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CLASSIFICATION OF NATURAL DISASTERS IN WEST SEMARANG BASED ON WEATHER DATA USING DEEP LEARNING

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Abstract*—Natural disasters like floods, landslides, and fires pose serious threats to both life and mental well-being, especially in vulnerable areas like West Semarang, which frequently experiences extreme weather. To mitigate these risks, an accurate classification system is essential for timely prevention and response. This study compares the performance of three neural network models—Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU)—in classifying natural disasters using weather data. LSTM and GRU are particularly effective for handling long-term dependencies and addressing vanishing gradient problems common in time series data. Data for the study comes from the Semarang City Regional Disaster Management Agency (BPBD) and the Meteorology, Climatology, and Geophysics Agency (BMKG), spanning 2019 to 2022. The models achieved a high accuracy of 95.8%, but this is due to an imbalanced dataset—70 records of natural disasters versus 1377 without—resulting in classification favoring "no disaster." Among the models, LSTM performed the best, reaching optimal accuracy in just 20.0671 seconds per epoch. This suggests LSTM is the most effective model for this classification task.*

Keywords*: gated recurrent unit, long short-term memory, natural disaster, recurrent neural network, west semarang.*

Intisari*—Bencana alam seperti banjir, tanah longsor, dan kebakaran merupakan ancaman serius bagi kehidupan, terutama di wilayah rawan seperti Semarang Barat yang sering dilanda cuaca ekstrem. Untuk meminimalisasi dampak negatif, diperlukan sistem klasifikasi yang andal guna membantu pemerintah dan masyarakat dalam mengambil langkah mitigasi dan pencegahan yang tepat waktu. Dalam penelitian ini, performa tiga model neural network—Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), dan Gated Recurrent Unit (GRU)—diuji untuk klasifikasi bencana alam di Semarang Barat. LSTM dan GRU dikenal karena kemampuannya dalam menangani long-term dependencies dan masalah vanishing gradient pada data deret waktu. Data yang digunakan diperoleh dari Badan Penanggulangan Bencana Daerah (BPBD) Semarang dan Badan Meteorologi, Klimatologi, dan Geofisika (BMKG) untuk rentang tahun 2019 hingga 2022. Hasil menunjukkan akurasi 95.8% untuk ketiga model, meskipun hal ini disebabkan oleh ketidakseimbangan data—70 data dengan bencana alam dan 1377 tanpa bencana. Model LSTM mencapai performa terbaik dengan waktu terpendek, yaitu 20.0671 detik per epoch, menjadikannya model yang paling efisien dalam klasifikasi bencana alam di kasus ini.*

Kata Kunci*: unit rekursif terjaga, ingatan jangka pendek panjang, bencana alam, jaringan saraf rekursif, semarang barat.*

INTRODUCTION

Natural disasters such as floods, landslides and fires pose a serious threat to life, not only in terms of economic loss, but also mentally through loss of life, especially in highly vulnerable areas such as West Semarang [1]. The region often experiences natural disasters caused by extreme weather conditions, so it is important to develop a reliable classification system to minimize these negative impacts [2]. Accurate classification can help the government and community to take timely prevention and mitigation measures [3], [4].

Based on Sustainable Development Goals (SDG) number 13, natural disasters play a very significant role in increasing mortality, where areas experiencing natural disasters have a mortality rate 15 times greater than normal [5]. Therefore, natural disaster prevention and mitigation actions are very important to support the survival of people in natural disaster-prone areas [6], [7].

In recent years, advances in technology and data science have opened new opportunities to improve natural disaster classification capabilities. Machine learning methods, particularly artificial neural networks [8], [9], [10], [11], have shown great potential in the analysis and classification of weather data. Two main variants of artificial neural networks that are often used for modeling time series data are Long Short-Term Memory (LSTM) [12], [13] and Gated Recurrent Unit (GRU) [14]. Both methods are known for their ability to handle long-term dependencies [15], [16], [17], [18] and vanishing gradient [13], [19], [20], which are often an obstacle in modeling complex and dynamic weather data.

