

Supplementary Materials

List of Content

- **Table S1.** Related machine learning algorithm studies.
- **Table S2.** Description of fifty-nine subfeatures.

Table S1. Related machine learning algorithm studies.

Authors	Evaluated Tourist Destination/ Natural Disaster's Place of Occurrence	Methodology	Purpose of the Study	Significant Feature Selection Results
Caraka et al. [21]	Indonesia	<ul style="list-style-type: none"> • Feature Selection Using Logistics Variational Approximation • Hierarchical likelihood via structural equation modeling 	<ul style="list-style-type: none"> • Studied the two social media influencers' impact on visiting Indonesia's tourist destination places 	<ul style="list-style-type: none"> • Feature selection helped identify important factors affecting Generation Y's and Generation Z's intention to visit tourist spots
Yuan et al. [22]	Beijing, China	<ul style="list-style-type: none"> • Feature selection through text mining's term frequency • Pattern mining • Max-confidence based method 	<ul style="list-style-type: none"> • Proposal of a conceptual framework that determines common tourist locations and trip routes 	<ul style="list-style-type: none"> • Feature selection assisted in the pattern identification of tourists' activities
Sheykhmousa et al. [23]	Tacloban, Philippines	<ul style="list-style-type: none"> • Remote sensing-based methodology • Support vector machine • Feature selection - Hilbert-Schmidt independence criterion 	<ul style="list-style-type: none"> • Assessment of the land cover and land use changes data of a typhoon-affected area to recommend post-disaster recovery plans 	<ul style="list-style-type: none"> • Feature selection results were used as the primary feed of a designed machine-learning algorithm • Feature selection approach increased the algorithm's accuracy
Tien Bui et al. [24]	Lao Cai, Vietnam	<ul style="list-style-type: none"> • Deep Learning Neural Network algorithm • Feature selection through 	<ul style="list-style-type: none"> • Aimed to generate flashflood susceptibility mapping 	<ul style="list-style-type: none"> • Subset extracted from feature selection determined the

		Information Gain Ratio		most important flash flood susceptibility factors
Granados-López et al. [30]	General	<ul style="list-style-type: none"> Four feature selection methods: • Filter selection's Pearson • Permutation Importance • Recursive Feature Elimination • Boruta 	<ul style="list-style-type: none"> • Identification of the best feature selection method in assessing sky conditions 	<ul style="list-style-type: none"> • Reduced 43 features to multiple combinations from 2 to 34 features • Suggested purposes of each feature selection depending on the important features
Muñoz et al. [31]	Southern Norway	<ul style="list-style-type: none"> • Feature selection – filter method's permutation importance • Chi-square • Spearman rank correlation • Density-based clustering • Maximum entropy modeling 	<ul style="list-style-type: none"> • Investigated online platforms' spatial data to study nature's features 	<ul style="list-style-type: none"> • Nine factors contributed to respective models by identifying vital local and international tourism factors
Li et al. [32]	China	<ul style="list-style-type: none"> • Feature selection – filter method's permutation importance • Random Forest algorithm • Linear Regression • Support Vector Regression • Decision Tree Regression • Random Forest-global variable model • Random Forest important variable model 	<ul style="list-style-type: none"> • Created a model that would predict the distribution of power outages induced by the typhoon 	<ul style="list-style-type: none"> • Recalculated and increased model accuracy by employing permutation importance • Features were ranked accordingly to identify essential power interruption factors

