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Serious game for Flood Prediction Using Hinge Loss Function-Based Support Vector Machine (HLF-SVM) with QOBL-BWO Feature Selection

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Abstract: The increasing frequency of extreme weather events worldwide has driven the need for a robust flood prediction system to anticipate and mitigate its adverse impacts. This study aims to develop a comprehensive framework by integrating the Hinge Loss Function-based Support Vector Machine (HLF-SVM) with Quasi Opposition-Based Learning and Beluga Whale Optimization (QOBL-BWO) to enhance flood prediction accuracy. The dataset was collected from the Meteorological, Climatological, and Geophysical Agency or Badan Meteorologi, Klimatologi, dan Geofisika (BMKG) in Makassar city, Indonesia, encompassing variables such as rainfall, water level, water discharge, tides, temperature, and humidity. Data preprocessing steps included data cleaning, Min-Max normalization, and the implementation of the Synthetic Minority Oversampling Technique (SMOTE) to address class imbalance. The proposed QOBL-BWO methodology was applied for feature selection, eliminating less relevant factors while simultaneously optimizing SVM parameters. The optimized HLF-SVM model was then integrated into a serious game environment to provide interactive flood scenario simulations for educational and training purposes. Test results showed 99% accuracy, 98.8% precision, 99.6% recall, and 99.2% F1-score, surpassing the performance of conventional machine learning models such as LR, LDA, KNN, NB, SVM, and AdaBoost. These findings underscore the potential of the combined HLF-SVM and QOBL-BWO approach in improving flood prediction accuracy while simultaneously promoting risk awareness and more effective decision-making. Furthermore, this framework also simplifies computational complexity in the flood prediction process.

Keywords: Flood prediction, Hinge loss function, Support vector machine, Quasi opposition-based learning, Beluga whale optimization.

1. Introduction

Global climate change and the increasing frequency of extreme weather have triggered an increased risk of flooding disasters in various parts of the world [1-3]. Floods not only have an impact on significant economic losses and infrastructure damage, but also threaten the safety of human lives [4, 5]. Therefore, a reliable flood prediction system is increasingly needed to anticipate and reduce the impact of this disaster. The development of artificial intelligence methods, especially machine learning, has presented new opportunities in building prediction models that are increasingly accurate, efficient, and adaptive to changes in environmental conditions [6].

One of the widely used machine learning techniques for classification and regression is the Support Vector Machine (SVM). SVM has the advantage of maximizing the separation margin and handling high-dimensional data relatively well. However, SVM performance is highly dependent on the right selection of features and the determination of optimal parameters [7-9]. Therefore, the metaheuristic approach is often used to perform

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feature selection and optimization of SVM parameters [10]. In this study, the Beluga Whale Optimization (BWO) algorithm, a metaheuristic inspired by the social behavior of beluga whales, was used combined with Quasi Opposition-Based Learning (QOBL) to increase the scope of the solution search space. Through the integration of QOBL, the BWO exploration and exploitation process is expected to be more balanced, so that convergence on optimal solutions is achieved faster.

In addition to the algorithmic aspect, this research also seeks to increase awareness of flood disasters through serious game media. Serious games combine elements of the game with educational and training purposes, so that users can learn mitigation and response strategies interactively. In the context of flood prediction, the results of SVM modeling optimized by QOBL-BWO will be used to display various flood scenarios in a virtual environment. Thus, users (the public, students, and policy makers) will gain a better understanding of flood dynamics, triggering factors, and anticipatory actions that can be taken.

Although various flood prediction methods have been developed, several gaps remain unaddressed. First, conventional models often struggle to handle the complexity and non-linear nature of hydrometeorological data, which typically comprises a large number of high-dimensional variables. Second, model adaptability is frequently limited to local contexts, meaning that predictions in areas with unique characteristics such as extreme rainfall or differing infrastructure are not always optimally accommodated. Lastly, accurate predictions do not necessarily translate into adequate public understanding or preparedness, given the lack of interactive and easily comprehensible communication media. Therefore, this study aims to design a more accurate and efficient flood prediction framework by combining a Hinge Loss Function-based Support Vector Machine (HLF-SVM), Quasi Opposition-Based Learning, and Beluga Whale Optimization (QOBL-BWO) for feature selection and parameter optimization. By leveraging a metaheuristic approach capable of balancing exploration and exploitation in the solution space, it is expected that the model's adaptability to varied hydrometeorological conditions can be enhanced. In addition, the study develops an interactive serious game platform to visualize the flood prediction results, enabling the public and stakeholders to better understand flood risks and take appropriate mitigation measures. By integrating advanced algorithmic methods with a serious game as an educational medium, this research seeks to produce a more robust and comprehensive flood prediction model while contributing to greater preparedness and public awareness of flood hazards.

The main contributions of this research can be summarized as follows:

- Combining Hinge Loss Function-based SVM (HLF-SVM) with Quasi Opposition-Based Learning and Beluga Whale Optimization (QOBL-BWO) as feature selection techniques to improve flood prediction accuracy while reducing data dimensions.
- The application of hinge loss function in SVM offers a more effective approach in processing classification errors, while QOBL-BWO plays a role in determining the relevant subset of features and optimizing model parameters adaptively.
- Using serious games as proof-of-concept to display flood prediction results in an interactive and realistic manner, thus supporting training and education in the context of disaster mitigation.

With this integrated approach, it is hoped that flood prediction capabilities will increase, decision-making will become more effective, and public awareness of flood hazards can be increased through interactive learning. This research also opens up opportunities for further development, both in terms of optimization methods, machine learning modeling, and serious games connected to real-time environmental data.

The research structure consists of related works in Section 2, followed by an explanation of the proposed method in Section 3. Furthermore, the discussion of research results is elaborated in Section 4, and the research concludes with conclusions in Section 5.

