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Comparing Artificial Neural Network and Random Forest Technique for Detecting Flood Magnitude

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Abstract

Flood is one of the most dangerous natural disasters on earth and it cannot be completely prevented, however, accurate prediction can help save life and property. Our work focuses on evaluating and comparing the accuracy and effectiveness of using Random Forest (RF) technique and Artificial Neural Network (ANN) technique to predict the magnitude of flood. Both techniques were used to train and test the models using a dataset containing key hydrological variables, such as rainfall and temperature. The performance of these models was assessed using key evaluation/performance metrics including; accuracy, precision, recall, F1-score, confusion matrices, and ROC curves. The model developed using RF technique outperformed the ANN model. The RF model achieved an accuracy of 97.0%, while the ANN model achieved a 90.67% accuracy. It was further discovered that the RF model had better precision, recall, and F1-scores for both low and high flood severity levels. It was concluded that the RF offers more reliable and precise flood magnitude predictions, making it a more suitable option for real-world flood risk assessment and management. We recommend that future studies could explore further optimization techniques and the integration of additional hydrological variables to enhance predictive performance.

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1. INTRODUCTION

Flooding is arguably one of the most dangerous natural disasters in the world. It destroys lives and property. Flood magnitude is the degree and intensity of the flood, and accurate detection of the magnitude of flood is needed so that people can prepare, and governments can warn settlers so they can take appropriate actions in order to save lives and reduce property damage. A sudden flood calamity is being caused by overflowing river banks and excessive rainfall in a number of countries worldwide. Buildings, infrastructures and houses are at risk of serious damage by flood, resulting to loss of wealth for individuals and their community at large [1]. This might have a detrimental impact on a portion or the entire area where we live, and it usually happens as a natural disaster that causes fatalities, property damage, and environmental degradation. Many people are exposed to the possibility of being more susceptible to flood disasters [2]. For this goal, a number of Flood Prediction Models (FPM) have been created. Various methodologies have been utilized in the creation of flood prediction models. These include methods based on physical parameters (deterministic hydrological models), methods based on statistics (statistical models) like the Markov technique [3], methods based on machine learning techniques such as artificial neural networks [4], Fussy logic, time series, and support vector machines [5]. This study is an attempt at comparing Neural Network Technique and Random Forest Technique for detection of flood magnitude.

Because machine learning algorithms can assess complex, nonlinear correlations between many hydrological variables, including rainfall, river discharge, and topographical data, they have become increasingly popular in the field of flood prediction in recent years. For detecting flood magnitude, two well-liked methods—Neural Networks (NN) and Random Forests (RF)—have been applied extensively. Because they imitate the learning process of the human brain, neural networks are well-known for their capacity to identify complex patterns in data, whereas random forests use a collection of decision trees to generate reliable predictions. While techniques such as SVM and ARIMA have shown great results in short-term flood prediction, they have often fallen short in handling high-dimensional data or nonlinear dependencies. ANN and RF, on the other hand, are more robust in such scenarios. RF handles overfitting well and ANN is capable of modeling intricate, nonlinear relationships between variables. These strengths make them suitable for predicting flood magnitude across varying time scales. Past flood data can be trained using ML algorithms to predict future floods, their likelihood to occur and their intensity. These techniques can help map the magnitude of this natural disaster using remote sensing data, satellite photos, aerial photos and other relevant data [6].

Overflowing river banks and excessive rainfall cause flooding which leads to destruction of lives and property and environmental degradation [7]. As climate change becomes eminent, natural disasters including flood become more severe and frequent, and existing flood and other hydrological models are struggling seriously to keep up with the complexities of this natural disaster, leading to predictions that are inaccurate. Artificial Neural Network and Random Forests are Machine learning techniques that are capable of using large dataset to predict flood, its magnitude with higher accuracy and precision. It's important to know which of the two machine learning techniques will make perform better. This work will also offer significant insight on how to use effectively develop and implement accurate models for areas prone to flooding. The authors of this work aim to bridge the gap between theoretical machine learning techniques and its practical applications in natural disaster management.

While ANN does so well at revealing deep nonlinear patterns, it requires significant computational resources and tuning. RF, being an ensemble method, offers stability and interpretability but may struggle with temporal sequences. A comparison between both techniques will reveal trade-offs in performance, complexity, and practical deployment in flood-prone areas around the world.

Flood Prediction Models (FPM) predict floods using variables such as; water levels, temperature, rainfall, ground saturation and soil permeability. A variety of technologies, including rainfall, temperature run-off models, hydraulic models, and data-driven hydrological models, are used to estimate the level or magnitude of floods [8].

