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Development of Hidden Markov Model Based Hydrometeorological Disaster Prediction Model for More Effective Preparedness

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Abstract

Hydrometeorological disasters, such as floods, are significant threats that require an accurate prediction system to improve preparedness and risk mitigation. This study aimed to develop a Hidden Markov Model (HMM)-based hydrometeorological disaster prediction model using hydrological data from the Kelambu Dam in Demak Regency. The data used includes water levels upstream (Level Up), downstream (Level Down), and water discharge (Q Serang), as well as information on flood events in the period 2022-2024. The methods applied include data collection and preprocessing, model training using the Baum-Welch algorithm, and performance evaluation with accuracy, precision, recall, and F1-score metrics. The results showed that the HMM model was able to identify hydrological change patterns and predict flood events with a high level of accuracy, reaching 94.29% at the best iteration. The performance evaluation also indicated that the model has a good balance between precision and recall, making it a potential tool in early warning systems. Thus, the implementation of this prediction model can improve community preparedness and support decision-making in hydrometeorological disaster management.

Keywords: disaster; disaster preparedness; flood prediction; hidden markov model; hydrometeorological

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1. Introduction

Hydrometeorological disasters such as floods, landslides, and droughts are becoming more frequent due to climate change and anthropogenic activities. Demak Regency, as one of the regions in Indonesia vulnerable to hydrometeorological disasters, experienced several major flood events from February to March 2024. This phenomenon not only causes significant material losses but also threatens life safety and disrupts the social and economic activities of the community. Therefore, increased preparedness and disaster mitigation strategies are a must to reduce the negative impacts [1]. One approach that can be applied to improve disaster preparedness is the development of a data-driven prediction model. This model aims to identify patterns of change in hydrological and meteorological variables that contribute to disaster events [2], [3]. The Hidden Markov Model (HMM) is an effective method for modeling dynamic systems and predicting events based on historical patterns [4]. This method has been widely used in various fields, including weather prediction, anomaly detection, and time series analysis, so it is expected to be applied in the analysis of flood events in Demak Regency [5].

This research aims to develop an HMM-based hydrometeorological disaster prediction model with a case study in Demak Regency. The developed model will use historical data on hydrological variables, such as water level and river discharge (Q Serang), as well as relevant meteorological variables. By utilizing data on flood events that occurred during the period of February to March 2024, the model is expected to provide more

accurate early warnings and assist stakeholders in taking more effective mitigation measures [6], [7].
In addition, this research will also evaluate the performance of the prediction model using various evaluation metrics, such as accuracy, precision, recall, and F1-score [8], [9]. This evaluation aims to ensure that the developed model has a high level of reliability in detecting and predicting flood events [10], [11]. The results of this research are expected to be the basis for developing a more integrated early warning system, so as to reduce disaster risk and increase community resilience to hydrometeorological threats in the future [12], [13].

2. Methods

This research uses a quantitative approach with a Hidden Markov Model (HMM) based data analysis method to develop a hydrometeorological disaster prediction model. The data used in this study consists of two main variables, namely Level Up and Level Down (water level upstream and downstream of the dam) and Q Serang (water discharge flowing through the dam) [14]. These two variables are recorded on daily basis during the period 2022 to 2024, thus allowing the analysis of hydrological change patterns that contribute to the occurrence of hydrometeorological disasters, especially floods. In this research, Python is used as the main software to develop the Hidden Markov Model (HMM). Python was chosen because it has extensive statistical and machine learning libraries, including hmmlearn and scikit-learn, which allow efficient implementation of HMMs. The stages of the method in this research include:

2.1 Data Collection

Hydrological data were obtained from the Serang Lusi Juana (Seluna) Water Resources Management Center (BPSDA) in Demak Regency, Central Java. The collected dataset includes daily measurements recorded from 2022 to 2024, comprising three key hydrological parameters: (a) Level Up, which refers to the water level upstream of the dam (measured in meters), (b) Level Down, the water level downstream of the dam (also in meters), and (c) Q Serang, the discharge of water flowing through the dam, measured in cubic meters per second. These primary data, obtained from BPSDA Seluna in Demak Regency, are presented in Table 1. The illustration of the primary data sample can be seen in Figure 1.