2. Related works

Logistic Regression (LR) is one of the simplest and most widely used methods for binary classification. However, its primary limitation lies in the assumption of a linear relationship between the independent variables and the log-odds of the dependent variable. When this relationship is not linear, the model may yield inaccurate results [11]. Additionally, LR is highly sensitive to outliers, which can disproportionately affect coefficient estimates and, consequently, the model's accuracy [12]. Another drawback is that LR cannot directly handle interactions among variables without explicitly including interaction terms as new features, potentially increasing model complexity [13].

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Linear Discriminant Analysis (LDA) performs well when the normal distribution assumption and homogeneity of variance across classes hold. However, if these assumptions are violated, LDA can produce suboptimal results [14]. Another limitation is its inability to handle imbalanced datasets, where one class significantly outnumbers the other a common occurrence in real-world applications [15]. Moreover, LDA is not effective for high-dimensional data where the number of features far exceeds the number of samples, as this often leads to overfitting [16].

K-Nearest Neighbors (KNN) is intuitive and straightforward; however, it suffers from several drawbacks. First, it requires storing all training data, making it inefficient in terms of memory and computational time, especially with large datasets [17]. Furthermore, KNN is highly influenced by irrelevant features and feature scales, necessitating normalization or standardization prior to application [18]. Another weakness is that KNN does not provide class probabilities, offering only a class prediction based on the majority vote of nearest neighbors, which can reduce interpretability [19].

Naïve Bayes (NB) assumes independence among features, a condition rarely met in real-world data. When this assumption is violated, model performance can deteriorate significantly [20]. Additionally, NB cannot capture nonlinear relationships among features, limiting its applicability to more complex datasets [21]. Although NB is fast and efficient, particularly for large datasets, these limitations make it less suitable for applications where feature interactions are crucial [22].

Support Vector Machine (SVM) is a powerful classification algorithm but has notable weaknesses. First, SVM is highly sensitive to the choice of parameters and kernel, which can significantly affect model performance [23]. Moreover, SVM does not perform well with large, imbalanced datasets, as it may lead to overfitting or underfitting [24]. Another drawback is that interpreting SVM models can be challenging, especially when using nonlinear kernels, making the approach less transparent compared to other methods [25].

AdaBoost is an ensemble technique that improves accuracy by combining multiple weak learners. However, its primary limitation is its sensitivity to outliers and noise in the data, which can affect the overall model [26]. Furthermore, AdaBoost tends to perform poorly if the base learners are not sufficiently strong, as weak learners may degrade overall performance [27]. Another disadvantage is that AdaBoost does not scale well to very large datasets because it requires repeated training of the base learners [28].

Unlike conventional methods that typically focus on data separation without specialized feature optimization, this study proposes a two-layered approach through Hinge Loss Function-Based Support Vector Machine (HLF-SVM) with QOBL-BWO Feature Selection. First, the use of the hinge loss function helps maximize classification margins and offers better tolerance to outliers, particularly in the context of extreme hydrometeorological data. Second, the Quantum Opposition-Based Learning mechanism within Black Widow Optimization (QOBL-BWO) adaptively selects the most relevant features, not only reducing the complexity of non-linear flood data but also enhancing computational efficiency. This strategy is designed to overcome common limitations in conventional methods, such as the inherent complexity of flood datasets, overfitting risks, and inadequate adaptability to local conditions. The proposed holistic approach is further combined with a serious game to interactively visualize flood predictions, thereby enhancing disaster awareness and preparedness an essential component often overlooked in traditional flood prediction methods.

Flood prediction and classification have been widely explored through various AI and ML approaches, offering robust tools for areas prone to frequent flooding. For instance, El-Mahdy et al. [29] employed Artificial Neural Networks (ANNs) in South Sudan to predict flood risks, demonstrating that models such as Feed Forward Neural Networks (FFNN) and Gradient Boosting achieve high accuracy. Their findings underscore the importance of increasing hidden layers in neural networks to enhance predictive performance, particularly in data-scarce settings like South Sudan. In a different study, Saber et al. [30] investigated LightGBM and CatBoost for flash flood susceptibility in arid regions, revealing that these methods outperformed traditional algorithms such as Random Forest (RF) in both accuracy and computational efficiency. Their work emphasizes the potential of ensemble learning in flood risk assessment, especially where hydrological data are limited.

In addition to these methods, Long Short-Term Memory (LSTM) networks have gained traction for time-series forecasting in flood prediction. For example, Afendi [31] showed that applying the SMOTE to address imbalanced flood data significantly improves LSTM is precision and recall. This approach enables more accurate capture of flood occurrences under various meteorological conditions, although future studies are encouraged

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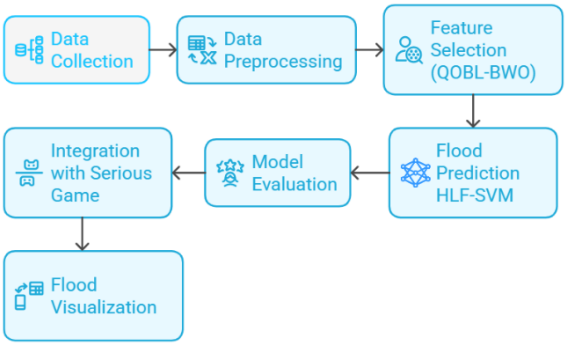


Figure. 1 Proposed methodology for flood prediction serious game

to explore further hyperparameter optimization. Ensemble learning techniques also prove beneficial in flood susceptibility assessments. Ren [32] demonstrated that combining Random Forest (RF) and XGBoost in mountainous urban areas not only yielded high AUC values but also improved robustness against training data variability outperforming single models like ANN and Support Vector Machines (SVM).

