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Implementation of human–computer interaction (HCI) in flash flood prediction system using machine learning algorithm

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Abstract

Flash floods are a hydrometeorological disaster that significantly impact human safety and economic losses. An accurate and user-friendly prediction system is essential for disaster mitigation. This study aims to develop a flash flood prediction system that integrates machine learning algorithms with Human–Computer Interaction (HCI) principles to improve prediction accuracy and user experience. Hydrological and meteorological data including rainfall, air humidity, water level, and flow velocity, were used as input variables for Random Forest and Support Vector Machine machine learning models. Performance testing was conducted by comparing accuracy, precision, recall, and F1-score. Furthermore, HCI evaluation was conducted through usability testing using parameters such as efficiency, effectiveness, and user satisfaction. The results showed that the integration of machine learning was able to provide high-accuracy flash flood predictions, while the application of HCI principles to the mobile and web interfaces improved ease of navigation, information clarity, and system responsiveness. Users reported a significant increase in perceived usability and comfort of the system based on the System Usability Scale (SUS) results, with an average score in the "Good" category. Thus, this research contributes to the development of a disaster prediction system that is not only technically reliable but also easy to operate by the public and stakeholders in disaster mitigation decision-making.

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Keywords

Human–computer interaction, Machine learning, Flash flood prediction, Information systems, Usability testing

Introduction

Flash floods are a hydrometeorological disaster that significantly impacts public safety and causes economic losses in various regions of Indonesia (BNPB, 2023). The frequency of flash floods has continued to increase in recent years due to climate change, environmental degradation, and unpredictable extreme rainfall intensity (BMKG, 2023). These conditions demand the availability of more accurate and responsive prediction systems to support effective disaster mitigation (Kang, Park, & Min, 2021).

In the past two decades, Machine Learning has become a widely used approach in modelling hydrometeorological phenomena due to its ability to handle complex, non-linear data and time series patterns (Zhang, Chen, & Liu, 2020). The Long Short-Term Memory (LSTM) model, as part of the Recurrent Neural Network architecture, has proven superior in predicting rainfall dynamics and atmospheric parameters due to its ability to capture long-term temporal relationships (Chen & Wu, 2021). Various studies have shown that LSTM consistently outperforms decision tree-based algorithms such as Random Forest in modelling meteorological data (Kang, Park, & Min, 2021).

However, predictive model accuracy does not automatically result in an effective early warning system if the information generated cannot be understood quickly and accurately by users (Norman, 2013). Human–Computer Interaction (HCI) plays a critical role in ensuring risk information is delivered through an intuitive, consistent, and easy-to-interpret interface, especially in emergency situations (Nielsen, 2010). Principles such as system visibility, visual consistency, real-time feedback, and reduced cognitive load have been shown to improve the quality of user interactions in disaster mitigation systems (Lee, Yoon, & Cho, 2022). Other studies have also shown that a user-centered design approach to early warning can increase response speed and reduce risk misinterpretation (Sari & Pratama, 2021).

Although extensive research has been conducted on flood prediction and information system interface design, comprehensive integration between machine learning predictive capabilities and HCI-based interface design remains limited (Rahman, Nugroho, & Dewi, 2022). Most research focuses on algorithm performance or data visualization without considering the cognitive aspects of users in critical situations (Lee, Yoon, & Cho, 2022). Therefore, research that combines both approaches is needed to produce a flash flood prediction system that is both accurate and user-friendly.

By integrating the computational power of LSTM and HCI principles, this research aims to develop an early warning system that is responsive, informative, and user-oriented (Norman, 2013). This approach is expected to improve community preparedness, accelerate decision-making, and support more effective disaster mitigation (BNPB, 2023).