Research on rainfall prediction in Denpasar using LSTM and GRU demonstrates the potential of these methods in modeling complex time-series data [21]. However, no studies have applied them to natural disaster classification in West Semarang. Our study extends the application of LSTM and GRU beyond rainfall prediction to natural disaster classification in West Semarang, an approach that has not been previously explored in this region. Similarly, while previous research has explored temperature prediction in Semarang using LSTM, this study broadens the scope by classifying areas with or without natural disasters, offering a more holistic perspective on disaster risk management in the region [22].

Although prior studies have used H2O deep learning to predict floods in West Kalimantan based on rainfall data, this study focuses on West Semarang and incorporates a more comprehensive set of meteorological variables to enhance model accuracy [23].

This research shows the GRU model in predicting floods in Ashland City, Tennessee effectively with high accuracy [24]. This model has advantages in efficiency and computational speed compared to LSTM in handling time-series data for flood prediction, showing potential in classifying natural disasters in West Semarang.

This research introduces an attention-based LSTM model (ALSTM-DW) using double time sliding windows and weighted loss to improve urban flood forecasting by enhancing rainfall feature extraction and reducing peak prediction errors [25]. Tested in three flood-prone areas in Shenzhen, China, the model outperforms traditional methods, showing strong predictive accuracy with high R^2 and low peak flow and timing errors, supporting the use of LSTM in disaster-related forecasting tasks. This supports the use of the LSTM model in our research where the model can handle long-term weather data in natural disaster classification.

This research analyzes the applications of ML and DL in disaster management, including prediction, disaster detection, early warning systems, and post-disaster response [8]. This study identified DL models such as CNN and LSTM produce significant performance in natural disaster data analysis. This study supports our approach using LSTM and GRU deep learning models for natural disaster classification.

This study uses a hybrid LSTM–GRU model with meteorological and water level data to predict floods, achieving high accuracy with an NSE of 0.942 and MSE of 3.92 [26]. It outperformed other setups, especially when using ASOS data, and showed strong performance even at historical peak water levels, supporting its use for flood risk management, relevant to our research using weather data and disaster data for natural disaster classification in West Semarang.

This report aims to present the results of research and analysis of natural disaster classification in West Semarang using historical weather data with Recurrent Neural Network (RNN) [27], LSTM, and GRU methods.

By understanding and utilizing weather data for natural disaster classification, it is hoped that this research can contribute to disaster risk mitigation efforts in West Semarang, and beyond, and provide practical recommendations for relevant parties in managing disaster threats more effectively.

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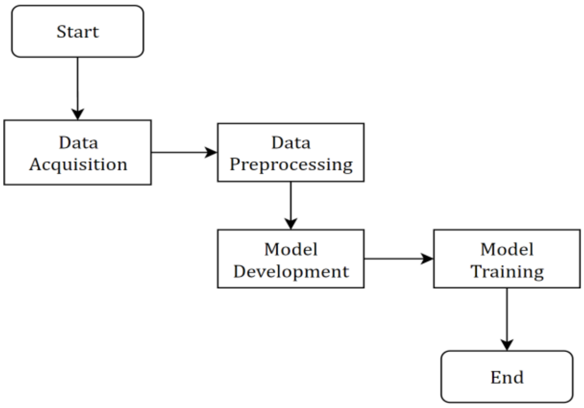
MATERIALS AND METHODS

Figure 1 shows the research procedure in flowchart form starting with data acquisition, data processing, model development, and model training. This research will compare the performance of RNN, LSTM, and GRU models in natural disaster classification based on daily weather data.



Source : (Research Results, 2024)

Figure 1. Research Procedure

A. Data Acquisition

This study uses data obtained from two sources, namely the Semarang City Regional Disaster Management Agency (BPBD) website [28], and from the Meteorology, Climatology and Geophysics Agency (BMKG) website [29], where the data used comes from the range of 2019 to 2022.

Table 1 contains details about the data obtained. The BPBD data for Semarang City contains information on the number of disasters at any given time, along with information on the location of the disasters. Meanwhile, the BMKG data contains information on Semarang city's daily weather data, such as temperature, rainfall, wind, and humidity obtained from Ahmad Yani Weather Station in West Semarang District.

Table 1. Initial Dataset Informations

Source	Date Count	Number of Features	File Format
Semarang City BPBD	210	17	xlsx
BMKG	1461	11	xlsx

Source : (Research Results, 2024)

Table 2 contains details of the features contained in the disaster data obtained.