3. Proposed methodology

This study proposes an integrated approach between flood prediction modeling using Hinge Loss Function-based SVM (HLF-SVM) optimized with Quasi Opposition-Based Learning and Beluga Whale Optimization (QOBL-BWO) and the application of the results in a serious game. Fig. 1 outlines the working of the proposed methodology.

Broadly speaking, the proposed stages include data collection, pre-processing, feature selection, SVM modeling, model evaluation and model integration in serious games, here is an explanation of each stage:

3.1 Dataset

The dataset used in this research was obtained from the Meteorology, Climatology, and Geophysics Agency or Badan Meteorologi, Klimatologi, dan Geofisika (BMKG). This dataset covers the period from January 1, 2018, to December 31, 2022, with attributes including rainfall, water level, water discharge, tides, temperature, and humidity. This five-year period provides comprehensive data that encompasses seasonal and annual variations relevant to flood prediction in Makassar City [33]. Dataset available https://github.com/rizalmakassar/machine-learning/blob/main/dataset-lengkap-flood.csv. This extensive timeframe ensures a sufficient dataset for training and testing machine learning models with high accuracy. The dataset, consisting of 1,826 records, was divided into two parts: 80% for training data and 20% for testing data. This division ensures that the majority of the data is used to train the model to effectively learn patterns, while the remainder is used to evaluate the model's prediction accuracy.

3.2 Preprocessing

The pre-processing stage is a crucial part of preparing the dataset before it is used by machine learning models for flood prediction and classification. This process aims to improve data quality, select relevant features, and help classifiers obtain accurate results. In the context of flood research, datasets are often faced with the problems of missing values, zero values, outliers, and imbalances in the amount of data between flooded and non-flooded classes. Therefore, some commonly applied techniques include data cleaning, Min-Max normalization, and Synthetic Minority Oversampling Technique (SMOTE).

Data cleansing includes handling missing values, zero values, and outliers. Missing values can be caused by sensor malfunction or recording failure, requiring a proper imputation method (e.g., average, median, or interpolation). Meanwhile, zero values can reflect the absence of rain or water discharge realistically, but can also indicate recording errors, so it is necessary to distinguish the cases carefully. In addition, outliers are also a concern, because they can be valid (extreme events) or invalid (technical errors). If the outlier represents an extreme phenomenon, it is usually maintained so that the model is able to better study critical flood conditions.

The next step is to address data imbalances. This is important because flood events tend to occur less frequently than normal conditions, so many models tend to be biased towards the majority class (not flooded). To overcome this, SMOTE (Synthetic Minority Oversampling Technique) is often used. SMOTE works by generating synthetic examples for minority classes through interpolation between adjacent samples, so that the distribution of data becomes more balanced and the model can learn to recognize flood patterns more accurately.

Furthermore, Min-Max normalization is applied to align the value ranges between variables, such as rainfall, humidity, and temperature. This technique converts the value of each feature to a scale of 0 to 1, which can facilitate the computational process and distance calculation in machine learning algorithms. Another commonly used alternative is standardization (z-score), depending on the type of

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Table 1. Notations

Variable	Description
X'	Normalization data
X	Actual data
X_{min}	Minimum data
X_{max}	Maximum data
S_i	Interpolated sample
X	Data sample in minority class
$rand(0,1)$	Random number in a range between 0 and 1
y_i	ith nearest neighbors
B_o	Initial value of parameter B
B_f	Final value of parameter B
T	Current time
T_{max}	Maximum time
T	Current iteration
$X_{i,j}^{T+1}$	Next iteration
r_i and r_2	Random numbers among 0 and 1
j	New position of ith beluga whale in jth dimension
$X_{r,p1}^{T+1}$	Current position of rth individuals
X_i^T and X_r^T	Current and random position of the beluga
X_i^{T+1} and X_{best}^T	Updated and best position
r_3 and r_4	Random numbers
u and v	Normal distributed random numbers
β	Constant value
C_1 and C_1	Parameters
W_f	Constant
n	Variable
$X_{i,j}^T$	Position of ith beluga whale on jth dimension developed through the random initialization
ub_j and lb_j	Upper and lower bounds for j-th element
S_i	Classifier to identify the class
w	Unidentified parameter vector
x	Feature vector
$\hat{g}(.)$	SVM result
ξ_i	Slack variable
C	Penalty parameter
N	Sample size
$minL$	Objective function L to be minimized
w	Weight vector
$\sum_i^N \xi_i$	Sums the slack variables ξ_i for every data point i from 1 to N
l_i	Loss integrated with ith data point
∞	Symbol used here unconventional
S_i	Target value integrated with ith data point
$\hat{g}(x_i)$	Predicted value
$max(.,0)$	Maximum function
$k(x,y)$	Kernel function
$exp(.)$	Exponential function
$\|x - y\|^2$	Squared Euclidean distance among x and y
σ^2	Variance parameter of Gaussian kernel
ε	Minimal value
y_i	Response value of x

model and data characteristics. Thus, the normalization process helps to lower the risk of overfitting and accelerate the model's performance during training. A detailed explanation of these techniques is described in the following sections.

3.2.1. Data cleaning

Data cleaning is a process to ensure the quality of datasets before being used by machine learning models, especially in the context of flood prediction. This stage includes handling missing values caused by recording failures or sensor damage, separating valid zeros (e.g. no precipitation) and zeros due to errors, as well as detecting and handling outliers that do not reflect actual natural phenomena. By doing data cleaning, the dataset becomes more consistent, accurate, and representative, so that it can improve the accuracy and reliability of the prediction model.