Kim et al. [33]	Gangwondo, Korea	<ul style="list-style-type: none"> • Feature selection – filter method's permutation importance • Maximum entropy 	<ul style="list-style-type: none"> • Investigated the factors affecting landslides in high-risk areas 	<ul style="list-style-type: none"> • The model was run twice and found 11 important landslide features
Kořakowska & Godlewska [36]	Poland	<p>Five feature selection methods:</p> <ul style="list-style-type: none"> • RFE with sequential backward elimination • LASSO regression model • Mutual information • Random forest accuracy decrease • Decision tree with sequential forward selection 	<ul style="list-style-type: none"> • Combination of process mining and machine learning to assess tourism operators' prices 	<ul style="list-style-type: none"> • Reduced the number of tourism features by generating a new subset derived from important feature selection predictors • Discovered the changes in tourists' perceptions before and after the pandemic • Tourists in Poland valued reimbursements, feedback, assurance, and comparison features
Xiao et al. [37]	Europe	<p>Machine learning algorithms</p> <ul style="list-style-type: none"> • Random Forest (RF) • Cubist • Gradient Boosted Machine (GBM) <p>Feature selection techniques:</p> <ul style="list-style-type: none"> • Recursive Feature Elimination (RFE) • Forward Recursive Feature Selection (FRFS) 	<ul style="list-style-type: none"> • Intended to mitigate climate change that could induce natural disaster aftermaths through unwanted soil properties 	<ul style="list-style-type: none"> • RFE defeated the existing machine learning algorithms by reducing 21 features to the least and most important 12 features

Peng et al. [8]	Chongqing City, China	<ul style="list-style-type: none"> • Text pre-processing • RFE • Latent Dirichlet Allocation (LDA) • Locally Linear Embedding (LLE) • Principal Component Analysis (PCA) • Knowledge graph modeling process 	<ul style="list-style-type: none"> • Creation and comparison of hybrid feature selection techniques integrated into multiple machine learning algorithms 	<ul style="list-style-type: none"> • Assessed 18 tourism features and nominal tourist data using feature selection and machine learning techniques • Supported the versatility of wrapper and embedded techniques because they were applied in supervised and unsupervised learning
Li et al. [42]	Songhua River, China	<ul style="list-style-type: none"> • Embedded feature selection • Logistic regression • Random forest 	<ul style="list-style-type: none"> • Integration of feature selection and machine learning techniques to explore factors triggering immense flash flood 	<ul style="list-style-type: none"> • Reduced 52 flashflood susceptibility factors to 28 significant features • Comparison of the model's accuracy model and embedded method's significant features • Feature selection results were fed into logistic regression to lessen flash flood impacts in China
Chang et al. [39]	General	<ul style="list-style-type: none"> • LASSO • Decision tree • Support Vector Machine-Recursive Feature Elimination (SVM-RFE) 	<ul style="list-style-type: none"> • Investigation of hotel features that affect tourists' travel and revisit intentions 	<ul style="list-style-type: none"> • LASSO could reduce 13 features into 8 and 10, and 10 hotel features had the highest

		<ul style="list-style-type: none"> • Back-propagation Neural Networks • Support Vector Machines 	accuracy rate when fed into other machine learning algorithms
Jones et al. [40]	Philippines	<ul style="list-style-type: none"> • Binary Logistic Regression • LASSO • Area Under the Receiver Operator Curve 	<ul style="list-style-type: none"> • Assessment of different typhoons to select preventive and triggering landslide factors with the highest accuracy rate • Accentuated the common landslide-related factors that were all present in 4 time points • The highest accuracy produced was 82% for typhoons evaluated from 2009 to 2018
Guzzetti et al. [43]	Multiple countries	<ul style="list-style-type: none"> • Historical data analysis • Logistic regression ANN 	<ul style="list-style-type: none"> • Utilized environmental features such as morphology, drainage, geology, and soil for areas affected by landslides • Designed a warning system for residents, tourists, and foreigners • Modeled low, moderate, and high landslide susceptibility
Tsaur et al. [13]	Taiwan	<ul style="list-style-type: none"> • Logistic regression ANN 	<ul style="list-style-type: none"> • Identification of the best machine learning algorithm that would yield important factors affecting tourist loyalty • Employed machine learning to determine if tourists would recommend, revisit, and provide referrals to hotels. • Logistic regression identified the top three loyalty factors: (1) tangible, (2) responsiveness, and (3) empathy

