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RESEARCH ARTICLE

Flood Area Prediction using a Stacked Ensemble of Tree-Based Algorithms

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ABSTRACT
Floods cause significant loss of life, property damage, and long-term socioeconomic disruptions, with over 100 annual deaths globally. This research addresses the drawbacks of the existing models, such as overfitting effects, inadequate dataset and limited study areas through the adoption of a stacked ensemble-based model. The model contained five different tree - based models namely hoeffding tree, decision tree, functional tree, reduced error pruning (REP) tree and decision stump algorithms. The model was implemented as a system using MATLAB Simulink, version 2020a on laptop with 4GB Memory. Experimental results indicate that REP Tree performed better than other four individual tree algorithms with accuracy of 98.74%, 97.81% and 97.43% for Dataset A, Dataset B and Dataset C respectively. For Dataset A, stacked ensemble model performed better than single algorithms with accuracy, precision, specificity, f1score and recall of 99.62%, 99.51%, 99.51%, 99.63% and 99.73% respectively. For Dataset B, stacked ensemble model also performed better than single algorithms with accuracy, precision, specificity, f1score and recall of 98.45%, 99.11%, 98.12%, 97.37% and 99.06% respectively. For Dataset C, stacked ensemble model performed better than single algorithms with accuracy, precision, specificity, f1score and recall of 98.75%, 99.25%, 99.64%, 99.90% and 99.24% respectively. Our model's 99.62% accuracy on Dataset A demonstrates potential for integration with real-time sensor networks, enabling scalable flood early-warning systems in vulnerable regions like Lagos and Kuala Lumpur.
Keywords: Ensemble, Flood, Stacked, Tree Based

1. Introduction

Flooding is the leading contributor of natural disasters that occurs in a situation, in which the soil are supplied with water, more than its retentive capacity [1–4]. Different factors contribute to the occurrence of flood and these factors are categorized into natural and human factors [3]. Floods are caused naturally as a result of houses built near river, insufficient or no vegetation and nature of soil [5–8] while human causes include dam overflow or dam break down and poor town planning [1], [9]. Considering and examining different types of flood, flash flood is prevalent and most fatal form due to its sudden mode of actions [10, 11]. Other types include coastal, riverine and urban flooding [12]; coastal flood is caused by storm sudden rise [13]; urban flooding occurs in cities where there is no or less proper drainage to accommodate the passage of water; riverine flooding occurs when water fills the river or stream to the extent of spreading on its bank [1]. Globally, flood occurrence results to greater than 100 deaths on average of 10 times a year [14]. Several measures can be taken in controlling and preventing different categories of floods, such measures include effective town planning system, construction of proper drainage structures, effective flood waste management system; conservation of soil along drainage areas which helps in reducing soil erosion caused by flood and also, improved ecosystem protection and planting of trees by relevant authorities [22,23]. Machine learning algorithms, artificial intelligence and decision support systems have been widely applied for the prediction of different categories of diseases and natural disasters [4, 17, 24, 25, 46, 47]. Examples of such machine learning models for the prediction of floods are Artificial Neural Networks [11, 17, 26, 27]; Support Vector Machine [11, 28, 29, 37]; decision tree [2, 30–32]. Artificial Neural Network was developed for the prediction of floods[17, 26, 27] and compared with the performance of logistic regression [26]. Different conditioning factors (CgFs) were considered in the data employed for flood prediction using Artificial Neural Network (ANN) and those conditioning factors were rainfall, aspect ratio, curvature, distance to rail, distance to water, nature of soil, roughness, slope, stream power index, topographic wetness index, temperature, elevation, land use, curve number and road [17, 26]. Authors in [26] compared the performance of artificial neural network (ANN) model with logistic regression. Artificial Neural Network performed better than logistic regression (LR) with accuracy and performance success of 76.4% and 96.4% respectively. The model developed by [17] employed parameter tuning approach to enhance its predictive performance. The novel model gives more enhanced predictive performance with testing accuracy of 96.54% and training accuracy of 98.91%. Decision tree model was developed with synthetic minority oversampling technique (SMOTE) and compared with or without dataset imbalance by [33 - 38]. The dataset has eight variables with distinct variables from the dataset employed by [17]. Those variables include wind, temperature, humidity, water level, date daily rainfall, monthly rainfall and class for the prediction of floods.

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Ensemble methods are known for improving prediction accuracy and robustness by combining prediction of multiple single models [21]. Some of the works where ensemble techniques have been applied are summarized in the Table 1. Authors in [15] Applied ensemble algorithms for the prediction of flood areas. Those ensemble algorithms are extreme gradient boosting ensemble model, adaptive boosting, boosted generalized linear model and deep boosting model and carried out on Talar Watershed, Mazandaran Province, Iran study area.. The experimental results showed that all the applied models are efficient for the flood hazards prediction with area under curve of 0.91, 0.88, 0.89 and 0.87 for deep boosting model, boosted generated linear model, adaboost and extreme gradient boosting ensemble model respectively. Considering other evaluation metrics, deep boosting model outperformed the performances of other ensemble models with sensitivity, specificity, positive predictive value (PPV) and NPV of 0.88, 0.86, 0.88, 0.86 and 0.86 respectively. Stacked ensemble of decision tree classifier, K-nearest neighbor, binary logistic regression and support vector classifier were applied by [18] flood areas prediction. Ensemble model outperformed other individual classifiers with accuracy and standard deviation of 93.3% and 0.098 respectively [18]. Random Forest with Bagged CART, XG Boost, Stochastic Gradient Boosting were applied for the prediction of floods by [19] and with AdaBoost, Gradient Boosting, Random Forest and Random Forest – Gradient Boosting by [20]. Random Forest performed better than other ensemble models in both works [19, 20] with accuracy of 91% for the work of [19] and 83% for the work of [20]. Authors in [4] compared and applied four different ensemble models. The experimental results showed that the performance of Adaptive Neuro-fuzzy inference system (ANFIS) ensemble with genetic algorithm exceeded the performances of other three models with highest success rate area under curve of 0.922, prediction rate AUC of 0.924 and the accuracy of training and validation with 0.886 and 0.883 respectively. Authors in [11] developed a novel model that combined Bayesian belief network model with extreme learning machine and back propagation (BP) structure optimized by a genetic algorithm (GA) named GA-BN-NN model. The experimental results indicated that the novel model (GA-BN-NN) model has better goodness-of-fit with prediction accuracy of 0.966. Some of the drawbacks of these existing single and ensemble models are overfitting effects, inadequate datasets and limited study areas, hence this work addresses these drawbacks by developing stacked ensemble models for improving predictive capacity, presentation of three different Datasets in three different study areas. Other sections are section 2, section 3 and section 4 which depict materials and method, results and discussion and conclusion respectively.

Table 1. Related Ensemble Models and Current Works

Author	Focus	ML algorithm used	Source of dataset	Result
[15]	Flood hazard areas prediction using different boosting ensemble models	Adaptive Boosting, Boosted Generalized Linear Model, Extreme Gradient Boosting and Deep Boost (DB)	Talar Watershed, Mazandaran Province, Iran	DB has most efficient Area Under Curve (AUC) with 91%, compared with other boosting ensemble models.
[16]	Adoption of ensemble machine learning model for flood prediction	Bagging, Random Subspace, Random Forest, Support Vector Machine and Artificial Neural Network (ANN)	Teesta sub catchment, Northern region of Bangladesh	Bagging Model has the maximum performance with Area Under Curve (AUC) of 87.3%
[18]	Compare performance of single classifiers and stacked ensemble model for flood prediction	Stacked ensemble of K-Nearest Neighbors (KNN), Support Vector Classifier (SVC), Decision Tree (DT), Binary Logistic Regression,	Kerala dataset of Southern region of India.	Stacked ensemble model has accuracy of 93.3%
[19]	Adoption of ensemble model for the prediction of floods	Bagged CART, Random Forest, XG Boost, Stochastic Gradient Boosting	36 States of Nigeria and Federal Capital Territory	Random Forest and XG Boost performed better than other models with the same accuracy of 91%.
[20]	Flood prediction using different ensemble models.	Random Forest, AdaBoost, Random Forest – Gradient Boosting and Gradient Boosting	Oum Er Rbia watershed, located in the Khenifra Province	Random Forest performed better than other ensemble models with accuracy of 83%
[48]	Ensemble of ANN for Urban flood prediction	Ensemble ANN model	Chinese City of Macao	The model has Root Mean Square (RMS) and coefficient of determination of 0.20 and 0.96 respectively
[49]	Flood prediction using google earth engine and remote sensing	Gradient boosting ensemble, adaboost and gradient boostung	Oum Er Rbia watershed, Morocco	Gradient boosting ensemble has accuracy of 0.96
Current work	Stacked ensemble of tree-based algorithms for the prediction of flood areas.	Stacked Ensemble of Decision Stump, Hoeffding Tree, Functional Tree, Decision Tree and Reduced Error Pruning Tree	Dataset A: NiMeT/NIHSA: Nigeria, Dataset B: USGS/DEM/NASA and Dataset C: Jabatan Meteorologi Malaysia Dataset, Kuala Lumpur Area, Malaysia	Stacked ensemble of trees performed better than single classifiers with accuracy of 99.62%, 98.45% and 98.75% for Datasets A, B and C respectively.

2. Materials and Methods

A stacked ensemble model was developed with MATLAB (R2020a version) platform. MATLAB R2020a version was installed on laptop computer hardware with two Intel Celeron (N3060) processors each having 1.60 GHz speed and 4GB Memory. Wrapper feature selection techniques integrated with particle swarm optimization algorithm (PSO) were employed for the selection of features on the Datasets. Tree-based classifiers namely Functional Tree (FT), Hoeffding Tree (HT), Decision tree (DT), Decision Stump (DS) and REP tree as depicted in the Figure 1 were selected as base classifiers. Tree based algorithms were selected based on their performances in the preliminary evaluation and have been known for better accuracy, stability and ease of interpretation. Also, fine-tuned particle swarm optimization algorithm was employed as a meta learner for stacked ensemble model.

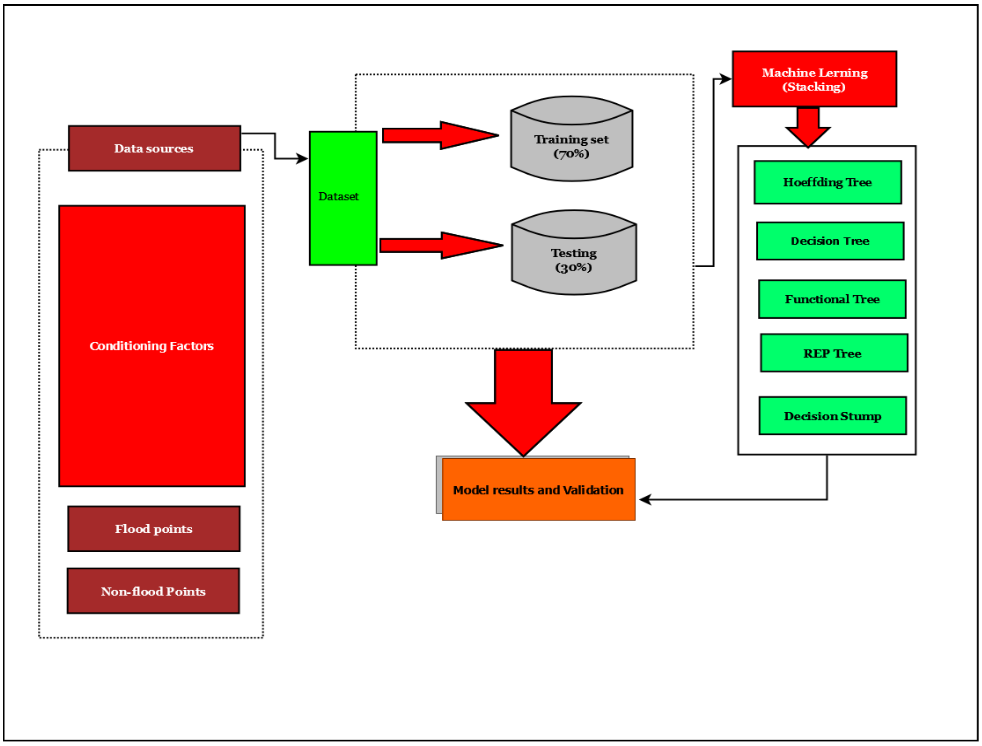


Figure 1. Flowchart of model developed for flood prediction

2.1 Data Acquisition and Data Sources

Three distinct sets of dataset were employed for this research; the first dataset (NiMeT/ NIHSA Dataset) was obtained from two different organizations in Nigeria, namely Nigerian Meteorological Agency (NiMeT) and Nigerian Hydrological Service Agency (NIHSA); the second dataset (USGS/DEM/NASA dataset) is also Nigeria dataset and was collected from different sources such as United State Geological Survey Earth Explorer, digital elevation model (DEM), Nigerian Aeronautics and Space Administration (NASA) and lastly, the third dataset (JMM dataset) was obtained from Jabatan Meteorologi Malaysia. The first, second and third Datasets are labelled Dataset A, Dataset B and Dataset C respectively.