3.2.2. Min -max normalization

Min-Max Normalization is a data scaling method that changes the value range of each feature to [0, 1]. The goal is to standardize variables so that they have equal weight in the machine learning process. The procedure involves the Eq. (1):

$$\frac{x-x_{min}}{x_{max}-x_{min}} \quad (1)$$

Where, x' is the original, x_{min} and x_{max} values and is the minimum and maximum value of the related feature, respectively. As such, each feature will have a minimum value of 0 and a maximum of 1, which can help machine learning algorithms, such as SVMs or neural networks, to work more efficiently and avoid bias due to scale differences between variables.

3.2.3. Data imbalance handling

Data imbalance dataset is a condition when one class (e.g. flood event) has far fewer examples than another class (non-flooded), so the model tends to be biased towards the majority class. The Synthetic Minority Oversampling Technique (SMOTE) is one popular method to address this imbalance. SMOTE

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works by oversampling minority classes synthetically, rather than simply duplicating existing data.

SMOTE is interpolation approach is mathematically represented by the following expression in Eq. (2):

$$S_i = X + \text{rand}(0,1) \times (y_i - X) \quad (2)$$

Where, S_i is a sample of interpolated results, X is a sample of data from minority classes, $rand(0,1)$ It is defined as a random number between 0 and 1, while yi signifies the nearest ith neighbor.

The dataset undergoes multiple preprocessing stages including cleansing, normalization, and balancing procedures. The preprocessed data is then divided, with 80 percent allocated for training purposes and the remaining 20 percent reserved for testing. Following this division, the balanced dataset moves forward to feature selection.data

3.3 Feature selection

The results of the preprocessing stage are used as input for the feature selection process. This feature selection process reduces training time and minimizes computational complexity. Model accuracy can be improved due to proper subset selection. QOBL-BWO is implemented in this process to select relevant features, and a detailed explanation of the technique will be outlined below:

3.3.1. Beluga whale optimization algorithm

The BWO algorithm, which falls under the category of swarm intelligence, was developed based on beluga whale behavior patterns that include swimming, hunting, and whale falling. The Levy flight (LF) function is implemented at the exploitation stage to accelerate the convergence rate of BWO. In this context, the beluga whale is seen as a solution agent, with each individual representing a single solution candidate that undergoes an update during the optimization process. The Bf balancing factor plays a role in determining the exploration and exploitation phase of BWO, which is mathematically formulated in Eq. (3) below.

$$B_f = B_0 \left(1 - \frac{T}{2} \times T_{max}\right) \quad (3)$$

Where, B_0 is the value of parameter B in the initial condition, Bf indicates the value of parameter B in the final condition, T represents the running time, and $Tmax$ is the maximum time limit. The exploration phase is characterized by a Bf value exceeding 0.5, while the exploitation phase occurs when Bf is equal to or less than 0.5. The value of Bf will gradually decrease from the range (0.1) to reach the range (0.0.5) along with the increase in the value of T.

3.3.1.1. Exploration stage

The mathematical model at the exploration stage of the BWO was inspired by the whale's swimming pattern. Based on the whale's swimming behavior strategy, they swim in pairs with synchronized movements. As a result, the position of the whale is updated as shown in Eq. (4) below.

$$\begin{cases} X_{i,j}^{T+1} = X_{i,pj}^{T+1} + \left(X_{r,p1}^{T+1} - X_{i,pj}^{T+1}\right)(1 + r_1) \\ \quad \times \sin(2\pi r_2), j = \text{ even} \\ X_{i,j}^{T+1} = X_{i,pj}^{T+1} + \left(X_{r,p1}^{T+1} - X_{i,pj}^{T+1}\right)(1 + r_1) \\ \quad \times \cos(2\pi r_2), j = \text{ odd} \end{cases} \quad (4)$$

Where, T indicates the current iteration; represents the next iteration; $R1$ and $R2$ are random numbers with a range of 0 to 1; j indicates the new position of the I beluga whale in the jth dimension; while $X_{i,j}^{T+1}$ represents the current position of the rth individual.

3.3.1.2. Exploitation phase

Model To accelerate convergence, the BWO exploitation phase adopts the Levy flight (LF) strategy, with its mathematical formulation shown in Eq. (5) below.

$$X_i^{T+1} = r_3 \times X_{best}^T - r_4 \times X_i^T + C_1 \times L_F \times \left(X_r^T - X_i^T\right) \quad (5)$$

Where, and symbolizes the current position and random position of the beluga whale; X_i^T and X_{best}^T represent the updated results and optimal positions; $R3$ and $R4$ are random numbers; The formulations of $C1$ and LF are described in Eqs. (6) and (7) below.

$$C_1 = 2r_4 \times \left(\frac{1-T}{T_{max}}\right) \quad (6)$$

$$L_F = 0.05 \times \left(\frac{u \times \sigma}{|v|^{\frac{1}{\beta}}}\right) \quad (7)$$

Where, u and v represent a normally distributed random number; while β is the value of a constant.

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3.3.1.3. Whale falling

The beluga whale made a move and descended to the bottom of the ocean. To maintain a fixed population size, beluga whale positions and whale fall quantities are used to calculate the updated positions, which are formulated in Eqs. (8) to (11).

$$X_i^{T+1} = r_5 X_i^T - r_6 X_{\text{step}} \tag{8}$$

$$X_{\text{step}} = (u_b - l_b)\exp\left(-\frac{C_2 T}{T_{max}}\right) \tag{9}$$

$$C_2 = 2 \times W_f \times n \tag{10}$$

$$W_f = 0.1 - 0.05 \times \frac{T}{T_{max}} \tag{11}$$

Where, the parameters are represented by $C1$ and $C2$, while Wf and n are denoted as constants. Traditional BWO faces certain limitations, particularly in terms of premature convergence, which hinders the system's ability to identify optimal solutions due to getting trapped in local optima. To address this, improvements are made to enhance the development of candidate solutions within BWO, thereby speeding up the search process and improving the learning approach for the selected solutions.