Table 2. Semarang City Disaster Data Features

Features	Description
NO	Data number
TGL KEJADIAN	Date of occurrence
LOKASI	Location of the incident
KELURAHAN	Name of urban village
KECAMATAN	Name of district
B	Flood
RB	Tidal flood
TL	Landslide
PB	Tornado
RR	House collapse
KB	Fire
PT	Tree fall
MD	Death
Luka2	Injured people
Hilang	Missing people
KERUGIAN	Losses from disaster
KETERANGAN	Description of disaster

Source : (Research Results, 2024)

Table 3 contains details of the features contained in the weather data obtained.

Table 3. BMKG Daily Weather Data Features

Features	Description
Tanggal	Date of data recording
Tn	Minimum temperature
Tx	Maximum temperature
Tavg	Average temperature
RH_avg	Average humidity
RR	Rainfall
ss	Length of sunshine
ff_x	Wind speed
ddd_x	Wind direction at maximum speed
ff_avg	Average wind speed
ddd_car	Most wind direction

Source : (Research Results, 2024)

B. Data Preprocessing

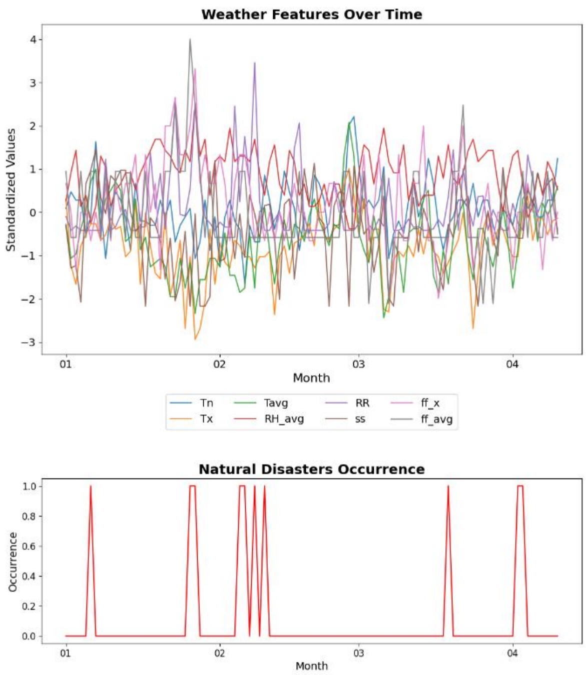
First, natural disaster data from 2019 to 2022 was merged, and then the data was cleaned in the following order: (1) Deleting some unused features, such as “NO”, “PT”, “RR”, “MD”, “Wounded”, “Missing”, “DAMAGE”, and “DESCRIPTION”, (2) Deleting data with writing errors and data with incorrect contents in the appropriate columns, (3) Filling in the blank data in the number of disasters with zeros, (4) Replace the incorrect date format, (5) Retrieve the data in West Semarang sub-district and delete the “LOCATION”, “FAMILY”, and “KECAMATAN” features, (6) Add data on dates without disasters and fill each disaster category with zeros.

Second, daily weather data from 2019 to 2022 were merged, after which data addition was carried out for missing data: (a) Data filling with average values on features “Tn”, “Tx”, “Tavg”, “RH_avg”, “ddd_x”, “ff_x”, and “ff_avg”, (b) Data filling with zero values on features “RR”, and “ss”, (c) Data filling with “C” values on features “ddd_car”. After that, one-hot encoding is performed on the “ddd_car” feature into 9 new features.

Accredited Rank 2 (Sinta 2) based on the Decree of the Dirjen Penguatan RisBang Kemenristekdikti No.225/E/KPT/2022, December 07, 2022. Published by LPPM Universitas Nusa Mandiri

After the processing of disaster data and weather data is done, both data are combined into one data and converted into CSV format. then each disaster category is combined into 1 feature and each combination of disaster events is converted into binary numbers. Through this data merging, 1447 data were generated with a percentage of 1377 data without disasters, and 70 data with disasters.

Then standardization is done using sklearn.StandardScaler to prevent overfitting. Then, the normalized data is converted into a time series dataset with a time span of 14 days at each data index.



