	Safe



The data studied are the results of flood prediction testing using machine learning methods with several variables as inputs, namely rainfall, humidity, river water level and risk score, all of which play an important role in identifying the potential for flooding. Rainfall, as one of the main variables, shows a direct impact on flood risk, with negative values indicating little or no rain, while positive values indicate more significant rainfall. An increase in rainfall is strongly associated with a higher likelihood of flooding.

Humidity also affects flood predictions, as high humidity levels can increase the likelihood of heavy rainfall, which can exacerbate flood risks. On the other hand, river water levels reflect the existing water level in the river and are directly related to flood potential. High water levels indicate that the river is approaching or even exceeding its normal capacity, which increases the risk of flooding in the area. Therefore, the river water level is a very important variable in this prediction model.

The risk score, which is the result of the calculation of various parameters, gives an idea of the level of flood hazard. Lower risk score values indicate safer conditions, while higher values indicate an increased risk of flooding. The data is categorized into condition states such as "Danger," "Alert," or "Safe," which are determined based on a combination of rainfall, humidity, river levels, and risk score. Most of the data in this set is classified in the "Danger" category, indicating that conditions in the area have a very high risk of flooding.

The use of SVM model for flood prediction with complex data to be processed to produce more accurate predictions. By identifying patterns in rainfall, humidity and river water level, the model can categorize the condition status as "Danger" when all three variables show signs of increase. To improve the accuracy of the prediction model, the SVM module has been optimized to achieve an accuracy rate of 95%, which is very useful in disaster mitigation planning, such as evacuation or river flow management to reduce the impact of flooding.

6. Conclusion

This research implements the Support Vector Machine (SVM) algorithm to predict flood potential with categories rainfall, soil moisture, river water discharge and water level. The research shows that SVM is able to provide predictions with an accuracy of up to 95%, making it an effective tool for recognizing complex data patterns and providing condition status classifications such as "Safe," "Alert," and "Danger". These results are expected to assist local governments and communities in disaster mitigation, such as evacuation planning or water resource management.The study recommends further development by integrating SVM prediction models with Language for real-time data monitoring. This approach could improve the accuracy and speed of response to flood threats, especially in vulnerable areas. With optimization and wider application of technology, the model is expected to become a sustainable solution in flood risk management and disaster impact protection.

Based on the research results, it is recommended to develop a real-time flood monitoring system that uses the SVM algorithm and is implemented with the Python programming language. This system can be designed to automatically process environmental data, such as rainfall, soil moisture, river water discharge, and water level, which are processed by the SVM model to produce flood condition predictions with status classifications such as "Safe," "Alert," and "Danger." The use of Python enables fast and efficient data processing thanks to the support of various libraries, such as Scikit-learn for prediction model development and Pandas for data analysis. With this approach, local governments can respond more quickly and accurately to flood threats, especially in vulnerable areas, and provide local communities with access to early warning information that can be used for disaster mitigation. The system can also be further developed to integrate historical and predictive data analysis, supporting more sustainable and effective flood risk management in the future.

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