3.3.2. Quasi opposition-based learning of BWO

QOBL begins by generating an initial beluga whale population using OBL, which offers stronger optimization performance. The QOBL-BWO procedure is represented mathematically in Eq. (12):

$$\begin{cases} X_{l,i}^{T+1} = H_{i,j} + \left(x_i^T - H_{i,j}\right) \times \text{rand}(0,1), \\ \qquad x_i^T < H_{i,j} \\ X_{l,i}^{T+1} = x_i^T + \left(H_{i,j} - x_i^T\right) \times \text{rand}(0,1), \\ \qquad x_i^T \geq H_{i,j} \end{cases} \tag{12}$$

Eqs. (13) and (14) provide the mathematical definitions for the terms $x_{i,j}^T$ and $H_{i,j}$.

$$x_{i,j}^T = \left(ub_j + lb_j\right) - x_i^T \tag{13}$$

$$H_{i,j} = \frac{\left(ub_j + lb_j\right)}{2} \tag{14}$$

The variable $x_{i,j}^T$, which describes the randomly initialized position of the ith beluga whale in dimension j, is constrained between the upper limit ub_j and lower limit lb_j of the jth element

3.3.3. Support vector machine

Support Vector Machine (SVM) is a widely used method for solving classification and regression problems, including flood prediction tasks that leverage features such as rainfall, water level, water discharge, tides, temperature, and humidity. One of SVM is strengths lies in its ability to address overfitting by seeking an optimal hyperplane in a high-dimensional space to separate different types of samples efficiently particularly useful in predicting whether a region is at risk of flooding based on these six features. In classification tasks (e.g., predicting "flood" vs. "no flood"), SVM relies on optimizing the Hinge Loss Function (HLF) through the Lagrange function LLL, formulated in Eq. (15) as follows:

$$minL = \frac{1}{2} w^T w, \text{ s.t. } S_i\left(\hat{g}(x)\right) \geq 0 \tag{15}$$

where S_i represents the classifier used to label the class (flood vs. no flood), w is the unknown parameter vector defining the hyperplane, x denotes the feature vector (in this case, rainfall, water level, water discharge, tides, temperature, and humidity), and $\hat{g}(x)$ is the predicted result from the SVM model. When soft intervals and kernel functions are introduced, the optimization problem is reformulated with Eq. (16) as follows:

$$minL = \frac{1}{2} w^T w + C \sum_{i=1}^{N} \xi_i \tag{16}$$

where $\xi_i$is the slack variable, handling instances in which some flood prediction data points cannot be perfectly separated by the decision boundary. The parameter C serves as the penalty parameter, balancing the trade-off between maximizing the margin and minimizing classification errors. Meanwhile, N is the total number of samples in the dataset (e.g., historical flood records), providing essential context for assessing model performance.

This optimization function combines a regularization term pushing data points away from the hyperplane to prevent overfitting and a loss function ξ_i , which tolerates certain classification errors. The Hinge Loss function is defined Eq. (17) as follows:

$$l_i = max(\infty[1 - S_i \hat{g}(x_i)], 0) \tag{17}$$

Where l_i is the loss associated with the i-th data point, measuring the penalty for the discrepancy between predictions and actual targets. The symbol ∞ signifies an infinite penalty, typically assigned for

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significant misclassifications S_i indicates the true label (e.g., "flood" or "no flood"), while $\hat{g}(x_i)$ is the predicted value. Collectively, these elements ensure the model's predictive accuracy for flood events based on rainfall, water level, water discharge, tides, temperature, and humidity. For non-linear data common in flood prediction scenarios due to complex weather and water system interactions SVM can employ kernel functions like the Gaussian kernel, Eq. (18) expressed as:

$$k(x,y) = \exp\left(-\frac{|x-y|^2}{2\sigma^2}\right) \quad (18)$$

Where $k(x,y)$ is the kernel function exp (·), is the exponential function, $|x-y|^2$ is the squared Euclidean distance between feature vectors x and y and σ^2 is the variance parameter of the Gaussian kernel. By substituting dot products with kernel functions and converting the unidirectional loss function to a bidirectional form, SVM can be generalized as a non-linear regression model, useful for predicting continuous flood-related variables (e.g., exact water level).

The bidirectional loss function in SVM, as formulated in Eq. (19), is:

$$l_i = \max(y_i - \hat{g}(x) - \epsilon, 0) + max(\hat{g}(x) - y_i - \epsilon, 0) \quad (19)$$

where a linear penalty is introduced if the predicted value deviates from the actual value by more than ϵ. This setup encourages the model to learn new functional relationships underlying floods, thus improving the prediction accuracy regarding potential flood events as indicated by rainfall, water level, water discharge, tides, temperature, and humidity.

4. Experiment result

The effectiveness testing of the QOBL-BWO method was conducted using datasets obtained from BMKG. This method was implemented on a computer running Windows 11 64-bit operating system, using Python version 3.10.10, supported by an Intel i7 processor, GPU 4060 RTX and 16 GB RAM memory. To ensure the reliability of the QOBL-BWO method, evaluation was performed using several performance measurement parameters, including Accuracy, Precision, Recall, F1-Score [34]. These parameters were calculated using mathematical formulas shown in Eqs. (20) to (23).

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+TN+FP+FN)} \times 100 \quad (20)$$

$$\text{Precision} = \frac{TP}{(TP+FN)} \times 100 \quad (21)$$

$$\text{Recall} = \frac{TN}{(TN+FP)} \times 100 \quad (22)$$

$$\text{F1-Score} = 2 \times \frac{P \times R}{P+R} \times 100 \quad (23)$$

Where, TP - True Positive, FP – False positive, TN – True Negative, FN – False Negative.