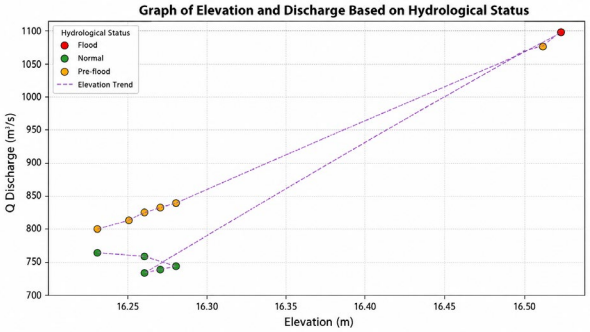


Figure 1. Primary Data Sample

Table 1. Primary Data

No	Date	Elevation Up	Elevation Down	Q Serang	Label
1	06/02/2024 02:00	16,23	16,2	800	Pre-flood
2	06/02/2024 03:00	16,25	16,22	813	Pre-flood
3	06/02/2024 04:00	16,26	16,24	826	Pre-flood
4	06/02/2024 05:00	16,27	16,25	833	Pre-flood
5	06/02/2024 06:00	16,28	16,26	839	Pre-flood
....					
....					
31	07/02/2024 08:00	16,51	16,49	1080	Pre-flood
32	07/02/2024 09:00	16,52	16,5	1100	Flood
33	07/02/2024 10:00	16,52	16,5	1100	Flood
34	07/02/2024 11:00	16,52	16,5	1100	Flood
35	07/02/2024 12:00	16,52	16,5	1100	Flood
....					
....					
141	09/02/2024 15:00	16,26	16,07	735	Normal
142	09/02/2024 16:00	16,27	16,08	740	Normal
143	09/02/2024 17:00	16,28	16,09	745	Normal
144	09/02/2024 18:00	16,26	16	760	Normal
145	09/02/2024 19:00	16,23	16,13	765	Normal
....					
....					
245	16/03/2024/22.00	16.61	16.60		Flood
246	16/03/2024/23.00	16.61	16.60		Flood
247	16/03/2024/00.00	16.61	16.60		Flood

This data was collected from official sources of BPSDA Seluna and validated to ensure accuracy and feasibility in the further analysis process. To clarify the classification of labels based on the primary data in Table 1, the following is the range of water level and discharge values used to determine the Normal, Pre-flood and Flood categories as shown in Table 2.

Table 2. The Range of Water Level

Label	Elevation Up (m)	Elevation Down (m)	Q Serang (m^3/s)
Normal	≤ 16.27	≤ 16.07	≤ 800
Pre-flood	16.28 – 16.51	16.08 – 16.49	801 – 1080
Flood	≥ 16.52	≥ 16.50	≥ 1100

2.2 Data Preprocessing

Before being used in modeling, the collected data underwent a series of preprocessing steps to enhance the quality and reliability of the analysis. The preprocessing process began with data cleaning, where incomplete, invalid, or anomalous data were removed to prevent any interference with the modeling process. As a result, 55 clean datasets were generated. The next step involved data normalization, which scaled the data to ensure that all variables had a comparable range of values. This step was crucial for improving the stability and accuracy of the model. Finally, data labeling was performed by adding flood category labels to the dataset based on predefined criteria, ensuring that the data were properly

categorized for further analysis and model training [15]. The results of data preprocessing from the primary data recording dataset can be seen in Figure 2.

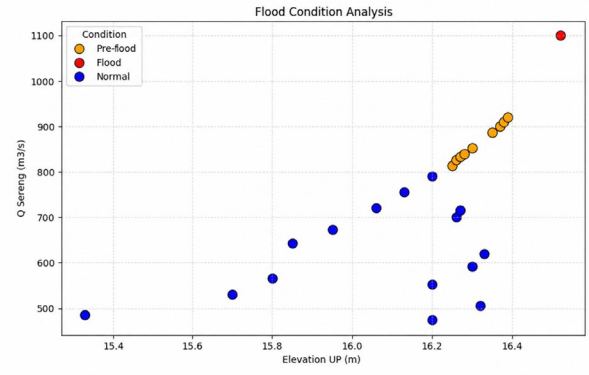


Figure 2. Data Preprocessing Results

This data preprocessing aims to ensure that the data used has optimal quality so that it can improve the performance of the model in flood prediction.

2.3 Data training

The total research data obtained in the period 2022-2024, 70% of the data is used for training, while the remaining 30% is used for testing. With a total of 245 samples, the training data used is 172 samples, and the test data is 73 samples. After the data is processed, the next step is to train the HMM model using the Baum-Welch algorithm to estimate the optimal parameters using Python software [11]. Model training is done with determine the number of states that represent different hydrological conditions, such as pre-flood, flood, and normal. Calculate the transition matrix A, which represents the probability of moving from one state to another based on historical data, Eqution 1.

$$a_{ij} = P(S_t = j \mid S_{t-1} = i), \quad \sum_j a_{ij} = 1 \qquad (1)$$

Calculates the emission probability B which indicates the probability of a certain hydrological observation occurring in a state, Equation 2.

$$b_j(o_t) = P(O_t = o_t | S_t = j), \quad \sum_o b_j(o) = 1 \qquad (2)$$

Training the model iteratively until the parameters obtained converge, so that the model can recognize flood event patterns more accurately [16].