2.1.1 NiMeT/NIHSA Flood Dataset

NiMeT/NiHSA Flood dataset was sourced from Eti - Osa area of Lagos State, Nigeria for five (5) years from January 2017 to December 2021 consisting of 1826 instances with 6 independent variables or input and 1 dependent variable or output. The attributes of Dataset A were examined with different characteristics as depicted in Table 2. The input features are date, water level, daily rainfall, temperature, wind and humidity while flood class which can be flood (1) or No flood (0). This Dataset A is related to Dataset employed for the work of [34]. The Dataset generally follows the principle depicted in the Equation 1.

$$\text{Dataset (A)} = (p_1, k_1), (p_2, k_2), (p_3, k_3)\ldots\ldots\ldots\ldots (p_n, k_n) \quad (1)$$

Where p_1 Ɛ P, is the i^{th} independent variable or input and q_1 Ɛ K, the corresponding dependent variable or output. $P = \mathbb{R}^d$, where $p_1 = (p_{i1}, p_{i2}, p_{i3}\ldots\ldots p_{id})$ is a d-dimensional vector or instance. Figure 2 depicts Pearson's correlation plot of the input and target variables for Dataset A. There is no strong correlation between the attributes. The major strong correlation exists between the daily rainfall (RF Daily) attribute and the flood (class) with 0.82. Therefore, there is high degree of association between the attribute, daily rainfall and the output, flood (class). Considering the attributes of the dataset in the Etiosa on the map, Figure 3 (A), 3(B), 3 (C), 3(D), 3(E) illustrate contexture view of humidity, daily rainfall, temperature, water level and wind speed respectively for the study area (Etiosa).

Table 2: Statistics of attributes of the Dataset A

Attribute	Min	Max.	Mean	Standard Deviation	25th Percentile	50th Percentile	75th Percentile	90th Percentile
Water Level (cm)	40	360	222	59.22	190	230	270	290
Rainfall Daily (mm)	0	136	4.07	12.20	0	0	0.28	11.90
Temperature (^{0}C)	11.85	31.35	26.95	1.87	25.75	26.75	28.35	29.40
Humidity (%)	19	99	80.22	7.96	77	81	85	88.5
Wind (m/s)	0.5	11.0	3.90	1.40	3	3.72	4.63	5.75

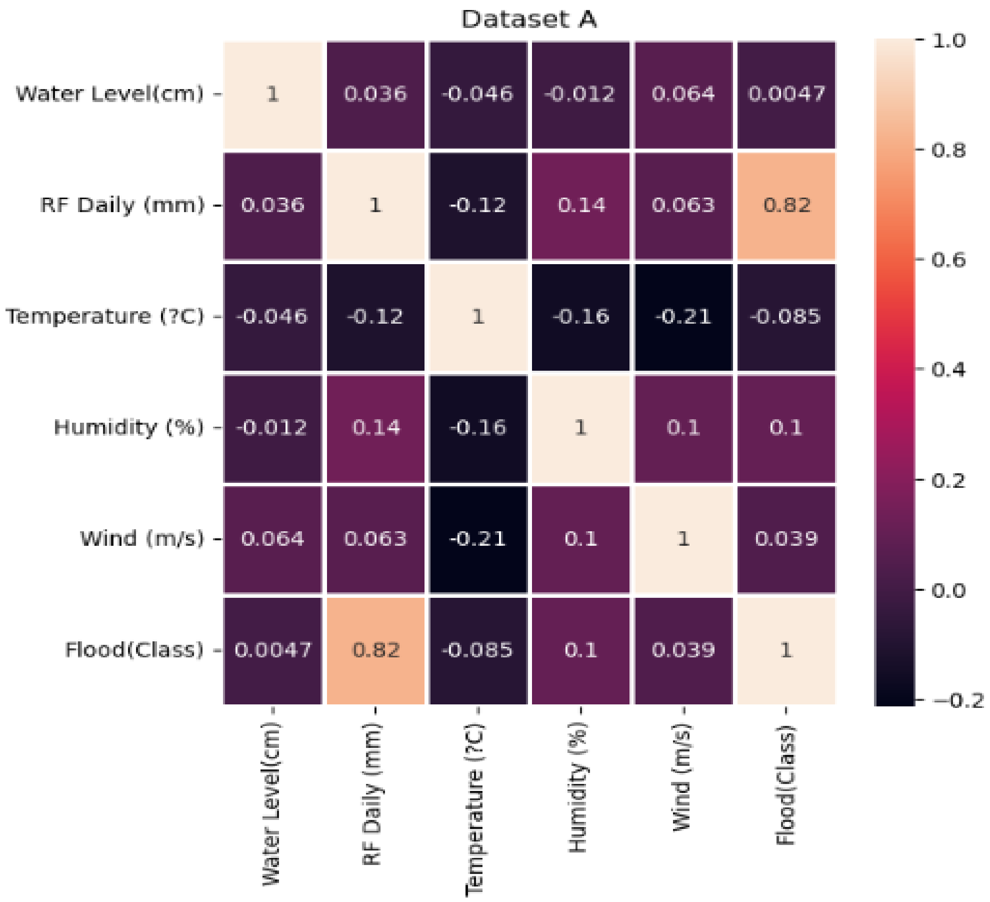


Figure 2. Pearson correlation's plot of the input and target variables for Dataset A

2.1.2 USGS/DEM/NASA Dataset

USGS/DEM/NASA Dataset was sourced majorly from United State Geological Survey Earth Explorer, digital elevation model (DEM), Nigerian Aeronautics and Space Administration (NASA). The dataset has 1530 samples with sixteen conditioning factors (CgFs). Those conditioning factors are rainfall, temperature, land cover, soil type, slope, aspect, elevation, road distance, river distance, roughness, curve number, stream power index, curvature, Topographic Wetness Index (TWI) and distance to trail. This Dataset B generally follows the form as illustrated in the Equation 1. The summary and some of characteristics of this Dataset B are elucidated in the Table 3.

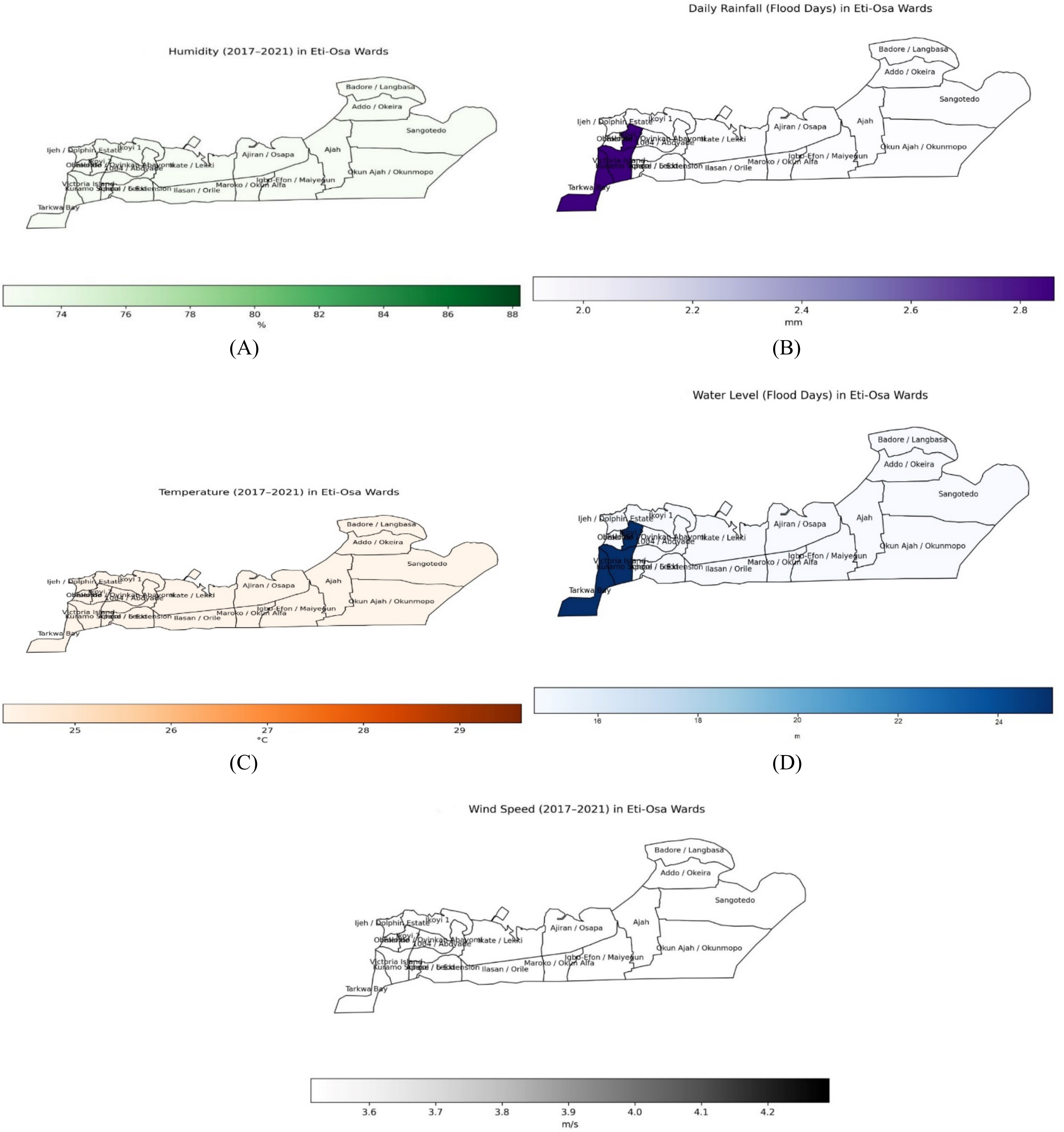


Figure 3. Contexture view of the attributes of Dataset A in the specified study area (Eti Osa): (A) Humidity; (B) Daily Rainfall; (C) Temperature; (D) Water Level; (E) Wind Speed

Figure 4 shows the Pearson's correlation plot between the input and output variables. There is no strong correlation between the input and output variables. The highest correlation is between the elevation and rainfall variables with a Pearson's correlation value of 0.6. Considering the attributes of the dataset in the Niger-Benue axis on the Nigeria map, Figure 5 (F), 5(G), 5 (H), 5(I), 5(J), 5(K), 5(L), 5(M) and 5(N) illustrate contexture view of Niger-Benue axis, states within the Niger-Benue axis, elevation, water level, soil type, slope, roughness, rainfall and land cover respectively.