4.1 Analysis of flood prediction

The application of the Hinge Loss Function-based Support Vector Machine (HLF-SVM) combined with Quasi Opposition-Based Learning and Beluga Whale Optimization (QOBL-BWO) for flood prediction exhibited outstanding performance. The model's results were estimated using 5-fold cross-validation.

In Table 2 and Fig. 2, the performance of the proposed QOBL-BWO method is presented using various evaluation metrics on the BMKG dataset. The effectiveness of this method is compared with several other optimization algorithms, such as the Arithmetic Optimization Algorithm (AOA), Genetic Algorithm (GA), Harris Hawks Optimization (HHO), Particle Swarm Optimization (PSO), and Whale Optimization Algorithm (WOA). Compared to these algorithms, the QOBL-BWO method demonstrates superior exploration capability and effectively identifies features across the search space, leading to a more optimal feature selection. The evaluation results indicate that the QOBL-BWO method achieves 99% accuracy, 98.80% precision, 99.60% recall, and an F1-score of 99.20% based on the BMKG dataset.

As shown in Table 3 and Fig. 3, the proposed model achieved 99% accuracy, 98.80% precision, 99.60% recall, and an F1 score of 99.20%. These results surpass all other evaluated models, such as LR, LDA, KNN, NB, Adabost, and SVM.

Table 4 presents a comparative analysis of the performance of various flood prediction models using data from BMKG. The results show that the proposed QOBL-BWO + HLV-SVM + Serious Game model outperforms existing models such as K-Nearest Neighbors (KNN) + Generative Adversarial Network (GAN) [35], Random Forest (RF) [36], Artificial Neural Networks (ANN) [37], Support Vector Machines (SVM) [37], and Long Short-Term Memory (LSTM) [38] in terms of accuracy, presisi, recall, dan F1-score. Specifically, QOBL-BWO HLV-SVM achieved the highest

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Table 2. Analysis of the feature selection results

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
PSO	93.50	93.20	93.50	93.30
HHO	92.20	92.00	92.20	92.10
AOA	91.50	91.30	91.50	91.40
WOA	90.80	90.60	90.80	90.70
GA	90.20	90	90.20	90.10
QOBL-BWO	**99**	**98.80**	**99.60**	**99.20**

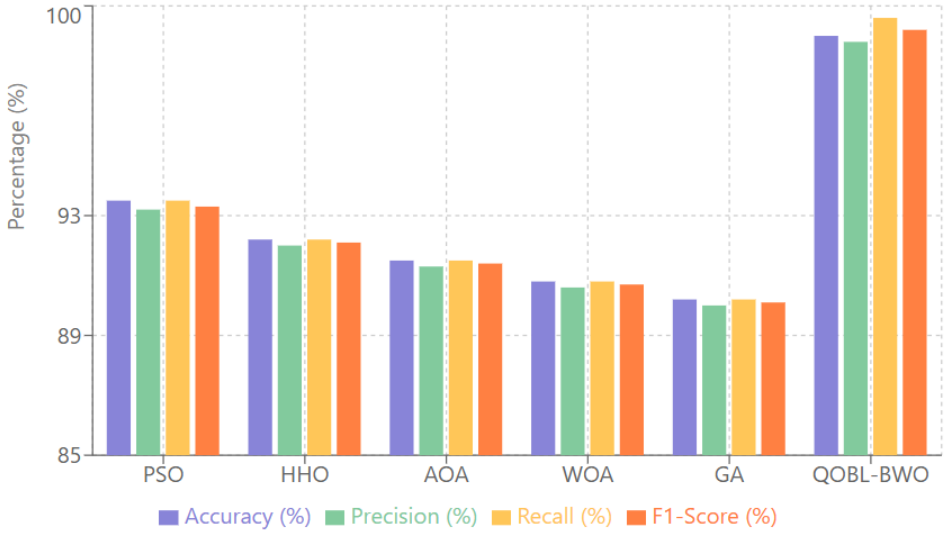


Figure. 2 Graphical representation of feature selection results

Table 3. Performance metrics of machine learning models for flood prediction on BMKG Dataset

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
LR	94.35	94.37	94.38	94.36
LDA	93.91	94.44	93.93	93.93
KNN	98.54	98.56	98.53	98.53
NB	97.01	97.07	97.03	97.01
SVM	96.15	96.52	96.16	96.19
AdaBoost	78.79	89.48	80	78.66
HLV-SVM	**99**	**98.80**	**99.60**	**99.20**

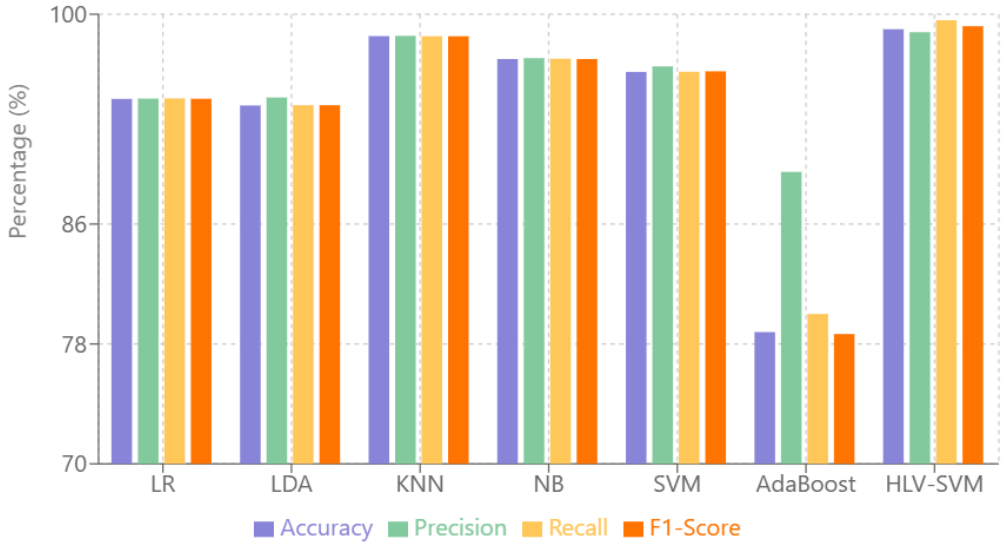


Figure. 3 Graphical representation of models results

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Table 4. Comparative performance of flood prediction models on BMKG Dataset