2.4 Model Evaluation

The performance of the developed prediction model was evaluated using several metrics, including accuracy measures how frequently the model correctly predicts flood events in comparison to historical data. Precision and recall are used to assess the model's ability to correctly identify flood events while minimizing false predictions. The F1-score, which combines both precision and recall, offers a balanced view of the model's overall performance. Additionally, the HMM model is compared with other statistical or machine learning methods to evaluate its effectiveness in predicting hydrometeorological disasters [10], [17], [18].

Through this stage, the research is expected to produce a reliable and accurate prediction model, so that it can be used as an early warning system in improving preparedness for hydrometeorological disasters in Demak District.

3. Results and Discussions

3.1 Parameter Initialization

Parameter initialization is done by determining the hidden state, the observed observations, and the transition matrix that represents the probability of moving between states. Hidden states represent disaster categories that are not directly observed but affect the observed data [19]. Based on the dataset, the hidden state can be defined as Normal (Conditions where there is no threat of flooding), Pre-flood (Conditions of increased flood potential), and Flood (Flood conditions have occurred).

In parameter initialization, Observation of variables that can be measured from the data is also done, namely elevation up (elevation of the upstream river), elevation down (elevation downstream of the river), and Q Serang (river flow discharge) [20].

Then, the state transition probability matrix is performed by representing the probability of moving between states in the system. From the data, it can be used to calculate the probability of moving from one state to another based on the pattern of label changes. The transition matrix estimated from the data can be seen in Table 3.

Table 3. Transition Matrix

From/To	Normal	Pre-flood	Flood
Normal	0.80	0.20	0.00
Pre-flood	0.10	0.85	0.05
Flood	0.00	0.30	0.70

In the developed Hidden Markov Model (HMM), the transition probabilities between states show how a hydrological condition can change over time. The Normal state has an 80% chance of remaining in the same state, but there is a 20% chance of increasing to pre-flood as the hydrological parameters increase. If the system is already in the Pre-flood state, then there is an 85% chance of this condition persisting, while there is a 10% chance of returning to Normal and a 5% chance of increasing to Flood. The Flood state has a 70% chance of remaining in the flooded state, but there is still a 30% chance of returning to Pre-flood if the hydrological parameters show a decrease. This transition pattern illustrates the dynamics of changing hydrological conditions, where the system tends to maintain the previous state, but still has the opportunity to shift depending on the development of the observed variables.

The emission matrix describes the probability of each observation appearing in a particular state. For this case, we assume that each state has a Gaussian distribution of observation values as shown in Table 4.

Table 4. Emissions Matrix

State	Elevation UP (Mean, Std)	Elevation Down (Mean, Std)	Q Attack (Mean, Std)
Normal	(15.8, 0.4)	(15.5, 0.5)	(600, 120)
Pre-flood	(16.4, 0.3)	(16.3, 0.3)	(950, 100)
Flood	(16.5, 0.2)	(16.5, 0.2)	(1100, 50)

The emission matrix in the Hidden Markov Model (HMM) represents the probability of occurrence of observations in each state based on a Gaussian distribution. In this case, the Normal state has a distribution with an average Elevation UP of 15.8 meters with a standard deviation of 0.4, Elevation Down of 15.5 meters with a standard deviation of 0.5, and Q Serang of 600 m^3/s with a standard deviation of 120. The Pre-flood state shows an increase in hydrological parameters with an average Elevation UP of 16.4, Elevation Down of 16.3, and Q Serang of 950 m^3/s, with standard deviations of 0.3, 0.3, and 100, respectively. Meanwhile, the Flood state has the highest mean value, with Elevation UP 16.5, Elevation Down 16.5, and Q Serang 1100 m^3/s, and smaller variations with standard deviations of 0.2 for elevation and 50 for discharge. This Gaussian distribution illustrates that the higher the elevation and discharge, the more likely a condition is to be in the Pre-Flood or Flood state, while the Normal state has a lower distribution with greater variability, reflecting natural fluctuations outside of flood events.