Table 3: Statistics of attributes of the Dataset B

Attribute	Min.	Max.	Mean	Standard Deviation	25th Percentile	50th Percentile	75th Percentile	90th Percentile
Slope	0	89.99	89.44	5.62	89.84	89.93	89.96	89.98
Soil Type	1	117	27.20	33.66	1.00	1.00	54.00	73.00
Elevation	-3	1595	309.60	218.39	154	297	433	564.30
Land Cover	10	90	25.42	19.76	10	20	30	50
Roughness	0	553	34.38	51.17	11	22	36	68
Rainfall	587	2647	1278	440	901	1162	1544	1891
Water	0	1.89	0.38	0.29	0.15	0.31	0.56	0.80
Road	0	0.64	0.04	0.05	0	0.02	0.05	0.09
Rail	0	3.07	0.63	0.59	0.18	0.48	0.90	1.49
Curvature	-4080	3360	-6.15	285.22	-82.83	0	85.87	219.19
Aspect	1.39	360	181.50	104.34	90	180	270	330.37
Temperature	0	33.41	29.05	4.48	28.00	29.71	30.92	32
TWI	-22.65	-1.41	-15.93	2.09	-16.06	-16.06	-16.06	-14.54
SPI	-47.33	5.09	-0.24	1.44	-0.12	-0.05	-0.03	0
Curve Number	0	100	78.73	10.87	71	81	83	83

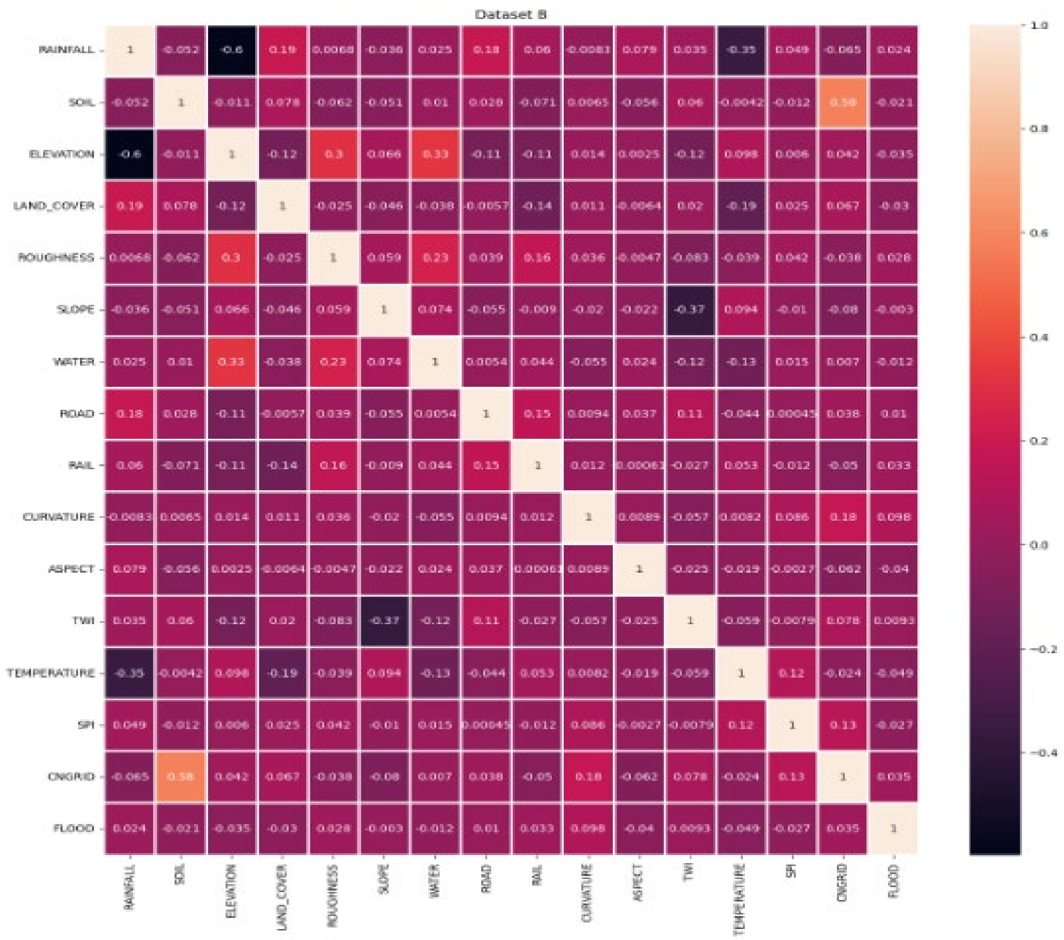
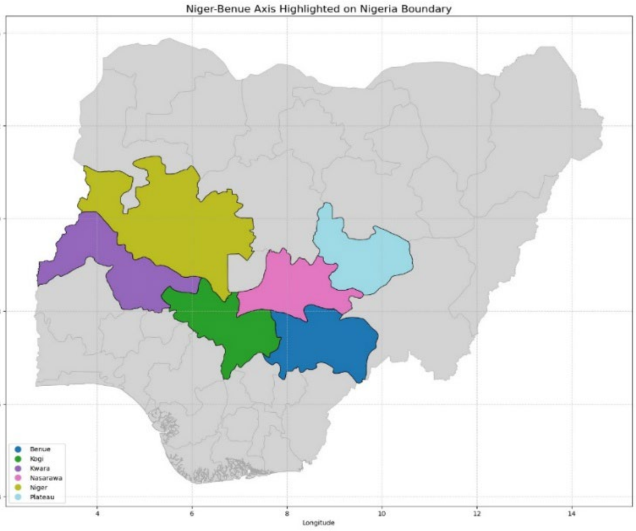
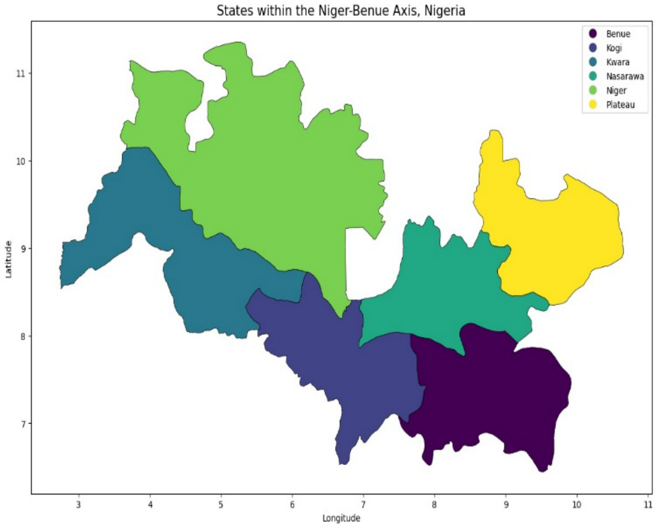


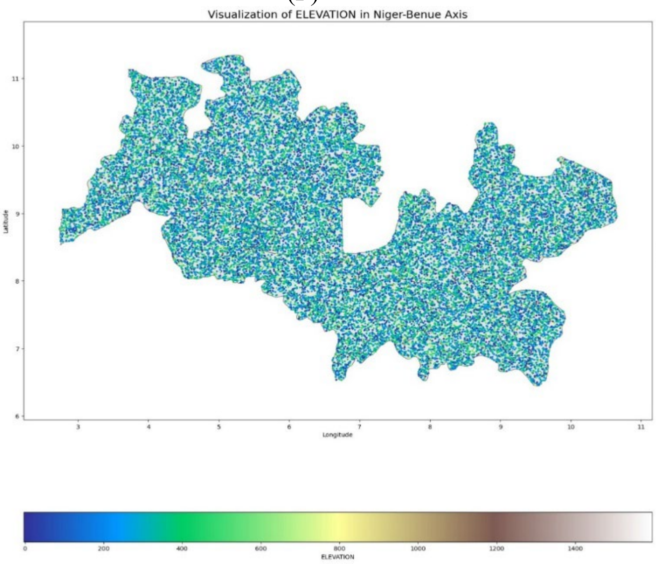
Figure 4: Pearson correlation’s plot of the input and target variables for Dataset B


Niger-Benue Axis Highlighted on Nigeria Boundary
Latitude
Longitude
Benue
Kogi
Kwara
Nasarawa
Niger
Plateau

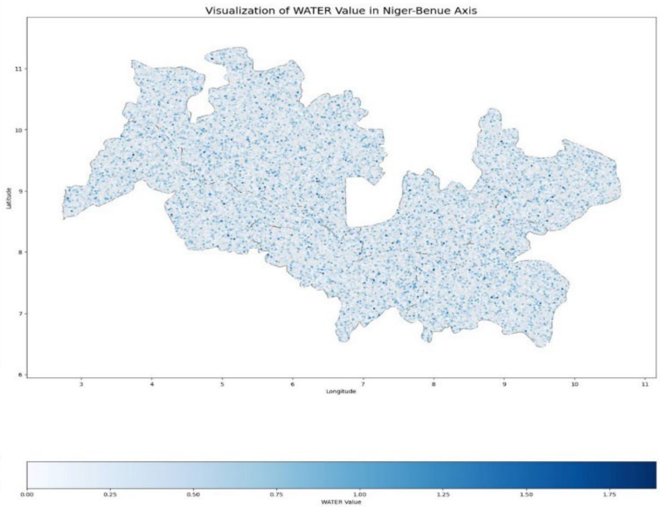
(F)


States within the Niger-Benue Axis, Nigeria
Latitude
Longitude
Benue
Kogi
Kwara
Nasarawa
Niger
Plateau

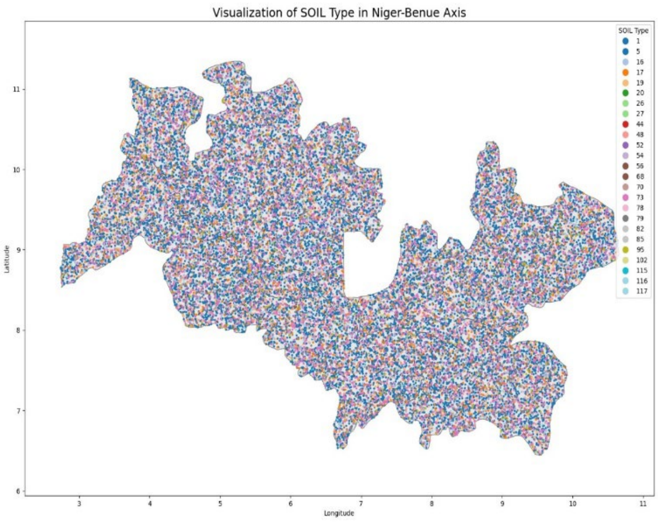
(G)


Visualization of ELEVATION in Niger-Benue Axis
Latitude
Longitude
ELEVATION

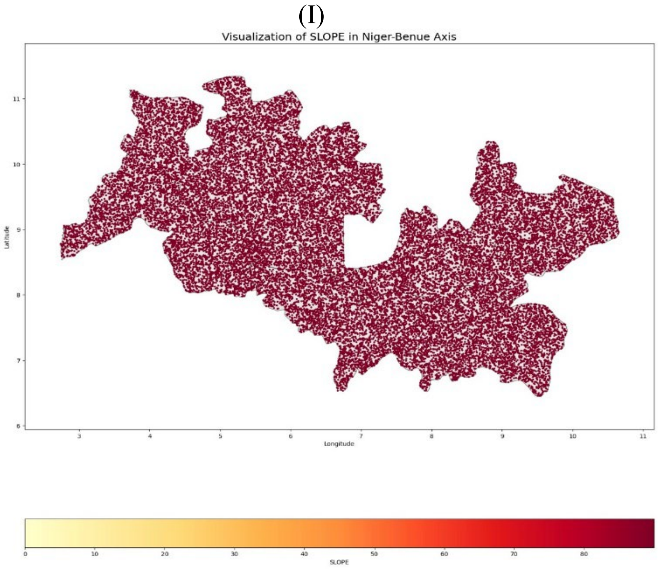
(H)


Visualization of WATER Value in Niger-Benue Axis
Latitude
Longitude
WATER Value

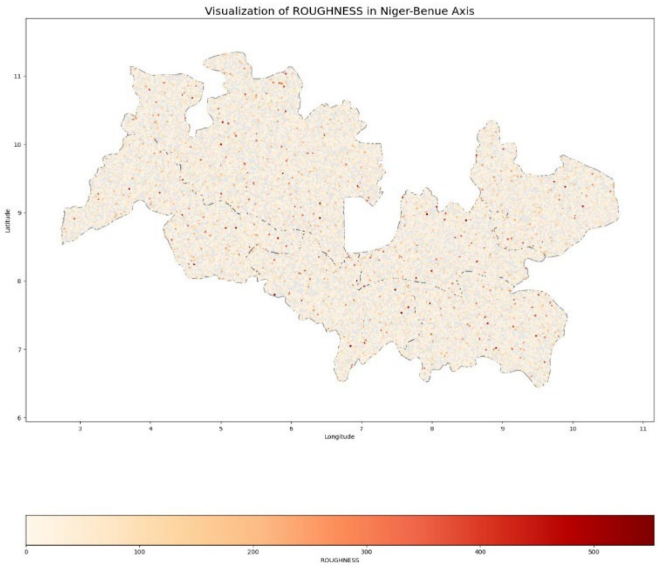
(I)