Ref	Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
[35]	KNN + GAN	93	93	93	93
[36]	Random Forest	94.93	94.34	99.97	97.08
[37]	Artificial Neural Network	N/A	94	66	75
[37]	Support Vector Machine	N/A	77	86	81
[38]	Long Short Term Memory	98.75	99	98.51	98.76
Ours	QOBL-BWO + HLV-SVM + Serious Game	**99**	**98.80**	**99.60**	**99.20**

accuracy of 99%, followed by LSTM with 98.75%. In addition, the precision, recall, and F1-score values of the proposed models (98.80%, 99.60%, and 99.20%) show superior prediction capabilities. In contrast, the ANN and SVM models showed lower performance, especially in recall and F1-score, which are important metrics in flood prediction.

These findings indicate that the integration of Hinge Loss Function-Based SVM with Quantum Opposition-Based Learning Black Widow Optimization (QOBL-BWO) significantly improves the model's performance, making it a more reliable approach in flood prediction. Compared to conventional models, the proposed model achieves a better balance between false positives and false negatives, thus providing more reliable predictions.

Table 5 presents a comparison of the dataset parameters used in various studies related to the total features analyzed. The study referred to in [35] used four main parameters, namely temperature and humidity data, rainfall, and wind speed. Meanwhile, the study in [36] involved four other parameters consisting of rainfall, river flow, land cover, and flooding. The reference [37] includes eight more complex features, including elevation, slope, curvature, topographic moisture index (TWI), distance from rivers, land cover, river flow power index (SPI), soil type, and precipitation. In the study [38], only three parameters were used, namely temperature, humidity, and rainfall. In this study, the dataset used includes six parameters, namely rainfall, water level, water discharge, tides, temperature, and humidity, which provides a wider scope than several previous studies.

Table 5. Dataset parameter comparison

Ref	Parameter	Total feature
[35]	Temperature and humidity data, rainfall, and wind speed	4
[36]	Rainfall, streamflow, land cover, and flood	4
[37]	Elevation, slope, curvature, topographical wetness index (TWI), distance from a river, land-cover, stream power index (SPI), soil type and precipitation	8
[38]	Temperature, humidity, and rainfall	3
Ours	Rainfall, water level, water discharge, tides, temperature, and humidity	6

The analysis of the confusion matrix presented in Fig. 4 confirms the model's reliability, demonstrating a high true positive count 256 and true negative count 141, along with very low false positive 3 and false negative 1 values. These results highlight the capability of the QOBL-BWO optimized HLF-SVM in accurately classifying flood and non-flood events with minimal error rates. Meanwhile, the ROC curve analysis shown in Fig. 5 further reinforces the model's robustness, as

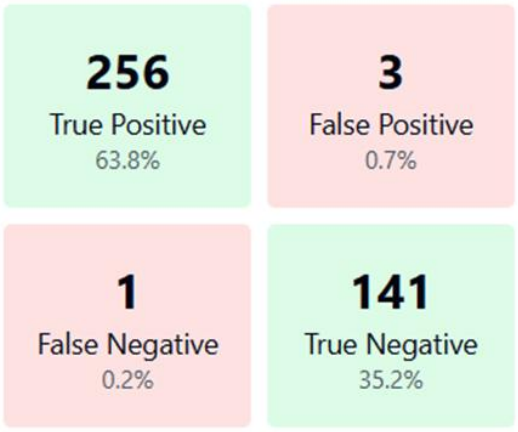


Figure. 4 Confusion matrix

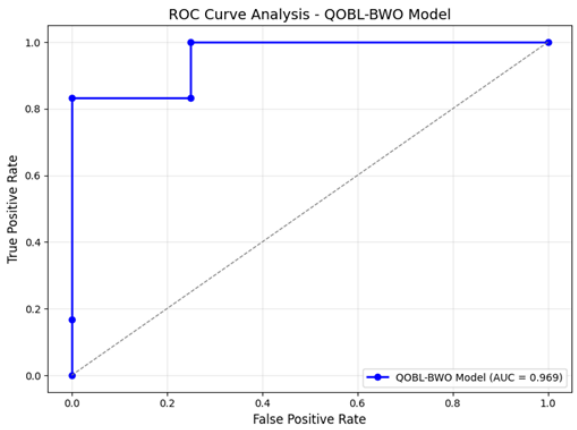


Figure. 5 ROC curve analysis for the QOBL-BWO model

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indicated by an Area Under the Curve (AUC) value of 0.969, which signifies high sensitivity and specificity.

4.2 Flood prediction visualization serious game

In this study, we conducted an experiment to develop a serious flood prediction game using the Unity Game Engine. By using a game engine, we obtained results in the form of creating user interfaces, menus, assets, and virtual environments to flood visualization. Fig. 6 shows the virtual environmnet flood prediction visualization main menu display when the game starts. Meanwhile, Fig. 7 shows the environment affected by the flood.

Serious Game features a flood parameter setting interface consisting of rainfall, water level, water discharge, tides, temperature, and humidity. Through a panel labeled Setting Parameters, users can manipulate rainfall, water level, river water discharge, to humidity and tides. Any change in the value of these parameters will be processed to predict and display the impact of potential flooding visually in a virtual environment, such as seen in houses along riverbanks, bridges, and public buildings. The effect of the rain displayed adjusts to the amount of rainfall that is set, while the water level will increase as the water level or water discharge is raised, so users can see firsthand how the flood spreads to residential areas. This interactive approach aims to provide an understanding of flood dynamics, increase awareness of disaster risk, and assist in the planning and mitigation process through testing various scenarios quickly and easily.