3.2 Model Training

Model training was conducted using historical data to train the model to recognize patterns of change in hydrological variables that contribute to flood events. Model training is conducted using historical data to recognize patterns of change in hydrological variables that contribute to flood events [21-23]. The model is trained incrementally through several iterations, where each iteration aims to improve the accuracy in classifying hydrological states based on observed parameters. Accuracy is calculated using sci-kit-learn's accuracy score metric, which compares the model's predictions with the actual labels [24-26].

Based on the training results, it can be seen that the model has increased in accuracy as the number of iterations increases. In the first iteration, the model achieved 85.71% accuracy, then increased to 88.57% in the second iteration, and continued to increase until it reached 94.29% in the seventh iteration. The significant increase in accuracy indicates that the model is increasingly able to recognize the hydrological change patterns better, along with the training process. However, after the fifth and sixth iterations, the accuracy started to reach 92.86% and only increased slightly in the seventh iteration, indicating that the model has reached a level of stability in the learning process. Figure 3 represents the training results of the HMM model with a total of 7 test results.

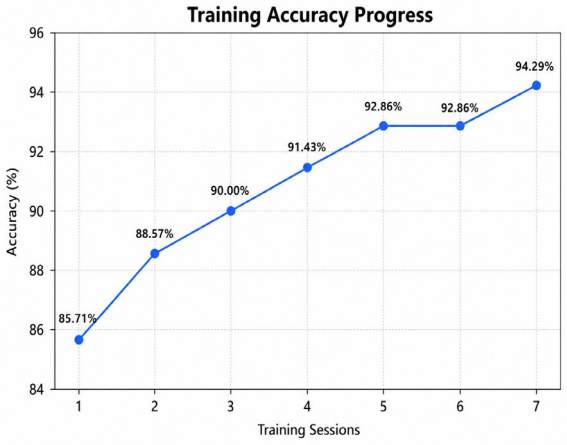


Figure 3. HMM Model Training

Based on the model training results, the accuracy of the model has increased consistently at each iteration, indicating that the model is getting better at recognizing patterns of hydrological change. In the first iteration, the model has an accuracy of 85.71%, which means that the model is already quite good at classifying hydrological states, but there is still room for improvement.

As the iterations increase, the accuracy gradually increases until it reaches 94.29% in the seventh iteration. A significant increase occurred between the first iteration and the fifth iteration, where the accuracy increased from 85.71% to 92.86%. However, after the fifth and sixth iterations, the model accuracy did not increase (92.86%), indicating that the model began to reach a plateau. In the seventh iteration, there was a slight increase again to 94.29%, which shows that the model can still experience slight improvements, but with a smaller increase than the previous iterations.

From this pattern, it can be concluded that the trained Hidden Markov Model (HMM) performs well in classifying hydrological states based on the observed hydrological variables. However, after a few iterations, the accuracy improvement starts to slow down, which may indicate that the model has reached its optimal point. If scaled up further, additional evaluation is required to ensure that the model does not suffer from overfitting, which is a condition where the model overfits itself to the training data and thus loses its generalization ability to new data.

The Baum-Welch algorithm is used to train the Hidden Markov Model (HMM) by updating parameters based on observed data. This algorithm is an implementation of the Expectation-Maximization (EM) method, which aims to optimize the state transition probabilities and emission probabilities within the model. The training process using Baum-Welch consists of several steps. First, the initial parameters are set, including the transition matrix, emission matrix, and initial probabilities. Then, in the Expectation Step (E-step), the Forward-Backward algorithm is applied to calculate the hidden probabilities based on observed data. In the Maximization Step (M-step), the model

parameters are updated according to the probabilities obtained in the E-step. This process is repeated iteratively until convergence is reached, meaning that the parameters no longer change significantly or the maximum number of iterations is achieved.

The Baum-Welch algorithm is selected for several reasons. First, it is highly effective in handling sequential data with time dependencies, such as hydrological data. Second, it can estimate optimal parameters without requiring prior knowledge of their exact values. Lastly, it is flexible and can be implemented with various probability distributions, making it well-suited for HMM-based flood prediction modeling.

3.3 Model Evaluation

The performance of the model was evaluated using several metrics to measure its effectiveness in predicting flood events. The evaluation metrics used include accuracy, the overall percentage of correct predictions compared to the actual data. Precision is the ability of the model to identify correct (positive) flood events compared to all flood predictions generated. Recall is the ability of the model to find all flood events that actually occurred.

This evaluation aims to measure the reliability of the model in detecting and predicting floods in Demak Regency. With comprehensive metrics analysis, the developed model can be improved and optimized to increase accuracy and effectiveness in hydrological data-based flood prediction systems. The model is evaluated to assess its performance of the model in detecting flood events. The validation results will be presented in a table that includes accuracy, precision, recall, and F1-score for each experiment as shown as Table 5.