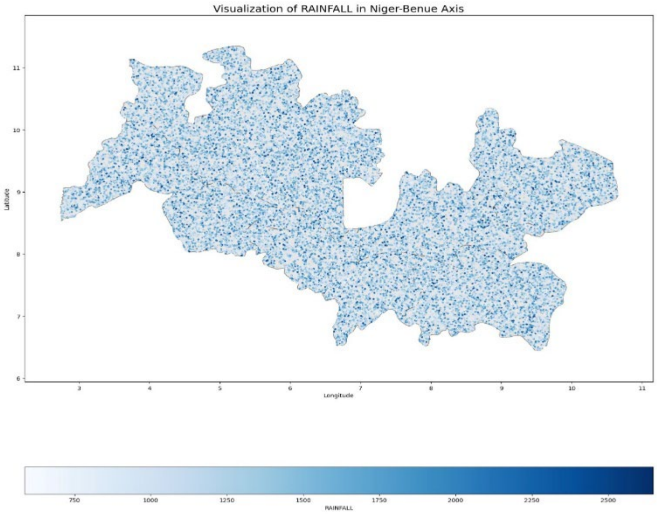

Visualization of SOIL Type in Niger-Benue Axis
Latitude
Longitude
SOIL Type

(J)

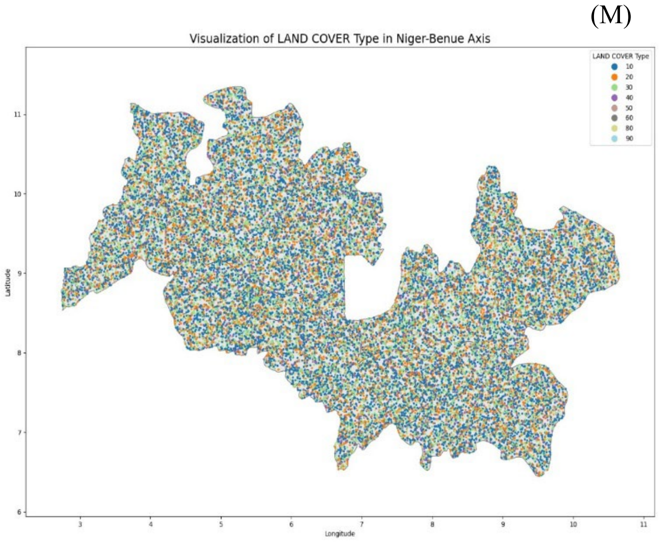

Visualization of SLOPE in Niger-Benue Axis
Latitude
Longitude
SLOPE

(K)





(L) (M)



(N)

Figure 5. Contexture view of the attributes of Dataset B in the specified study area (Niger – Benue Axis, Nigeria): (E) Niger-Benue Axis on Nigeria boundary; (G) States within the Niger -Benue Axis, Nigeria; (H) Elevation; (I) Water Level; (J) Soil Type; (K) Slope; (L) Roughness; (M) Rainfall; (N) Landcover.

2.1.3 Jabatan Meteorologi Malaysia Dataset

Jabatan Meteorologi Malaysia Dataset is the dataset sourced for five years between 2014 – 2019 in Kuala Lumpur area of Malaysia and contained 1823 instances with date, temperature, rainfall (daily), humidity, temperature, rainfall (monthly), wind and class (either flood or no flood) attributes. This Dataset C generally follows the form as illustrated in the Equation 1. The summary and some characteristics of this Dataset C are elucidated in the Table 3. Figure 6 illustrates the Pearson's correlation plot of the input and output variables. There is no strong correlation between the input and output variables. The highest correlation is between the daily rainfall (RF Daily) attribute and class variable with a Pearson's correlation value of 0.47. Considering the attributes of the dataset in the Kuala Lumpur, Malaysia, Figure 7 (O), 7(P), 7 (Q), 7(R), 7(S) and 7(T) illustrate contexture view of wind, temperature, monthly rainfall, daily rainfall, water level and humidity of the specified area respectively.

Table 3: Statistics of attributes of the Dataset C

Attribute	Min.	Max.	Mean	Standard Deviation	25th Percentile	50th Percentile	75th Percentile	90th Percentile
Water Level (cm)	1703	2543	1898	194	1796	1863	1930	2084
Rainfall Monthly (mm)	1053	1275	1134	69	1071	1121	1173	1275
Rainfall Daily(mm)	0	102	13.12	22.03	0	6	12	45
Temperature (^{0}C)	23.2	26.7	25.04	0.85	24.3	24.9	26	26.2
Humidity (%)	80.5	95.9	87.71	4.08	84.1	84.1	91.2	92.8
Wind (m/s)	0.4	1.4	0.85	0.19	0.7	0.87	1	1

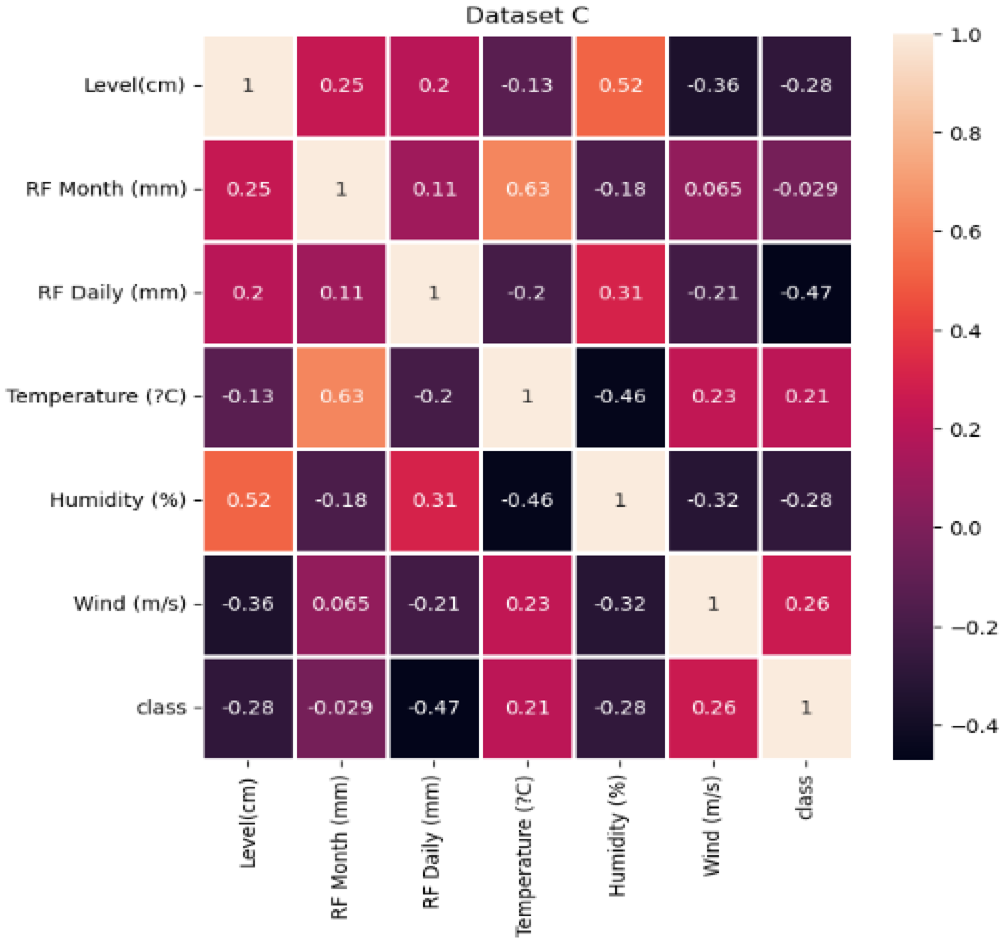
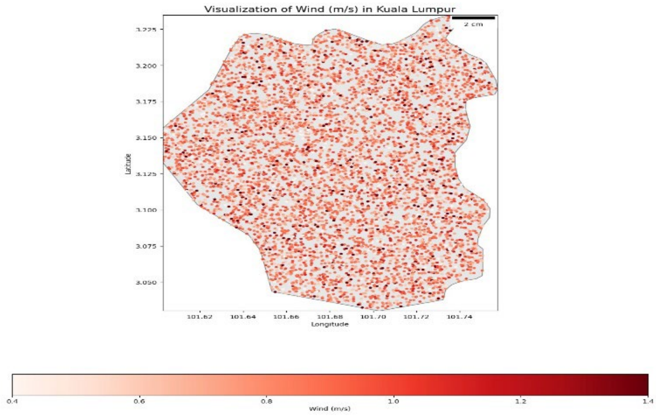
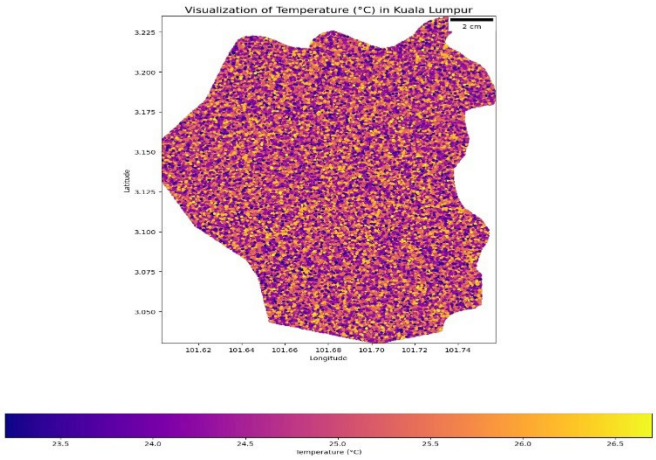


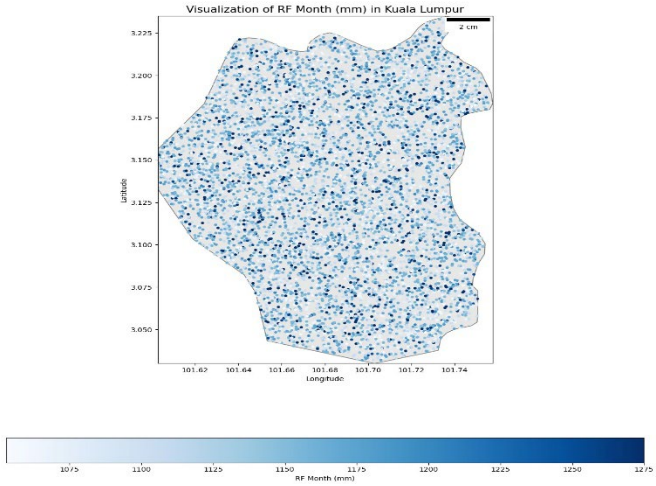
Figure 6: Pearson correlation's plot of the input and target variables for Dataset C



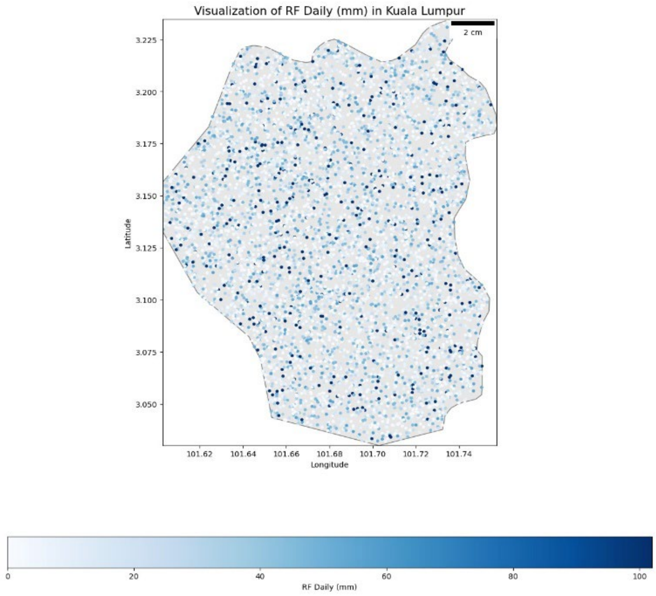
(O)



(P)



(Q)