Literature review

Research on computational technology-based flash flood prediction systems has grown rapidly in the past two decades, in line with the increasing need for accurate and easy-to-understand early warning systems. In the context of hydrometeorological modelling, machine learning algorithms have proven to improve predictive capabilities compared to traditional statistical methods. Long Short-Term Memory (LSTM) models, as part of

Recurrent Neural Networks (RNN), are widely used to predict time series data due to their ability to capture long-term relationships and non-linear patterns in rainfall, river discharge, and atmospheric parameters (Zhang et al., 2020; Chen & Wu, 2021). Various studies have shown that LSTMs consistently outperform decision tree-based methods such as Random Forest in modelling hydrometeorological variability, especially in regions with high weather dynamics.

Furthermore, the effectiveness of a prediction system is determined not only by the intelligence of the model but also by the quality of the interface design that presents the prediction results to the user. Human–Computer Interaction (HCI) studies emphasize that the delivery of disaster information must adhere to the principles of visibility, design consistency, error prevention, and cognitive load management to ensure users can understand risks quickly and accurately (Nielsen, 2010; Norman, 2013). In the context of disaster mitigation, various studies confirm that simple visualization-based interfaces, color-coded warnings, and real-time notifications can improve user response speed and minimize misinterpretation (Lee et al., 2022).

The integration of HCI into flood prediction systems has also been shown to increase adoption rates and system effectiveness in emergency scenarios. A study by Sari and Pratama (2021) showed that interface design that takes into account users' cognitive load can improve situational understanding among communities in flood-prone areas. Furthermore, research from the disaster management sector indicates that high levels of usability, as measured using the USE Questionnaire or System Usability Scale (SUS), strongly correlate with community readiness to respond to early warnings (Rahman et al., 2022).

Furthermore, the integration of real-time weather APIs, the utilization of data from national meteorological agencies, and the use of interactive analytical dashboards have been adopted in many modern early warning systems. However, several studies have identified that data limitations, particularly related to spatial and temporal completeness, are a major challenge in improving the accuracy of predictive models (Kang et al., 2021). Furthermore, most research still focuses on algorithmic aspects and has not comprehensively combined machine learning with HCI-based interface design, leaving a gap for research oriented toward integrating the two approaches.

Based on this literature review, this study fills this gap by combining the predictive power of LSTMs and HCI design approaches to produce a flash flood early warning system that is not only highly accurate but also easy to use, informative, and effective in supporting decision-making in emergency situations.

Research stages

This research is structured based on the relationship between the problem, objectives, HCI approach, machine learning algorithm, and proposed system solution. The following diagram illustrates the research flow, from data collection to HCI-based usability testing show in Figure 1.