Table 5. Model Validation Results

Experiment	Accuracy (%)	Precission (%)	Recall (%)	F1-Score (%)
1	85.71	86.67	85.71	86.18
2	88.57	89.47	88.57	89.02
3	90.00	90.91	90.00	90.45
4	91.43	92.31	91.43	91.86
5	92.86	93.33	92.86	93.10
6	92.86	93.33	92.86	93.10
7	94.29	94.74	94.29	94.51

The illustration of accuracy, precision, recall, and F1-score from 7 trials can be seen in Figure 4.

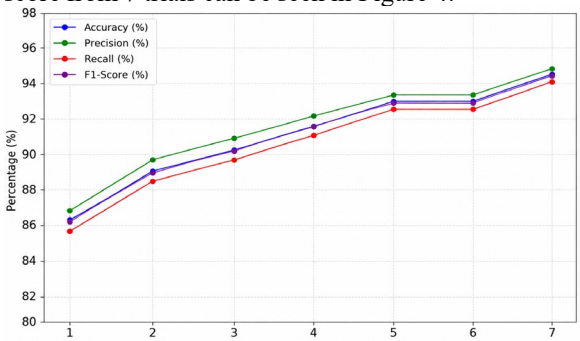


Figure 4. Experimental Results Accuracy, Precision, Recall, F1-Score

3.4 Explanation of Metrics

Model evaluation is performed to assess the effectiveness of the model in predicting flood events using hydrological data. Several key metrics are used for this evaluation, including accuracy, precision, recall, and F1-score. Accuracy represents the proportion of correct predictions out of all predictions made by the model. Precision indicates how many of the predicted flood events were correct out of all the flood predictions. Recall focuses on the model's ability to detect all actual flood events. The F1-score combines precision and recall into a single value by calculating their harmonic mean, providing a balanced view of the model's performance. These metrics together offer a comprehensive evaluation of the model's prediction capabilities.

From the validation results shown in the table, it can be seen that the accuracy of the model increases as the training iterations increase, starting from 85.71% in the first trial to reach 94.29% in the seventh trial. This increasing trend shows that the model is increasingly able to recognize flood event patterns better. Precision also increased from 86.67% in the first trial to 94.74% in the seventh trial, which means the model is getting better at avoiding errors in identifying flood events.

Recall also showed a similar pattern of improvement, starting from 85.71% in the first experiment and reaching 94.29% in the seventh experiment. This indicates that the model is increasingly able to capture actual flood events. F1-score, as a metric that balances precision and recall, also increased from 86.18% to 94.51%, indicating that the model has a stable and balanced performance between correctly identifying flood events and capturing all existing flood events.
From this analysis, it can be concluded that the developed model performs well and improves with training iterations. However, although the accuracy and other metrics show high results, it is necessary to conduct further testing with data that has never been used in training to ensure that the model does not experience overfitting. Thus, the model can continue to be optimized to improve accuracy and effectiveness in the hydrological data-based flood prediction system in Demak Regency

4. Conclusions

This research has successfully developed a Hidden Markov Model (HMM) based hydrometeorological disaster prediction model by utilizing hydrological data from Kelambu Dam in Demak Regency. The developed model shows good performance in identifying flood potential based on key hydrological variables, such as water levels upstream and downstream of the dam and water discharge. Through the model training and evaluation process, the results obtained show a high level of accuracy, with the model's performance improving with each training iteration. The model is able to predict flood events with an accuracy of up to 94.29%, precision of 94.74%, recall of 94.29%, and F1-

score of 94.51%, so it can be used as a tool in early warning systems and disaster risk management.

The results of this study prove that the HMM-based approach can be an effective alternative in supporting hydrometeorological disaster mitigation efforts, especially in flood prediction. This model allows early detection of changes in hydrological conditions and provides an overview of transition patterns between normal, pre-flood, and flood conditions. However, the effectiveness of the model still depends on the quality and availability of the data used. Therefore, improvements in hydrological data management, integration with additional data sources such as satellite-based weather predictions, and exploration of more adaptive modeling methods are strategic steps in improving the accuracy and reliability of flood predictions in the future.

With this prediction model, it is expected that stakeholders, such as local governments and related institutions, can be better prepared for hydrometeorological disasters. The implementation of this model in an early warning system can help make faster and more precise decisions so that mitigation efforts can be carried out more effectively. In the future, further research can be directed at developing more complex artificial intelligence-based models, as well as testing the model in other regions with different hydrological characteristics to ensure generalization and flexibility of its use

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