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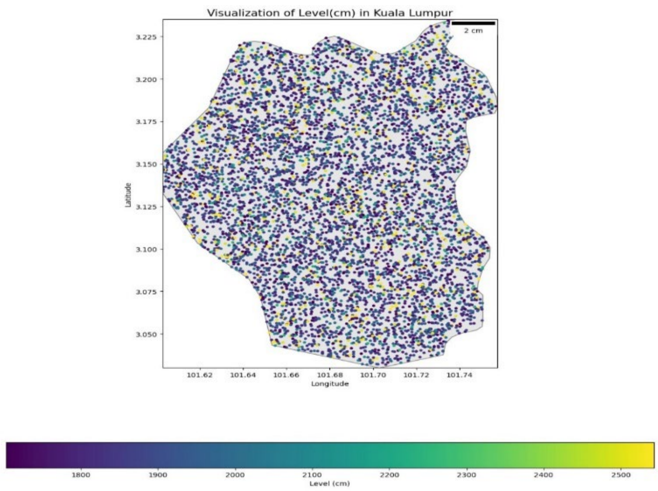
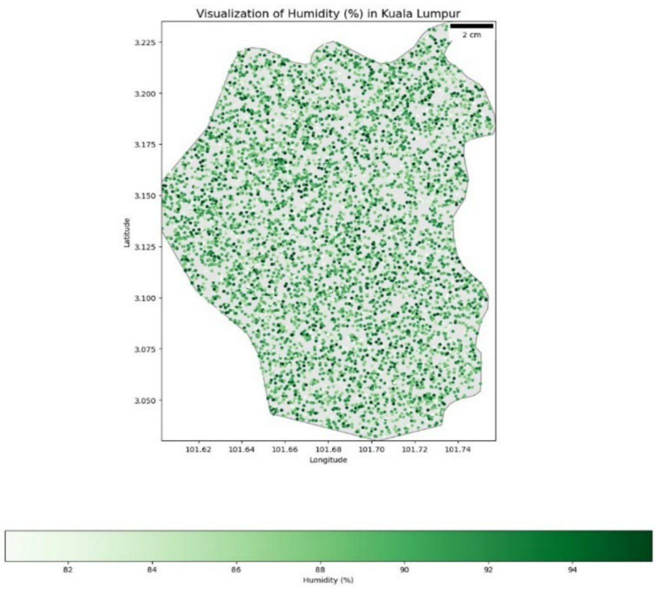


(S)



(T)

Figure 7. Contexture view of the attributes of Dataset C in the specified study area (Kuala Lumpur): (O) Wind; (P) Temperature; (Q) Monthly Rainfall; (R) Daily Rainfall; (S) Water Level; (T) Humidity

2.2 Wrapper Feature Selection

Wrapper method of feature selection was employed for the selection of the features in three datasets using particle swarm optimization algorithm to improve the predictive performance of the model. In this case, features are selected iteratively based on particle swarm optimization machine learning algorithm. Particle swarm optimization (PSO) selects features based on this solution vector which represents feature subset of as depicted in the Equations 2, 3 and 4.

$$x = [x_1, x_2, x_3, \ldots\ldots\ldots x_d];\ x_i \in [0,1] \quad (2)$$

Where d represents the number of features in a given dataset. Considering using the threshold of 0.5 to ascertain tendency of selecting feature (s) and this is given as:

$$x_i = \begin{cases} 1, \\ 0, \end{cases} \text{if } x_i > 0.5, Otherwise \quad (3)$$

Optimization of the following function occurs,

$$f(x) = \propto \times\ (1 - P) \times (1 - \propto) \times \frac{N_{selected}}{N_{features}} \quad (4)$$

Where $\propto$ determines trade-off between classifier performance and selected features with respect to the total of all features.

2.3 Tree Based Machine Learning Algorithms

The developed model (stacked ensemble model) consists of five different tree-based algorithms (base classifiers). The algorithms were Hoeffding Tree, Decision Tree, Functional Tree, REP Tree and Decision Stump. Generally, Tree based algorithms are predictive algorithms with high accuracy, stability, ease of interpretation and also map non-linear relationship well. Tree based model trees also require less effort for data preparation during pre – processing, normalization and does not require scaling of data as well.

2.3.1 Hoeffding Tree Algorithm

A very fast decision tree algorithm for streaming data instead of the reuse of instances was proposed by [39]. The main problem of decision tree is the need to reuse instances to compute the best splitting features. The estimation confidence interval of the entropy at a node on a basis of bond is

$$\epsilon = \sqrt{\frac{R^2\, In^1/_\delta}{2n}} \quad (5)$$

WhereR = range of randomvariable

$\delta =$ is the probability of estimate not being within ϵ of its expected value,δ is the desired probability of the estimate *not* being within ϵ of its expected value, and *n* is the number of examples collected at the node.

Algorithm 1: Hoeffding Tree Listing Algorithm [39]

Hoeffding Tree Algorithm (Stream,δ)
Input: a stream of labelled examples, confidence parameter δ
Let HT be a leaf with a single leaf (root)
init counts n_{ijk} at root
for each example (x, y) in Stream
do HTGROW $(x, y), HT, \delta$
HTGROW $((x, y), HT, \delta)$
sort (x, y) to $leaf\ l\ using\ HT$
update counts $n_{ijk}\ at\ leaf\ l$
if examples seen so far at *l* are not all of the same class
then
Compute G for each attribute
if G (attribute) - G (Second best)> $\sqrt{\frac{R^2 in\ ^1/_\delta}{2n}}$
then
split leaf on best attribute
for each branch
do start new leaf and initialize counts

2.3.2 Functional Tree Algorithm

Functional trees can be categorized as the generalization of multivariate trees. Multivariate decision nodes are built when growing the tree, while functional trees are developed when pruning the trees [40]. Functional tree has the merit of using logistic regression function to isolate the internal nodes and prediction at the leaves [41]. Functional tree has regression model (RM) which is used in internal nodes and leaves [42].

Algorithm 2: Functional Tree Listing Algorithm [41]

Functional Tree Algorithm (Dataset, Constructor)
If Stop Criterion (Dataset)
Return a Leaf Node with a constant value
Construct a model $\emptyset$ using constructor
For each example $\vec{x} \in$ DataSet
Compute $\hat{y} = \emptyset(\vec{x})$
Extend $\vec{x}$ with new attributes $\hat{y}$
Select the attributes of original as well as of newly constructed
Attributes that maximize some merit-function
For each partition i of the Dataset using the selected attribute
$\mathrm{Tree_i} = \mathrm{GrowTree}\ (\mathrm{Dataset_i}, \mathrm{Constructor})$
Return a Tree, as functional node based on selected attribute
Containing the $\emptyset\ model$, and descendant $Tree_i$
End Function
.

2.3.3 Decision Stump Algorithm

Decision Stump Algorithm makes use of only one attribute for splitting and discrete attributes, simply consist of single interior node (root has only leaves as successor nodes). Tree becomes more complex for numeric attributes [43]

Algorithm 3: Decision Stump Listing Algorithm [43]

A decision stump is defined by
$f(X|j,t) := \begin{cases} +1 & x^{(j)>t} \\ -1 & \text{otherwise} \end{cases}$
$where\ j \in \{1, \ldots\ldots, \ldots d\}$ indexes an axis in $\mathscr{R}^{d}$.
Weighted data
Training data $(\widetilde{X_1}, \widetilde{Y_1})$…………., $(\widetilde{X_n}, \widetilde{Y_n})$.
With each data point $\widetilde{X_i}$, we associate a weight $w_i \geq 0$
Training on weighted data
Minimize the weighted misclassification error:
$(j^*,t^*) := arg^{min}_{j,t} \frac{\sum_{i=1}^{n} w_i \amalg\{\widetilde{y_1} \neq f(\widetilde{X_i}|j,\ t)\}}{\sum_{i=1}^{n} w_i}$

2.3.4 Reduced Error Pruning Tree Algorithm (REP Tree Algorithm)

Reduced Error Pruning (REP) tree adopts regression tree logic and creates diverse trees in different iterations. The end point of a regression tree is predicted function value rather than predicted classification [44]. In pruning tree, mean square error is measured on the predictions made by the trees. The sum of mean square errors is given and shown in the Equations 6, 7 and 8.

$$S = \sum_{E \in leaves(RT)} \sum_{i \in E} (Y_i - N_T)^2 \quad (6)$$

Where N_T is expressed as,

$$N_T = \frac{1}{P_C} \sum_{i \in T} Y_i; \quad (7)$$

Hence,

$$S = \sum_{E \in leaves(RT)} P_c V_c; \quad (8)$$

Where, $N_T =$ Predictions for leaf N; $\mathrm{V_c} =$ leaf within variance and P_c is the class prediction.

2.3.5 Decision Tree Algorithm

Decision tree is one of the classification techniques in data mining method that is employed for decision support systems and machine learning processes [41, 43]. The basic structure of decision tree is shown in the Figure 8

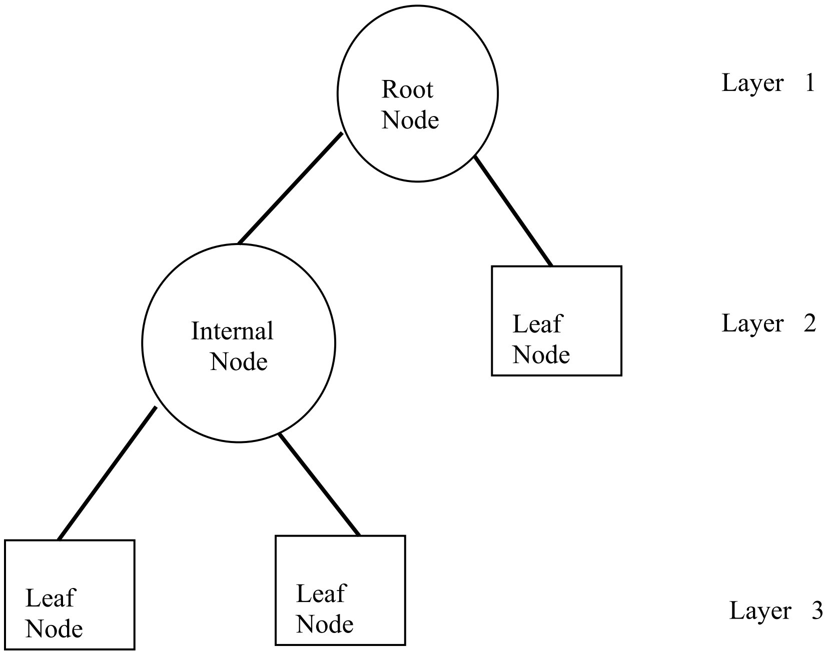


Figure 8. Basic Structure of Decision Tree [45]

Algorithm 3: Decision Tree Listing Algorithm [43]

```
Decision Tree Learner (examples, features)
if all examples are in the same class then
      return the class label.
else if no features left then
      return the majority decision.
 else if no examples left then
        return the majority decision at the parent node.
 else choose a feature f.
      for each value v of feature f do
      build edge with label v.
      build sub-tree using examples where the value
     of f is v
```

2.4 Implementation of Stacked Ensemble Model

The tree-based classifiers (base classifiers) employed are functional tree (FT), hoeffding tree (HT), decision tree (DT), decision stump (DS) and REP tree as depicted in the Figure 9. Fine Tuned particle swarm optimization (PSO) algorithm was used as Meta classifier. Parameters of all the tree based and particle swarm optimization algorithms were set to achieve optimal results as shown in Table 4 and Table 5. Equations 11 and 12 indicate ensemble of the tree-based algorithms

Table 4: Parameter settings for Particle Swarm Optimization Algorithm

Particle Swarm Optimization Algorithm

lb = 0;
ub = 1;
thres = 0.5;
c1 = 2; % cognitive factor
c2 = 2; % social factor
w = 0.9; % inertia weight
Vmax = (ub - lb) / 2; % Maximum velocity

Table 5: Parameter settings for Tree Based Algorithms

Each Tree Based Algorithms is set with:
Min Leaf Size = 1; Min Parent Size = 2; Num Variables To Sample = 'all'; Score Transform = 'none'; Prune Criterion= ‘error’; Split Criterion = 'deviance‘

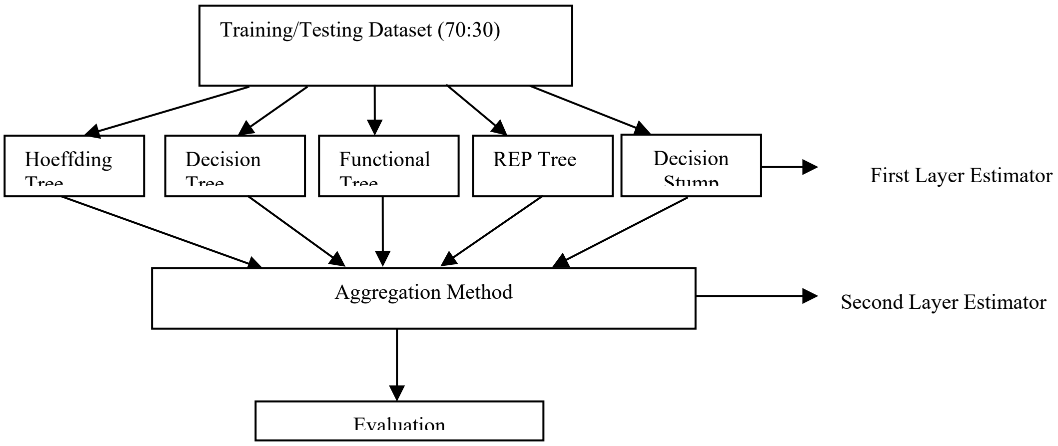


Figure 9. Visualization of Developed Stacked Ensemble Model

$$R_{leaf} = \prod_{m=0}^{k-1} \frac{n_t - n_{Label(t),t} + \lambda(j-1) + m}{n_t + \lambda J + m} \tag{9}$$

$$R_{tree} = \sum_{c \in Children(t)} \frac{n_c + \eta}{n_t + \eta K_t} \tag{10}$$

$$R_{tree} < R_{leaf} - \in \left(\text{or } \sqrt[k]{R_{leaf}}\right) < \sqrt[k]{R_{leaf}} - \in)$$

$$D_{t+1}(i) = \frac{D_t(i) esp(-\alpha_t y_i h_t(x_i))}{Z_t} \tag{11}$$

$$z_t = \sum_{i=1}^{m} D_t(i) esp(-\alpha_t y_i h_t(x_i))$$

$$\text{Ensemble Model } (x) = sign\left(\sum_t^T \propto_t h_t\right) \tag{12}$$

Where Zt = Base classifier
H_t = Meta Classifer
D_t. = Train base learner using distribution
Z_t = Normalization factor
S = Dataset; d_1 = Machine learning algorithms; t= Base level classifier

2.5 Evaluation of the Developed Model

The performance of the developed prediction model was determined based on accuracy, specificity, f1-score, recall and precision. The statistical formulae as defined in the Table 6; where TP = True Positive, TN= True Negative, FN = False Negative, FP = False Positive.