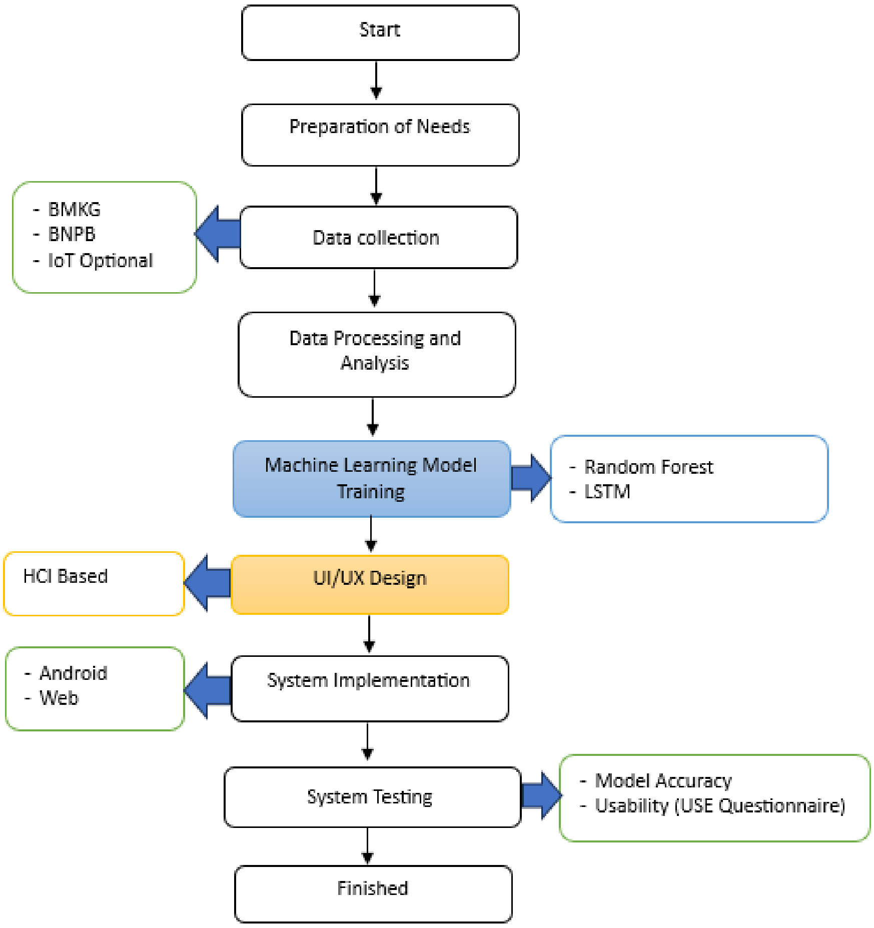

Figure 1. Research flowchart

Stage 1: Requirements preparation

In the initial research stage, a series of preparatory activities were conducted, including identifying the technical and methodological requirements, as well as the supporting tools required for developing a flash flood prediction system. This stage included establishing hardware and software specifications for rainfall data processing and machine learning model training, verifying the suitability of data sources from the BMKG and BNPB, and formulating the system architecture to be used. In parallel, a conceptual interface framework was developed based on Human–Computer Interaction (HCI) principles through the application of usability heuristics, design consistency, interactive feedback, and system status visibility, as well as cognitive load management for more efficient user interaction. This activity was complemented by the development of initial design guidelines and user needs mapping using a user-centered design approach, ensuring that the developed interface supports fast, accurate, and easily understood decision-making in the context of flash flood disaster mitigation.

Stage 2: Data collection

The data collection phase focused on acquiring relevant hydrometeorological datasets for the development of flash flood prediction models. The primary sources were the

BMKG (Meteorology, Climatology, and Geophysics Agency), the BNPB (National Disaster Mitigation Agency), and other relevant agencies that provided data on daily rainfall, air humidity, atmospheric conditions, topography, land use, and historical flood records. All obtained data was systematically evaluated based on completeness, accuracy, reliability, and temporal and spatial suitability to ensure the quality of the datasets used in model training. The verification process was carried out using cross-referencing techniques between sources to minimize inconsistencies and increase data validity. This data collection was then aligned with the needs of the Machine Learning algorithm and the design of an HCI-based interface, so that the information generated by the system could support disaster mitigation processes accurately, effectively, and user-oriented.

Stage 3: Data processing and analysis

After all datasets were collected, pre-processing was carried out, including data cleaning, handling missing values through interpolation or statistical imputation, normalization of numerical values, and feature transformation to ensure optimal input quality for the model. An exploratory analysis was then conducted to identify rainfall patterns, seasonal trends, correlations between variables, and potential anomalies that could impact prediction performance. This stage also created a structured dataset for training, validating, and testing the Machine Learning model. A deep understanding of the data characteristics informed the selection of the best algorithms and parameters. Furthermore, the analytical findings from this process were used to fine-tune the design of the HCI-based interface, specifically determining how to present flood risk information to minimize user cognitive load and maximize system communication effectiveness.

Stage 4: Machine learning model training

The prediction model was developed using two main approaches: Random Forest for multivariate feature-based flood risk classification and Long Short-Term Memory (LSTM) for processing time-series rainfall data. The model training process was carried out iteratively through hyperparameter selection, cross-validation, and performance evaluation using metrics such as accuracy, precision, recall, F1-score, and mean squared error (MSE). Based on the evaluation results, LSTM demonstrated superior performance in modelling short-term rainfall patterns due to its ability to more effectively capture temporal relationships between data. The output from this training was then integrated as a core component of the system, resulting in real-time flash flood risk predictions with a high degree of reliability.