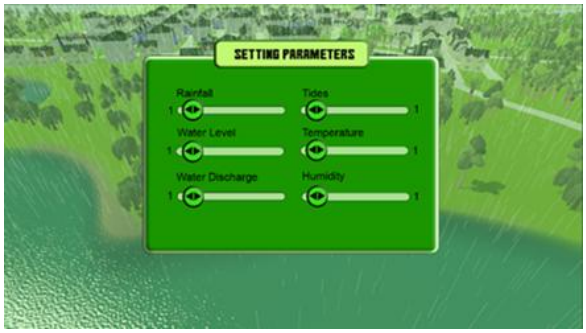


Figure. 6 Main menu flood prediction visualization serious game

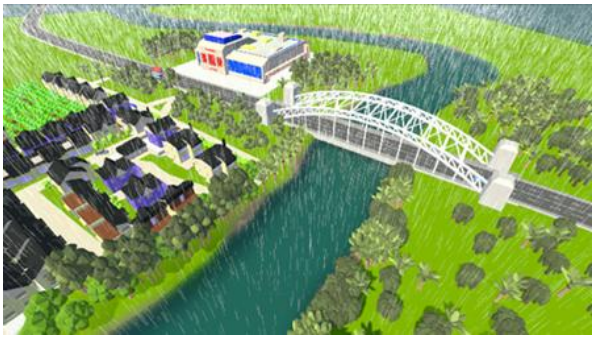


Figure. 7 Flood affected virtual environment

4.3 Effect of Serious game on awareness and decision-making in flood preparedness

To evaluate the impact of the serious game on flood risk perception and decision-making confidence, a testing session was conducted involving 40 respondents from various backgrounds, including students and members of communities in flood-prone areas. Before playing the game, participants completed a pre-test survey measuring two main variables on a 1–5 scale: (1) perceived flood risk and (2) confidence in decision-making. After approximately 30 minutes of interaction with the game, each participant then took a post-test survey containing the same items. By comparing the pre-test and post-test responses, it became possible to determine whether users' perceptions and confidence levels had changed as a result of their experience with the game. As shown in Fig. 8, the 3D scatter plot reveals a marked shift in data points from the lower-left area (pre-test) to the upper-right area (post-test), signifying an increase in perceived flood risk and greater confidence in decision-making regarding flood preparedness. Notably, many respondents who initially reported moderate risk awareness and confidence (blue points) moved to higher levels (red points) after engaging with the serious game. This change underscores the potential effectiveness of using an interactive and educational platform to enhance both the cognitive and behavioral aspects of flood preparedness.

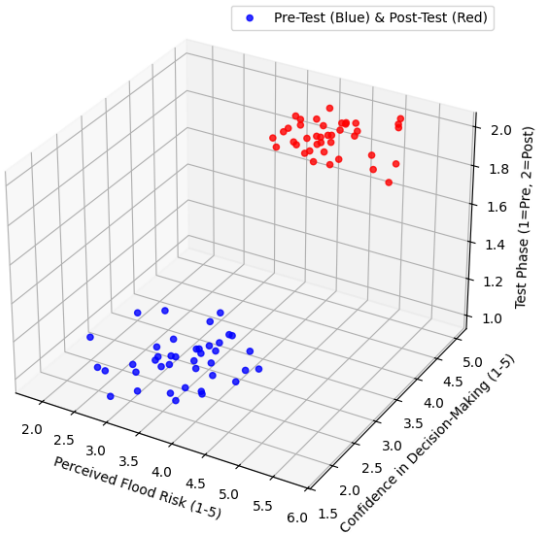


Figure. 8 3D Scatter Plot of Serious Game Effect on Awareness and Decision-Making

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5. Conclusion

This study presents an innovative approach to flood prediction by integrating the Hinge Loss Function-based Support Vector Machine (HLF-SVM) with Quasi Opposition-Based Learning and Beluga Whale Optimization (QOBL-BWO) for feature selection. The proposed model demonstrated superior predictive performance, achieving 99% accuracy, 98.8% precision, 99.6% recall, and 99.2% F1-score, outperforming existing state-of-the-art methods. These results highlight the model's ability to handle imbalanced datasets while maintaining a high level of robustness and efficiency.

Furthermore, the integration of predictive modeling into a serious game environment provides a new platform for disaster education and preparedness. This interactive application enables users, including policymakers and the public, to visualize flood scenarios adaptively, enhancing understanding and supporting better decision-making in flood mitigation and response.

The findings of this study make a significant contribution to the field of flood prediction and risk management. Future research could explore real-time data integration, more advanced optimization techniques, and broader functionality development of serious games to improve system adaptability and impact. The proposed approach represents a valuable step forward in bridging predictive technology with educational tools for disaster resilience.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, M. Rizal; methodology, M. Rizal, Y.M. Arif, M. Hariadi, E. Warni and F.A. Damastuti; software, Y.M. Arif and M. Rizal; validation, M.Rizal, E. Warni, and F.A. Damastuti; formal analysis, M. Rizal, Y.M. Arif, M. Hariadi, and F.A Damastuti; investigation, M. Rizal, Y.M. Arif and E. Warni; resources, M. Rizal, Y.M. Arif; data curation, M. Rizal, Y.M. Arif and M. Hariadi; writing—original draft preparation, M. Rizal; writing—review and editing, M. Rizal, Y.M. Arif, M. Hariadi, and E. Warni; visualization, F.A Damastuti; supervision, E. Warni and F.A Damastuti; project administration, E. Warni; funding acquisition, M. Rizal.

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