3. Results and Discussion

Experiments were conducted on the three datasets (A, B and C) using the five tree algorithms individually as well as in a stacked ensemble from the developed model. A stratified percentage split evaluation methodology was employed in all experiments with 70% of the data for training and 30% for testing. Experimental results indicate that REP Tree performed better than other four individual tree algorithms with accuracy of 98.74%, 97.81% and 97.43% for Dataset A, Dataset B and Dataset C, respectively. For Dataset A, stacked ensemble model outperformed individual algorithms with accuracy, precision, specificity, f1score and recall of 99.62%, 99.51%, 99.51%, 99.63% and 99.73% respectively. For Dataset B, the performance of stacked ensemble model exceeded the performances of individual algorithms with accuracy, precision, specificity, f1score and recall of 98.45%, 99.11%, 98.12%, 97.37% and 99.06% respectively. For Dataset C, the performance of stacked ensemble models is better than the performances of individual algorithms with accuracy, precision, specificity, f1score and recall of 98.75%, 99.25%, 99.64%, 99.90% and 99.24% respectively. Furthermore, the results of the area under curve (AUC) for the models indicate that tree-based algorithms are suitable for the effective classification of flood occurrence as shown in the Figure 12. Stacked ensemble model has area under curve of 0.99. Figure 10 and Figure 11 present visualization of dataset loading process and experimental results obtained from the prediction model.

Table 6: Evaluation definition and formula

Metrics	Definition	Formula
Accuracy (Acc)	The percentage of the correctly classified instances i.e. accuracy, is obtained by subtracting the percentage of incorrectly classified instances from 100.	$\text{Acc} = \frac{\text{Tp} + \text{TN}}{\text{TP} + \text{TN} + \text{FN} + \text{FP}} \times \frac{100}{1}\%$
Precision	Precision is calculated as the number of true positives divided by the total number of true positives and false positives.	$\text{Precision} = \frac{\text{TP}}{(\text{TP}) + \text{FP}} \times 100\%$
Specificity	Specificity is the metric that evaluates a model's ability to predict true negative of each available category. Specificity can be defined mathematically as the ratio of true negative with respect to the sum of true negative and false positive	$\text{Specificity} = \frac{(\text{TN})}{(\text{TN}) + (\text{FP})} \times 100\%$
Recall	Recall quantifies the actual proportions of positive label that is identified as positive. Recall can be mathematically represented as the ratio of true positive with respect to the sum of true positive (TP) and false negative (FN).	$\text{Recall} = \frac{(\text{TP})}{(\text{TP}) + (\text{FN})} \times 100\%$
F1-score	F1-score is the measure of model's accuracy on a given dataset.	$\text{F1} - \text{score} = \frac{2 \times (\text{precison} \times \text{Recall})}{(\text{Precison} + \text{Recall})} \times 100\%$

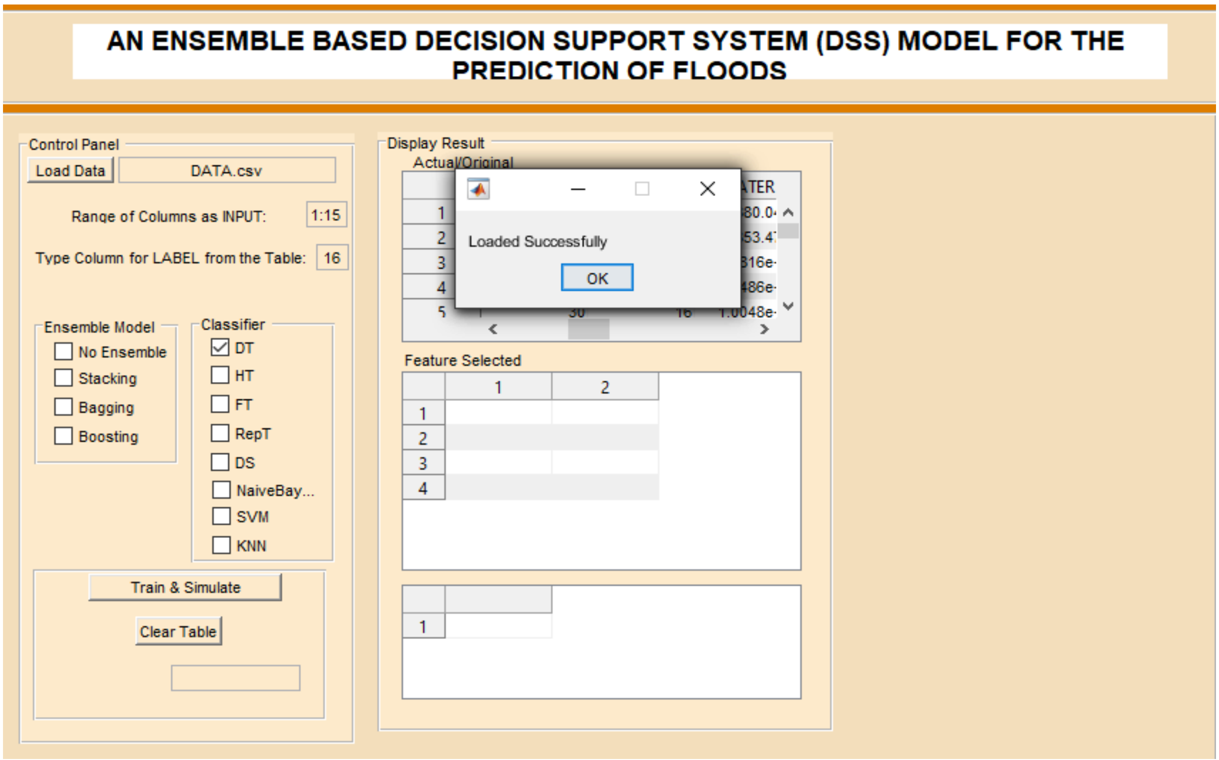


Figure 10. Visualization of the dataset loading process into the prediction model