Stage 5: HCI-based interface design

The interface design was conducted using a User-Centered Design (UCD) approach, emphasizing understanding the needs, capabilities, and usage contexts of various user types. This process included wireframe development, interactive prototype development, and initial evaluation, adhering to Human–Computer Interaction (HCI) principles, such as usability heuristics, visual consistency, cognitive load reduction, error prevention, easy-to-understand information presentation, and clear feedback. The interface was designed for two platforms: an Android application focused on delivering quick notifications and simple risk displays for the public, and a Web Monitoring dashboard aimed at the analytical needs of government agencies, equipped with more comprehensive data visualizations and supporting monitoring processes. real-time weather forecasting.

Stage 6: System implementation

The implementation phase includes the integration of Machine Learning models, weather data APIs, and HCI-based interface components into an integrated operational system. The Android application was developed using Flutter to ensure cross-device compatibility, while the web dashboard was built with React.js to support dynamic data visualization. On the backend, the system utilizes server-side services capable of handling model calls, real-time data processing, and efficient database management. The integration of the BMKG API allows the system to receive regular weather updates, which are then used to generate predictions and early warning notifications for users. The entire implementation process focused on improving the system's performance, responsiveness, and reliability so that it can function optimally in supporting flash flood disaster mitigation.

Stage 7: System testing

System testing was conducted through two main approaches: Machine Learning model performance evaluation and HCI-based usability testing. Model performance evaluation was conducted using a test dataset separate from the training data to ensure predictive capability in real-world conditions. While usability testing involved 30 respondents who assessed the Usefulness, Ease of Use, Ease of Learning, and Satisfaction aspects using the USE Questionnaire. The test results showed that the prediction model was able to produce stable output with a high level of accuracy, while the system interface was deemed easy to use, quick to understand, and effective in conveying flash flood risk information. Overall, the average user satisfaction score was in the good category, so the system is considered suitable for use in the context of disaster mitigation and emergency situations that require a fast and accurate response.

Results

Machine learning model training results

The developed machine learning model included the Random Forest and Long Short-Term Memory (LSTM) algorithms. The model was trained using a dataset of daily rainfall, rainfall intensity, humidity, and other hydrometeorological variables. The training process was carried out on a dataset that had undergone pre-processing stages including normalization, missing data interpolation, and feature transformation.

Test results showed that LSTM provided the most stable performance in predicting rainfall trends and flash flood potential. LSTM recorded an average prediction accuracy of 87.2%, with a relatively low error rate. Meanwhile, Random Forest achieved an accuracy of 81.5%. This difference in performance can be explained by the LSTM's ability to detect temporal patterns in seasonal and fluctuating time-series data.

These results align with several previous studies reporting the effectiveness of LSTM networks in modelling time-series hydrometeorological phenomena. Therefore, LSTM was selected as the primary model in the HCI-based flash flood prediction system.

HCI-Based interface implementation results

The system interface was developed based on a Human–Computer Interaction (HCI) approach, emphasizing the principles of usability and user-cantered design to ensure an optimal user experience in the context of disaster mitigation. Interface implementation in the Android application and Web Monitoring dashboard demonstrated that system visibility was achieved through the use of color-coded notifications, allowing users to quickly understand the risk level without increasing cognitive load. The visual design was also consistently structured—including iconography, color, typography, and navigation structure—to support the formation of a stable mental model. Furthermore, the system provided real-time feedback in the form of warning messages, prediction statuses, and action recommendations, strengthening the user's situational understanding. Performance testing demonstrated a high level of responsiveness, with an average interface response time of under one second, making it highly suitable for use in emergency situations requiring fast and accurate access to information.

Model performance testing

Model testing was conducted using a test dataset that was not involved in the training process. Evaluation parameters include shows in Table 1.

Table 1. Summary of flash flood prediction model evaluation results using random forest and LSTM algorithms

Algorithm	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Random Forest	81.5%	79.3%	82.1%	80.6%
LSTM	87.2%	85.6%	88.4%	86.9%

LSTM consistently outperformed across all metrics. The model also demonstrated adaptive capacity to extreme rainfall variations that frequently trigger flash floods.