Source : (Research Results, 2024)
Figure 2. Sample Visualization of Weather Features and Natural Disaster Occurrences

The figure presents a visualization of the preprocessed dataset, showing a 100-day sample to illustrate the relationship between weather parameters and natural disaster occurrences in West Semarang. The upper panel displays standardized values of eight weather features: minimum temperature (Tn), maximum temperature (Tx), average temperature (Tavg), average relative humidity (RH_avg), rainfall (RR), sunshine duration (ss), and wind speed components (ff_x and ff_avg). The standardization process brings these diverse measurements onto a comparable scale, enabling clearer visualization of their temporal patterns.

The lower panel uses a line plot to represent the binary occurrence of natural disasters, where peaks at value 1 indicate days when natural disasters were recorded, while values at 0 indicate days without disasters. This visualization allows us to observe the temporal distribution of disaster events in relation to the weather parameters shown above.

While this figure shows only 100 days of data for clarity, the complete analysis utilizes the full dataset spanning from 2019 to 2022.

Finally, the time series dataset is divided into 3 parts, 80% for training data, 15% for validation data, and 5% for testing data. After that, the three datasets were saved into the data loader with a batch size of 48.

This split is designed to maximize the model's learning capability by allocating a large portion of the data to training. Given the imbalanced nature of the dataset, where only 70 samples are labeled as disasters while 1377 samples represent non-disaster events, it is crucial to provide the model with sufficient examples during training to effectively learn patterns associated with rare disaster events.

Additionally, a moderate portion is reserved for validation to fine-tune the model and prevent overfitting, while a smaller portion is set aside for testing to ensure unbiased evaluation. The datasets are then stored in a data loader with a batch size of 48 for efficient processing during training.

C. Model Development

Table 4 contains information about the hyperparameters used in the development of the three deep learning models used (RNN, LSTM, GRU).

Table 4. RNN, LSTM, and GRU Model Hyperparameter

Hyperparameter	Value
Input Size	11
Hidden Unit	5
Number of Layer	5
Number of Class	1
Dropout	20%
Batch Size	48
Learning Rate	0.001
Epoch	100

Source : (Research Results, 2024)

These models will be used to classify whether a disaster, namely flood (B), tidal flood (RB), landslide (TL), tree fall (PT), or fire (KB), will occur based on weather-related features.

Each disaster type is classified using a binary approach, where 0 indicates the absence of the disaster and 1 signifies its occurrence. By analyzing the weather features, the models predict the

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likelihood of each disaster, providing a structured framework for disaster classification and early warning systems.

D. Model Training

To perform natural disaster classification, the model is first trained using the data available in the test data loader. Then the model is optimized using the ADAM optimizer with a weight decay of 0.01, and its performance is seen using the Binary Cross Entropy with Logits Loss loss function. After being trained, the model will be validated using the data available in the validation data loader, this training and validation process will continue to be repeated as many epochs as there are. After completion, the model will be tested using the data available in the test data loader.

RESULTS AND DISCUSSION

After training for 100 epochs, it was found that the RNN, LSTM, and GRU models in the classification of natural disasters have a performance with a not too significant difference.

Table 5 contains information about the best results of training loss, error, and accuracy of the RNN, LSTM, and GRU models in 100 epochs.It can be seen that the RNN model has better training loss, and error values than the other two models, followed by LSTM, and GRU. However, the LSTM model can achieve its best performance earlier than the other two models at the 83rd epoch, followed by RNN at the 99th epoch, and GRU at the 100th epoch.

Table 5. Training Result Comparison

Model	Loss	Error	Accuracy	Best Epoch
RNN	0.1678	0.0036	95.8549%	99
LSTM	0.1680	0.0036	95.8549%	83
GRU	0.1847	0.0040	95.8549%	100

Source : (Author's last name, year of publication)

Table 6 contains information about the best results of validation loss, error, and accuracy of the RNN, LSTM, and GRU models in 100 epochs. It can be seen that the GRU model has a slightly better validation loss value compared to the RNN, and LSTM models which have identical values. However, as mentioned earlier, the LSTM model achieved its best performance at the 83rd epoch, followed by RNN, and GRU.