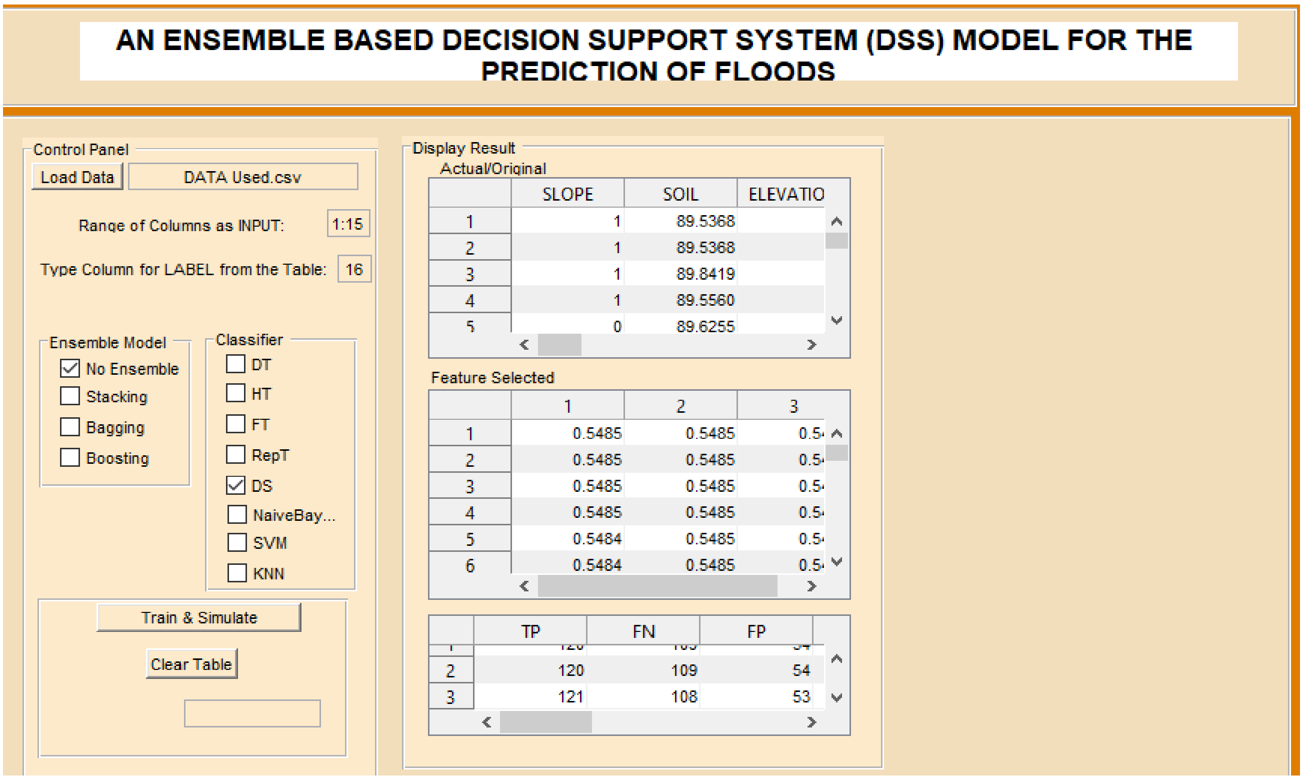


Figure 11. Visualization of the results obtained from the prediction model

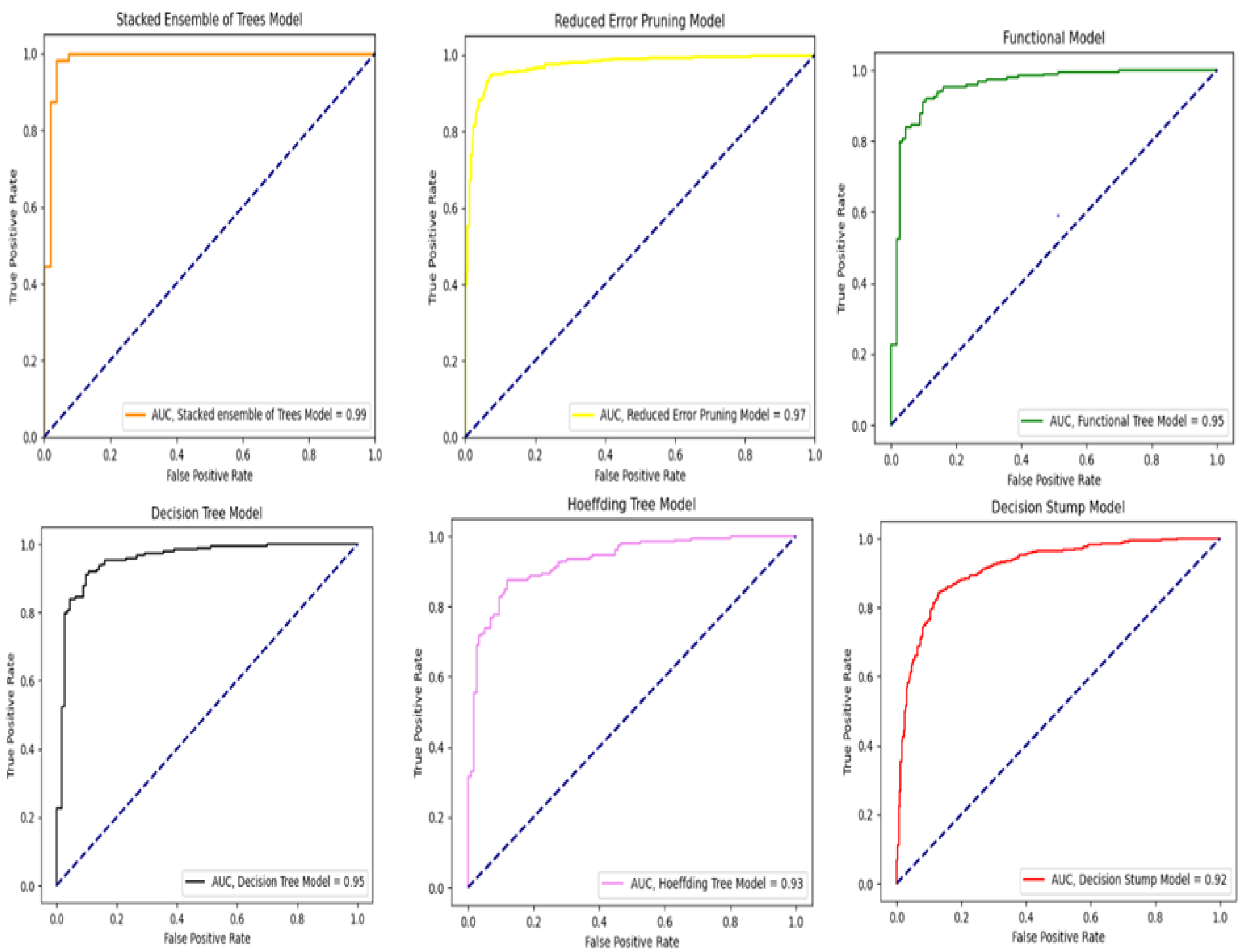


Figure 12: Visualization of ROC-AUC of the prediction models

3.1 Experimental Results from Dataset A

Three different iterations (T1, T2 and T3) were observed and the average experimental results are computed. The experimental results showed that, the performance of Reduced Error Pruning tree (REP Tree) algorithm is better than performances of other individual classifiers with accuracy, precision, specificity, recall and f1- score of 98.74%, 98.98%, 98.96%, 98.42% and 98.92%, followed by hoeffding tree with accuracy, precision, specificity, recall and f1- score of 98.29%, 9.88%, 98.91%, 97.21% and 98.21% respectively. Compared with the performance of stacked ensemble models, experimental results showed that the performance of ensemble models exceeded the performances of individual classifiers with accuracy, precision, specificity, recall and f1- score of 99.62%, 99.51%, 99.51%, 99.63% and 99.73% respectively.

Figure 13 shows the average experimental result obtained with Dataset A after three iterations (T1, T2 and T3). Figure 14 shows the average experimental result obtained with Dataset B after three iterations (T1, T2 and T3).

Table 7. Experimental results for the first iteration with Dataset A (T1)

Classifiers	TP	FN	FP	TN	Accuracy	Precision	Specificity	F1-score	Recall (%)
Decision Tree	266	6	3	272	98.35	98.89	98.91	98.34	97.80
Decision Stump	260	13	15	259	94.88	94.55	94.53	90.91	95.24
Functional Tree	240	21	12	274	94.00	95.24	95.80	93.57	91.95
Hoeffding Tree	267	6	2	272	98.54	99.26	99.27	98.52	97.80
REP Tree	271	2	3	271	99.09	98.91	98.91	99.09	99.26
Ensemble	272	1	1	273	99.98	99.63	99.63	99.63	99.63

Table 8. Experimental results for the second iteration with Dataset A (T2)

Classifiers	TP	FN	FP	TN	Accuracy	Precision	Specificity	F1-score	Recall (%)
Decision Tree	263	4	6	274	98.17	97.77	97.86	98.13	98.50
Decision Stump	262	12	11	262	95.79	95.97	95.97	95.80	95.62
Functional Tree	242	25	8	272	93.97	96.80	97.14	93.62	90.64
Hoeffding Tree	262	8	5	272	97.62	98.12	98.19	97.58	97.04
REP Tree	282	5	6	265	98.03	97.92	97.79	98.09	98.25
Ensemble	273	1	2	274	99.45	99.27	99.28	99.45	99.64

Table 9. Experimental results for the third Iteration with Dataset A (T3).

Classifiers	TP	FN	FP	TN	Accuracy	Precision	Specificity	F1-score	Recall (%)
Decision Tree	269	4	2	272	98.90	99.26	98.53	98.90	98.53
Decision Stump	260	13	16	260	94.22	94.55	94.91	91.91	95.91
Functional Tree	240	19	14	272	93.96	94.48	98.17	97.17	98.17
Hoeffding Tree	268	5	2	272	98.72	99.26	99.27	95.54	99.80
REP Tree	271	2	3	271	99.09	98.91	98.91	99.09	99.26
Ensemble	280	2	1	264	99.45	99.64	99.62	99.82	99.93

Table 10.Average experimental results obtained with Dataset A for the three Iterations

Classifiers	Accuracy	Precision	Specificity	F1-score	Recall (%)
Decision Tree	98.47	98.64	98.43	98.46	98.27
Decision Stump	94.96	95.02	95.14	92.87	95.59
Functional Tree	93.98	95.51	97.04	94.79	93.58
Hoeffding Tree	98.29	98.88	98.91	97.21	98.21
REP Tree	98.74	98.98	98.96	98.42	98.92
Ensemble	99.62	99.51	99.51	99.63	99.73

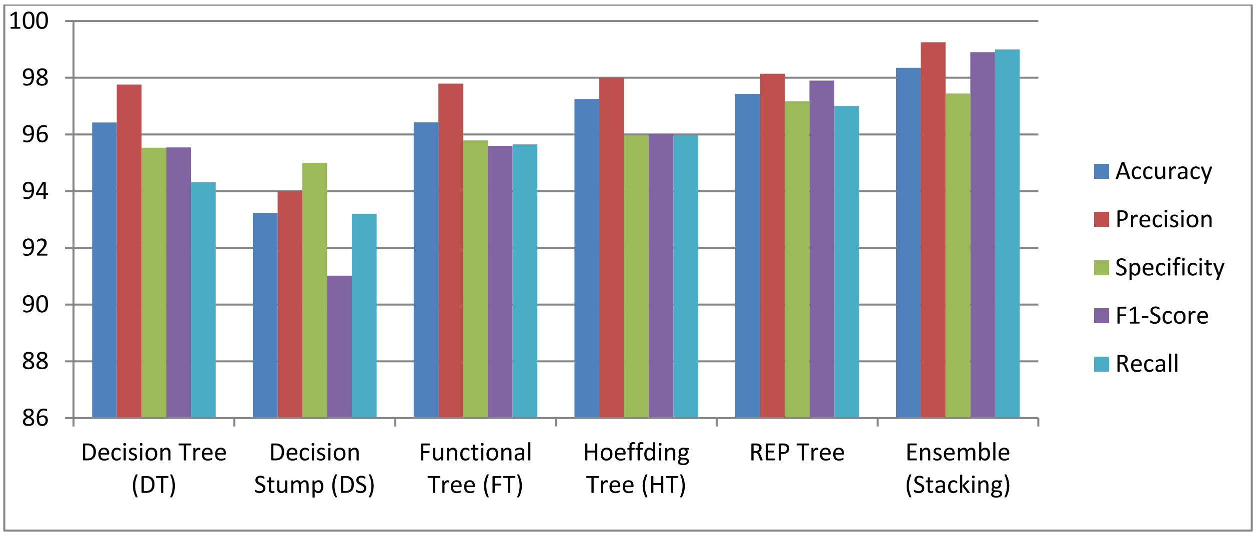


Figure 13. Visualization of average computational experimental results obtained with Dataset A

3.2 Experimental Results from Dataset B

Considering the average experimental results obtained after the three iterations (T1, T2, T3), Reduced Error Pruning tree (REP Tree) algorithm performed better than individual classifiers with accuracy, precision, specificity, f1-score and recall of 97.81%, 98.38%, 97.84%, 96.53%and 99.01% respectively. Improved experimental results are obtained with stacked ensemble model with accuracy, precision, specificity, f1-score and recall of 98.45%, 99.11%, 98.12%, 97.37% and 99.06% respectively. Figure 14 shows the average experimental result obtained with Dataset B after three iterations (T1, T2 and T3).

Table 11. Experimental results of the first iteration with Dataset B (T1)

Classifiers	TP	FN	FP	TN	Accuracy	Precision	Specificity	F1-score	Recall (%)
Decision Tree	219	11	26	203	91.94	89.39	88.65	94.00	95.00
Decision Stump	120	109	54	176	64.41	68.97	76.42	81.36	83.17
Functional Tree	108	122	29	200	67.10	78.83	87.34	89.26	85.72
Hoeffding Tree	224	6	7	222	97.38	96.97	88.94	95.12	92.05
REP Tree	224	5	3	227	98.14	95.11	90.13	95.19	99.06
Ensemble	231	5	2	221	98.47	99.11	96.13	97.37	99.06

Table 12.Experimental results of the second iteration with Dataset B (T2)

Classifiers	TP	FN	FP	TN	Accuracy	Precision	Specificity	F1-score	Recall (%)
Decision Tree	216	12	21	210	92.81	91.14	90.91	95.36	97.90
Decision Stump	120	109	54	176	64.41	68.97	76.42	81.36	91.17
Functional Tree	108	122	30	199	66.88	78.26	93.87	85.23	93.47
Hoeffding Tree	221	9	4	225	97.16	98.21	96.05	89.02	96.02
REP Tree	221	8	4	226	97.38	98.22	99.11	96.12	98.12
Ensemble	232	4	2	221	98.40	99.10	96.13	97.37	99.06

Table 13. Experimental results of the third iteration with Dataset B (T3)

Classifiers	TP	FN	FP	TN	Accuracy	Precision	Specificity	F1-score	Recall (%)
Decision Tree	200	22	18	219	91.29	91.74	92.41	90.90	90.09
Decision Stump	121	108	54	176	64.85	69.54	61.54	68.75	67.98
Functional Tree	120	109	17	213	72.54	87.59	74.48	87.42	76.19
Hoeffding Tree	221	9	4	225	97.16	98.21	96.05	85.02	86.02
REP Tree	224	6	5	224	97.60	98.81	98.06	91.13	96.00
Ensemble	230	3	2	224	98.47	99.11	99.13	97.37	99.06

Table 14. Average experimental results obtained with Dataset B for the three Iterations

Classifiers	Accuracy	Precision	Specificity	F1-score	Recall (%)
Decision Tree	92.01	90.76	90.65	93.56	96.70
Decision Stump	64.56	69.16	73.50	74.28	81.36
Functional Tree	68.84	81.56	85.23	75.30	87.79
Hoeffding Tree	97.23	97.23	97.80	93.92	88.05
REP Tree	97.81	98.38	97.84	96.53	99.01
Ensemble	98.45	99.11	98.12	97.37	99.06

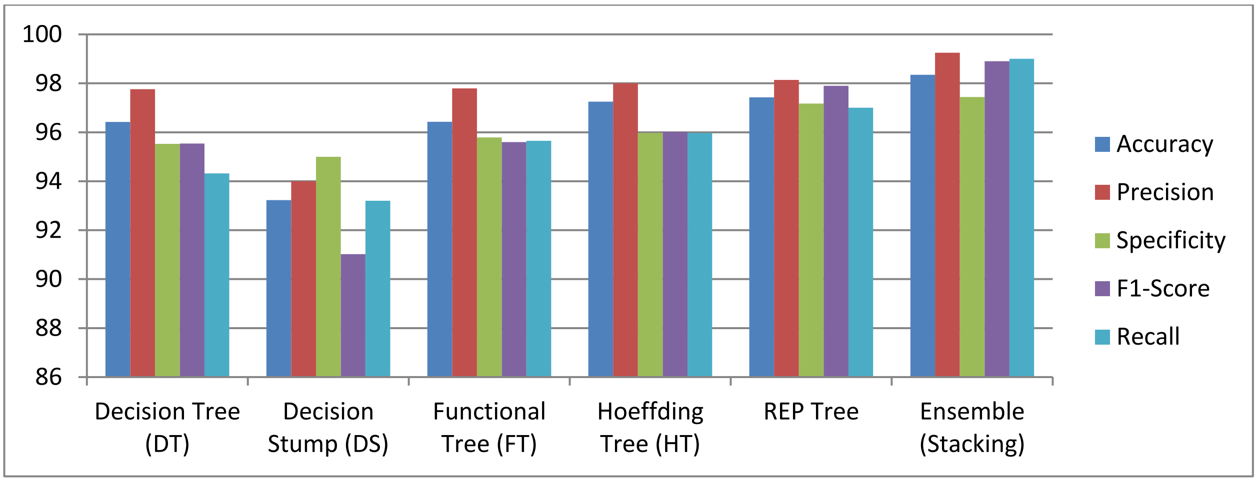


Figure 14. Visualization of average computational experimental results obtained with Dataset B

3.3 Experimental Results from Dataset C

Experimental results showed that the performance of Reduced Error Pruning (REP) tree algorithm outperformed performances of other individual classifiers with accuracy, precision, specificity, F1-score, recall of 97.43%, 98.14%, 97. 17%, 97.90% and 97.00% respectively. The performance of stacked ensemble model exceeded the performance of Reduced Error Pruning (REP) tree algorithm with accuracy, precision, specificity, F1-score, recall of 98.75%, 99.25%, 99.64%, 98.90% and 99.24% respectively. Figure 15 shows the average experimental result obtained with Dataset C after three iterations.