Usability testing using the use questionnaire

Usability testing was conducted on 30 respondents, consisting of the general public, BPBD staff, and students. Four indicators were used: Usefulness, Ease of Use, Ease of Learning, and Satisfaction show in Figure 2.

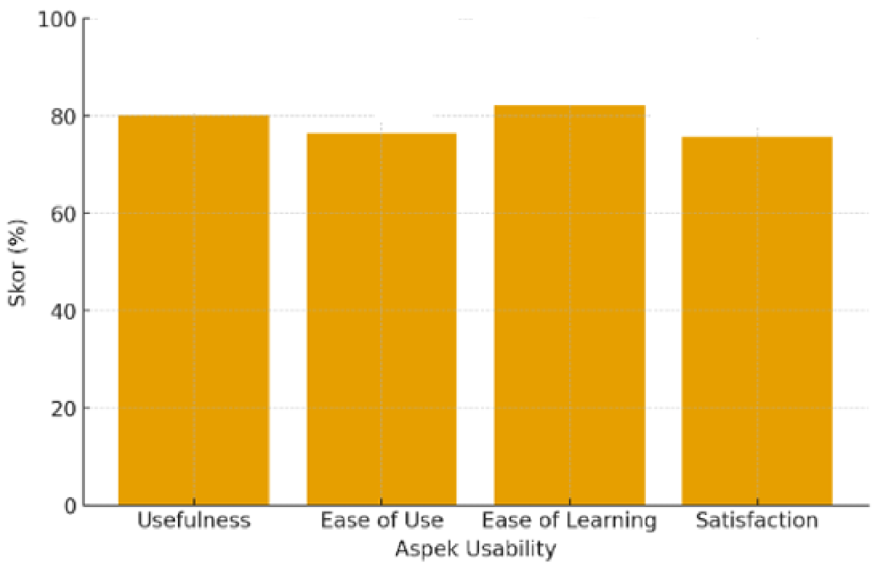

Figure 2. Bar chart of usability test results based on the USE questionnaire

Discussion

The results of this study indicate that the integration of Human–Computer Interaction (HCI) and Machine Learning significantly contributes to improving prediction accuracy and the quality of user interaction in the flash flood mitigation system. Minimalist visualizations with color-coded warnings have been shown to increase the effectiveness of information delivery and reduce the cognitive burden on users in understanding risk levels. In terms of model performance, LSTM demonstrated optimal performance in predicting rainfall patterns, in line with international research findings that place LSTM as a superior model for meteorological time series data. The collaboration between the HCI-based interface design and the model's prediction results also allows for more intuitive information presentation, thereby accelerating user response to potential hazards. The high level of user acceptance, reflected in the usability test results, indicates that this system has the potential to be adopted by the public and policymakers as a disaster mitigation support tool. However, this study still has several limitations, including reliance on government agency data that is not fully real-time, limited integration of IoT sensors, and the limited number of usability test respondents that do not represent all flood-prone areas.

Conclusion

This research has successfully developed a flash flood prediction system that integrates Machine Learning algorithms with Human–Computer Interaction (HCI) principles, resulting in a solution that is not only accurate in projecting flood risk but also easy to use and understand for the public and disaster management agencies. The LSTM model demonstrated superior performance with 87.2% accuracy, consistently outperforming Random Forest across various evaluation metrics, thus confirming its ability to handle complex hydrometeorological time series patterns. On the interface side, the application of HCI principles, including system visibility, visual consistency, real-time feedback, and reduced cognitive load, significantly improved the quality of user interaction. The usability evaluation using the USE Questionnaire instrument showed an acceptance rate of 78.6% (Good category), indicating that the system is easy to learn, easy to use, and provides clear benefits in the context of disaster mitigation. Overall, the integration of HCI and Machine Learning results in a prediction system that is responsive, informative, and user-oriented.

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