						<ul style="list-style-type: none">• ANN's top three tourist loyalty aspects: (1) responsiveness, (2) tangible, and (3) location• ANN had a better model fitting than logistic regression
Tien Bui et al. [11]	Cat Ba National Park, Vietnam	<ul style="list-style-type: none">• Kernel logistic regression• Receiver operating characteristic curve• Support vector machine	<ul style="list-style-type: none">• Proposed to create forest fire susceptibility map to manage forest fire management effectively and efficiently	<ul style="list-style-type: none">• Established a new logistic regression approach to control the quality of the forest fire susceptibility model• The customized LR model had a 92.2% prediction rate and overpowered other conventional algorithms		
Chen et al., [12]	Alishan Forestry Railway, Taiwan	<ul style="list-style-type: none">• Logistic regression• Receiver operating characteristic curve	<ul style="list-style-type: none">• Evaluation of landslide's environmental and hazard issues by combining geographical system and logistic regression	<ul style="list-style-type: none">• Customized logistic regression by maximizing Taiwan's geographical information system• Predicted landslides and plotted occurrence frequencies and risk levels		

Talwar et al. [17]	Japan	<ul style="list-style-type: none"> • ANN 	<ul style="list-style-type: none"> • Application of the five personality traits theoretical model to understand travel intention throughout the COVID-19 pandemic era 	<ul style="list-style-type: none"> • Extraversion feature greatly influenced leisure travel during a crisis • Openness to experience immensely affected leisure intention after a crisis
Leong et al. [51]	Malaysia	<ul style="list-style-type: none"> • Structural Equation Modeling (SEM) and ANN 	<ul style="list-style-type: none"> • Employed a service quality model to determine tourist satisfaction and loyalty in an airline company 	<ul style="list-style-type: none"> • Responsiveness, tangibles, and reliability were the most important features of tourist satisfaction • Tourist satisfaction had the strongest influence on tourist loyalty
Mikhailov & Kashevnik [46]	Saint Petersburg, Russia	<ul style="list-style-type: none"> • ANN 	<ul style="list-style-type: none"> • Evaluated driving-related features (e.g., distance, duration, speed, acceleration) to simplify the interpretation of tourist behavior 	<ul style="list-style-type: none"> • Determined the tourist approach to organizing trips • Proposed a smart digital pattern beneficial to tourism stakeholders
Claveria & Torra [14]	Catalonia, Spain	<ul style="list-style-type: none"> • Historical data analysis, autoregressive integrated moving average, self-exciting threshold autoregressions, and ANN 	<ul style="list-style-type: none"> • Aimed to increase the forecasting accuracy model by maximizing tourist behavioral data 	<ul style="list-style-type: none"> • Forecasting model of tourist arrival was more effective than an overnight stay
Law & Au [45]	Hong Kong	<ul style="list-style-type: none"> • Historical data analysis, multiple regression, naive, moving average, exponent 	<ul style="list-style-type: none"> • Prediction of Japanese tourist demands in traveling to Hong Kong 	<ul style="list-style-type: none"> • ANN outperformed traditional statistical techniques

			smoothing, and ANN			through the integrated six nodes of ANN input layer
Palmer et al. [7]	Balearic Islands, Spain	•	Historical data analysis and ANN	•	Forecast the tourist's expenditure by covering 60 different time points	• Proposed a time series tourism forecasting model to leverage one of Spain's popular tourist destinations

Table S2. Description of fifty-nine subfeatures.