Table 15. Experimental results of the first iteration with Dataset C (T1)

Classifiers	TP	FN	FP	TN	Accuracy	Precision	Specificity	F1-score	Recall (%)
Decision Tree	265	8	6	268	96.43	97.79	95.79	95.60	95.65
Decision Stump	264	9	6	268	93.23	94.25	95.00	91.02	93.20
Functional Tree	265	8	6	268	96.43	97.79	95.79	95.60	95.65
Hoeffding Tree	262	11	4	270	97.25	98.00	96.97	96.02	95.97
REP Tree	265	9	5	268	97.43	98.14	97.17	97.90	96.70
Ensemble	267	6	3	271	98.35	99.25	97.44	98.90	98.45

Table 16. Experimental results of the second iteration with Dataset C (T2)

Classifiers	TP	FN	FP	TN	Accuracy	Precision	Specificity	F1-score	Recall (%)
Decision Tree	263	10	4	269	96.40	97.70	95.02	95.41	91.65
Decision Stump	264	9	6	268	93.23	94.25	95.00	91.02	93.20
Functional Tree	265	8	6	268	96.43	97.79	95.79	95.60	95.65
Hoeffding Tree	260	13	2	272	97.25	97.23	96.27	95.97	96.00
REP Tree	264	9	5	268	97.43	98.14	97.17	97.90	96.95
Ensemble	267	6	3	271	98.35	99.25	97.44	98.90	97.65

Table 17. Experimental results of the third iteration with Dataset C (T3)

Classifiers	TP	FN	FP	TN	Accuracy	Precision	Specificity	F1-score	Recall (%)
Decision Tree	265	8	6	268	96.43	97.79	95.79	95.60	95.65
Decision Stump	264	9	6	268	93.23	94.25	95.00	91.02	93.20
Functional Tree	266	8	6	267	96.43	97.79	95.79	95.60	95.65
Hoeffding Tree	268	11	4	264	97.25	98.00	95.97	96.02	95.97
REP Tree	264	9	5	268	97.43	98.14	97.17	97.90	96.95
Ensemble	270	6	3	268	98.35	99.25	97.44	99.45	99.00

Table 18. Average experimental results obtained with Dataset C for the three Iterations

Classifiers	Accuracy	Precision	Specificity	F1-score	Recall (%)
Decision Tree	96.42	97.76	95.53	95.54	94.32
Decision Stump	93.23	94.00	95.00	91.02	93.20
Functional Tree	96.43	97.79	95.79	95.60	95.65
Hoeffding Tree	97.25	98.00	95.97	96.02	95.97
REP Tree	97.43	98.14	97.17	97.90	97.00
Ensemble	98.75	99.25	99.64	99.90	99.24

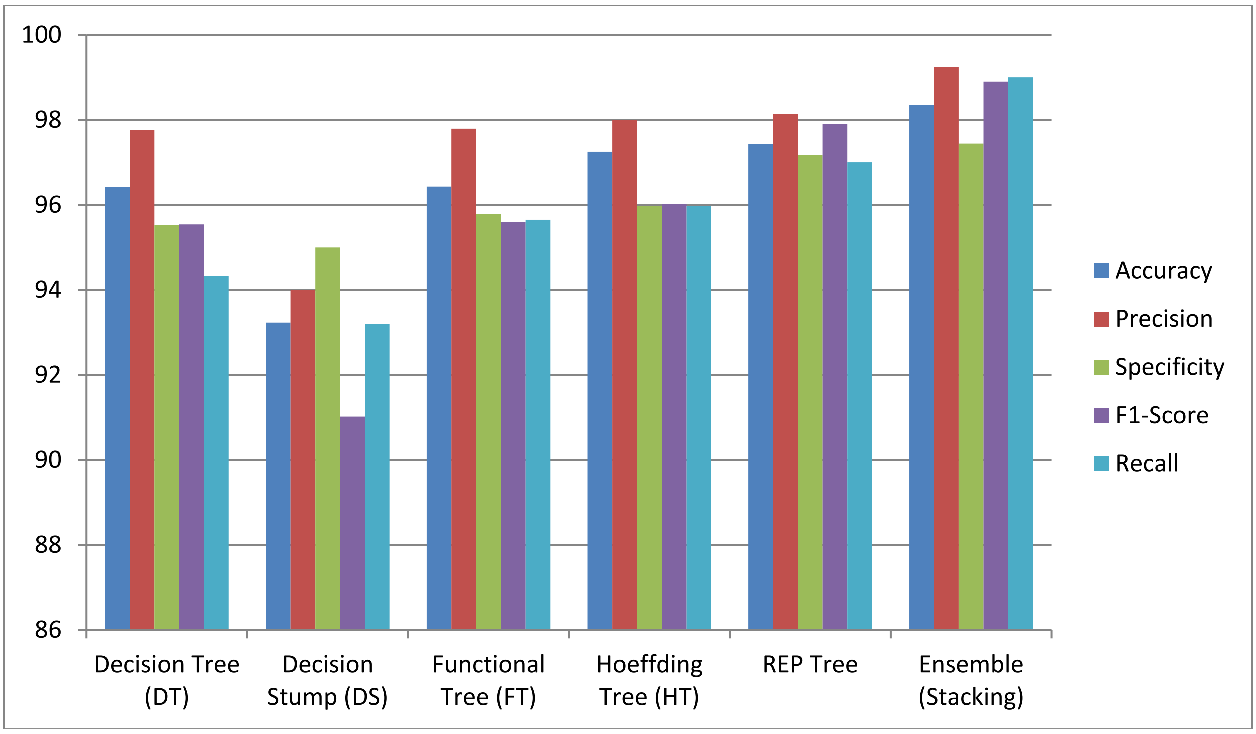


Figure 15. Visualization of average computational experimental results obtained with Dataset C

3.4 Comparison of the experimental results obtained with the three Datasets (Datasets A, B and C)

Five different performance evaluation metrics were assessed for the developed model which consists of stacked ensemble of single classifiers. Figure indicates graphical representation of these five-evaluation metrics obtained using the described Datasets A, B and C. The performances of the algorithms were generally better on Dataset A than the other two Datasets with accuracy, precision, specificity, f1-score and recall of 99.62%, 99.51%, 99.51%, 99.63% and 99.73% respectively. Figure 16 presents visualization of the comparison of the average experimental results obtained after three successful iterations with Dataset A, Dataset B and Dataset C.

Table 1: Experimental results obtained with Datasets A, B and C

Dataset	Ensemble Model				
Metrics	Accuracy	Precision	Specificity	F1-score	Recall (%)
Dataset A	99.62	99.51	99.51	99.63	99.73
Dataset B	98.45	99.11	98.12	97.37	99.06
Dataset C	98.75	99.25	99.64	99.90	99.24

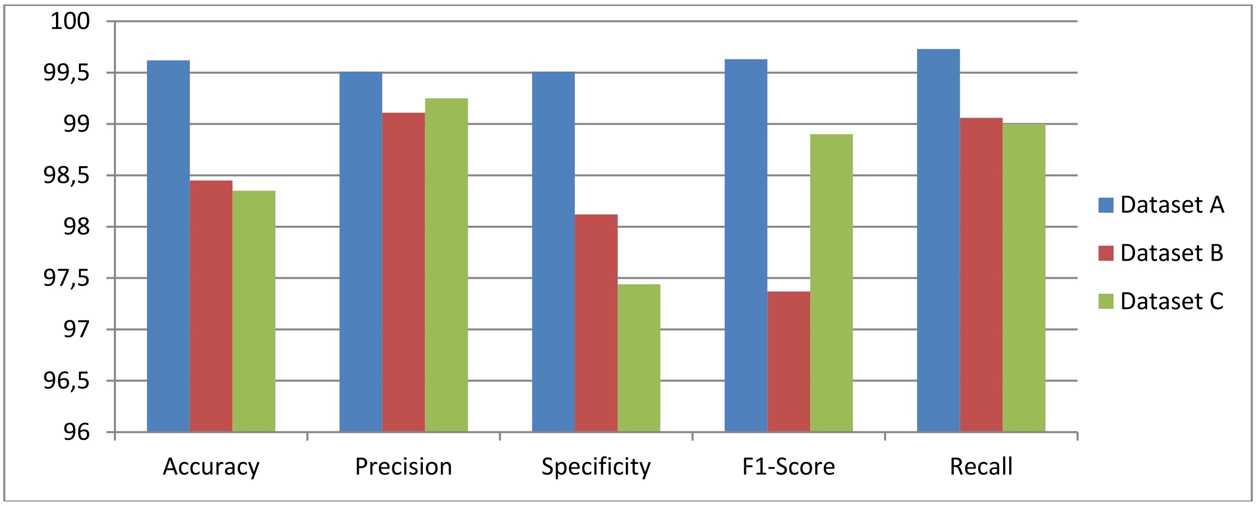


Figure 16. Visualization of average experimental results obtained with Datasets A, B and C.

4. Conclusion

This research addresses the drawbacks of existing models, such as overfitting effects, inadequate dataset and limited study areas through the adoption of a stacked ensemble model. The model contained five different tree - based models namely hoeffding tree, decision tree, functional tree, reduced error pruning (REP) tree and decision stump algorithms. Experimental results indicate that REP Tree performed better than other four individual tree-based algorithms with accuracy of 98.74%, 97.81% and 97.43% for Dataset A, Dataset B and Dataset C, respectively. For Dataset A, stacked ensemble model performed better than individual algorithms with accuracy, precision, specificity, f1score and recall of 99.62%, 99.51%, 99.51%, 99.63% and 99.73% respectively. For Dataset B, the performance of stacked ensemble model exceeded the performances of single algorithms with accuracy, precision, specificity, f1 score and recall of 98.45%, 99.11%, 98.12%, 97.37% and 99.06% respectively. For Dataset C, stacked ensemble model performed better than individual algorithms with accuracy, precision, specificity, f1score and recall of 98.75%, 99.25%, 99.64%, 99.45% and 99.24% respectively. The performances of the algorithms were generally better on Dataset A than the other two datasets. Furthermore, the stacked ensemble model has an area under curve of 0.99 which shows that it is effective for flood areas prediction. The methodology applied for this study is generally unique for the prediction of flood areas and significantly, no study has been done with the development of stacked ensemble of these specific five tree-based algorithms for floods prediction in the three study areas. Despite improved predictive performance of this work, the model is limited to only quantitative dataset of text format. The model developed in this research can be integrated with water monitoring sensors, process the response by microcontroller and transmit through communication modules as a scalable flood alert system.

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The author declares that there is no conflict of interest on the publication of this paper

Ethical Approval and Informed Consent

.It is declared that during the preparation process of this study, scientific and ethical principles were followed

Availability of data and material

Data are available on reasonable request from the corresponding author

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