Table 6. Validation Result Comparison

Model	Loss	Error	Accuracy	Best Epoch
RNN	0.1732	0.0461	95.8549%	99
LSTM	0.1732	0.0461	95.8549%	83
GRU	0.1729	0.0461	95.8549%	100

Source : (Research Results, 2024)

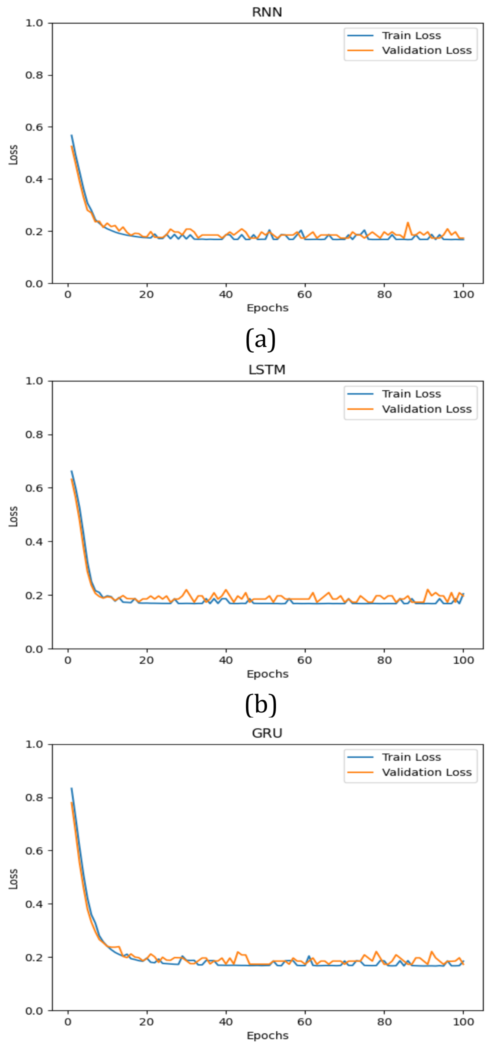
Table 7 contains information about the testing loss, error, and accuracy results of the RNN, LSTM, and GRU models. It can be seen that the LSTM model has a better testing loss compared to the other two models, followed by the RNN model, and the GRU model.

Table 7. Testing Result Comparison

Model	Loss	Error	Accuracy	Best Epoch
RNN	0.1732	0.0461	95.8549%	99
LSTM	0.1732	0.0461	95.8549%	83
GRU	0.1729	0.0461	95.8549%	100

Source : (Research Results, 2024)

Figure 2 shows the comparison plot between training loss and validation loss of (a) RNN, (b) LSTM, and (c) GRU models from epoch 1 to 100.



(a) (b) (c)

Source : (Research Results, 2024)
Figure 2. Comparison of Training Loss with Validation Loss Model, (a) RNN, (b) LSTM, (c) GRU

Table 8 contains information regarding the time required for each model to reach 100 epochs, to reach the best epoch, and the average time of each epoch in second. It can be seen that the RNN model has the shortest amount of training time, followed by the LSTM, and GRU models. However, the LSTM model takes the shortest amount of time to achieve its best results, followed by the RNN, and GRU models.

Table 8. Model Training Time

Model	Average Time per Epoch (s)	Until Best Epoch (s)	Total Time (s)
RNN	0.2329	23.0612	23.2922
LSTM	0.2407	20.0671	24.0713
GRU	0.2451	24.5111	24.5111

Source : (Research Results, 2024)

CONCLUSION

This research compares the performance of 3 models, namely RNN, LSTM, and GRU models in classifying natural disasters in West Semarang based on daily weather data. It is concluded that all three models are able to classify natural disasters based on weather data with an accuracy of 95.8%, this is due to the one-sided ratio of data with natural disaster labels and without natural disasters, where the dataset has 70 data with natural disasters, while there are 1377 data without natural disasters. So that the three models gave the classification of "no disaster" to each disaster features. From the conclusion of this research, it is highly recommended for other researchers who want to perform natural disaster classification to use the LSTM model, because with a larger amount of data, the training time will increase significantly, so a model that can be trained with the best time efficiency is needed. Furthermore, it is recommended for other researchers to use a wider range of data with the hope that the LSTM model created will provide even better results. In addition, it is expected for BMKG to record data with a more comprehensive coverage in each region, and it is also expected for each region to record the occurrence of their respective natural disasters as has been done by BPBD Semarang City, so that natural disaster classification can also be done in each region to improve and protect the safety and well-being of the people and environment.

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