Subfeature	Interpretation
ATI1	I am aware of the effects of typhoon Rai (Odette) on human lives.
ATI2	I am aware of the effects of typhoon Rai (Odette) on infrastructures.
ATI3	I am aware that the effects of typhoon Rai (Odette) are severe.
ATI4	I am aware that the effects of typhoon Rai (Odette) may last for a long time.
ATI5	I am aware that people might find it difficult to restore the old Siargao.
ATI6	I know where to access reliable information about the impacts of typhoon Rai (Odette).
ATI7	I can easily access platforms that provide reliable information about the impacts of typhoon Rai (Odette).
ATI8	I closely follow the impacts of typhoon Rai (Odette) through reliable platforms.
ATI9	The amount of available information about the impacts of typhoon Rai (Odette) is sufficient.
CM1	The government spearheaded typhoon response and recovery in Siargao.
CM2	Other organizations (private companies, nonprofit organizations, etc.) helped the government assist with the essential needs of the affected individuals in Siargao.
CM3	The government and other organizations genuinely listened to the concerns of the affected individuals in Siargao.
CM4	The government and other organizations provided relief programs to the affected individuals in Siargao.
CM5	The government and other organizations provided timely and rapid crisis responses to the affected individuals in Siargao.
CM6	The government and other organizations have ongoing infrastructure rehabilitation projects in Siargao.
CM7	The government and other organizations can finish post-typhoon recovery projects in Siargao.
HM1	Traveling to Siargao is fun.
HM2	Traveling to Siargao is exciting.
HM3	Traveling to Siargao is a new experience.
HM4	Traveling to Siargao is a once-in-a-lifetime experience.
HM5	Traveling to Siargao gives me pleasure.
HM6	Traveling to Siargao lets me experience a different lifestyle.
HM7	Traveling to Siargao makes me feel refreshed physically and mentally.
PTC1	I find it difficult to find a credible travel agency when planning a trip to Siargao.
PTC2	I find it uncomfortable to visit Siargao after typhoon Rai (Odette).
PTC3	I think there is limited access to public transportation in Siargao.
PTC4	I think my safety is not guaranteed in Siargao.
PTC5	I think my financial resources are not enough to revisit Siargao.
PTC6	I think I don't have enough time to revisit Siargao.
PTC7	I think I don't have updated information about the tourist spots in Siargao.
PTC8	I think tourism infrastructures haven't recovered from typhoon Rai (Odette) yet.

PTC9	I think no one is available to travel with me.
PTR1	I worry about recurring natural disasters in Siargao after typhoon Rai (Odette).
PTR2	I worry about safety problems in Siargao after typhoon Rai (Odette).
PTR3	I worry about poor quality of life in Siargao after typhoon Rai (Odette).
PTR4	I worry about unappealing tourist spots in Siargao after typhoon Rai (Odette).
PTR5	I worry about unsatisfactory environmental quality in Siargao after typhoon Rai (Odette).
PTR6	I worry that a trip to Siargao after typhoon Rai (Odette) will negatively affect my mental health.
PTR7	I worry that a trip to Siargao after typhoon Rai (Odette) will change how my friends think of me.
PTR8	I worry that a trip to Siargao after typhoon Rai (Odette) will be a huge financial burden than other local trips.
PTR9	I worry that a trip to Siargao after typhoon Rai (Odette) will not be worth the price.
ATT1	I think revisiting Siargao is a good idea despite the impacts of typhoon Rai (Odette).
ATT2	I think revisiting Siargao is beneficial despite the impacts of typhoon Rai (Odette).
ATT3	I think revisiting Siargao is convenient despite the impacts of typhoon Rai (Odette).
ATT4	I think revisiting Siargao can improve my social media engagement.
ATT5	I think revisiting Siargao leads to significant opportunities.
ATT6	I am extremely interested in revisiting Siargao despite the impacts of typhoon Rai (Odette).
SN1	People who are important to me think I should revisit Siargao.
SN2	People who influence my behavior think I should revisit Siargao.
SN3	People whose opinions I value prefer that I revisit Siargao.
SN4	I think I am under peer pressure to revisit Siargao.
SN5	I think society urges everyone to revisit Siargao.
SN6	I think I need to revisit Siargao if people around me do the same.
PBC1	I believe that my decision to revisit Siargao is completely up to me.
PBC2	I believe that it is acceptable to revisit Siargao despite the impacts of typhoon Rai (Odette).
PBC3	I can easily plan a trip to Siargao despite the impacts of typhoon Rai (Odette).
PBC4	I have financial resources to revisit Siargao.
PBC5	I have time to revisit Siargao.
PBC6	I am confident that I can revisit Siargao.