Using an artificial neural network and a modified runoff equation, [9] constructed a model that attempted to forecast the amount of flood in Afikpo local government area, of Ebonyi state in Eastern Nigeria. Their model produced 84.7% and 95.5% level of performance in rainfall and temperature, respectively. The major variables they employed were temperature and rainfall data. Unfortunately, the size of the dataset employed means that the finding cannot be trusted. A fairly modest dataset—temperature and precipitation data from 2012 to 2018—was utilized to train the algorithm. In order to improve the model's performance—which is dependent on time—the temperature should have also been captured at different times throughout the day. According to reference [10], there are noticeable variations when predicting the amount of flooding in a given area. While making sure that the variables that cause variations in flood in a region or area stay constant for a predetermined amount of time, they employed Annual Maximum Flood (AMF) time series to determine the trend at the local and regional scale utilizing time-dependent conditions. Monte Carlo trials were employed to assess the model's performance. Nevertheless, the variables that contributed to non-stationarity and were taken into account in their analysis can vary depending on the nation.

Reference [11], examined the use of the Nonlinear Autoregressive Exogenous model (NARX) to predict rainfall-based river flood forecasts in Malaysia. The method performed better when trained using Bayesian regularization than when trained using the Levenberg-Marquardt back propagation technique. In terms of rainfall-based flood prediction, NARX performed 99% of the time. But this was only a 24-hour forecast ahead of time. The prediction is aimed at months or even years ahead of time in the flood magnitude prediction methods that this page offers for comparison.

Reference [12], looked into a two-year knowledge based on 2005 and 2006 using the Support Vector Machine (SVM) approach. The data was gathered from seven lake floods that occurred in Chiang Mai, Thailand's city. According to the study, SVM outperformed Multilayer Perceptron Models (MLP) models and showed promise for floods predictions. Additionally, using real-world data, the model can be used to flood prediction systems in the actual world. SVM was also utilized by Reference [13], to predict flooding events. Bird Creek, America. The training data came from a catchment region, whereas the testing and model implementation used data that wasn't visible. Twelve rain gauges located throughout the catchment region were used to gather data on rainfall and river flow. After deployment, a comparison with alternative prediction algorithms was conducted. Compared to all other algorithms in the time data series, SVM performed the best. The outcome demonstrated that, for different conditions within the same catchment, linear and nonlinear kernel characteristics could offer noteworthy activities against one another. Reference [14], used

Rawal Lake, Islamabad as a case study to determine better attribute selection and discharge level estimation. The discharge time was predicted using SVM, RBF (Radial-Basis-Function), ANN (Artificial Neural Network), and ARIMA. Their model's primary flaw is its short-term forecast accuracy.

Reference [15], utilized an ANN to create a flood forecasting model. The usage of a single parameter was its main accomplishment. His model could not account for the likely flooding's breadth and depth. Reference [16], used the Neural System Autoregressive Model with Exogenous Feedback (NNARX) to create a five-hour flooding prediction model for Kuala Lumpur. The Neural Network Toolbox in Matlab was used to implement the model. 131 samples were used for training, 84 samples were used for validation, and 170 samples were used for testing the vector. The gradient descent algorithm was used for the training. 89.2% of the model's performance level was installed. However, the amount of data used was insufficient to forecast floods on a monthly or annual basis, which is probably why the performance was so low.

The goal of reference [17], was to create a five-hour advance flood prediction model for the Terengganu River using NARX. A total of 641 data samples were utilized for training, 641 more data samples were used for validation, and 1351 data samples were used to test the model. The model's performance level was above 80%, with a Root Mean Square Error (RMSE) score of 0.220, indicating that it correctly anticipated the occurrence of flooding five hours in advance.

Authors [18], utilized old flood data to forecast future occurrence of flood in Nigeria using logistic regression (LR) and artificial neural network (ANN) models. He compared both models and the ANN model outperformed the LR model, and both models classified low-lying areas as being extremely susceptible to floods.

Authors [19], developed a flood predicting model using teaching learning-based optimization (TLBO) and deep belief network (DBN) for the Daya and Bhargavi rivers in India. Their work looked at the impact of barrage construction and evaluated the performance of DBN against TLBO using the root mean square error (RMSE) and mean absolute percentage error (MAPE) for forecasting periods of 1 day, 1 week, and 2 weeks. The study highlighted on the importance of using ML for flood mitigation planning.

Author [20], opined that, using Machine Learning methods for flood prediction and classification can identify extreme flood events, promptly enable flood classification and prediction, promote flood disaster mitigation, and facilitate the efficient use of water resources.

Recent studies in deterministic AI and hybrid deep learning models offer new avenues for flood forecasting. However, these models often require massive computational power and extensive training datasets which are unavailable in many flood-prone areas in rural settlements. This study focuses on ANN and RF as they balance predictive power with feasibility in resource-constrained environments.

The major purpose of this work is to compare how effective ANN and RF machine learning techniques are in detecting flood magnitude. The authors intend to test and evaluate the models' accuracy, efficiency and suggest which method is better off.

2. METHODOLOGY

The authors used publicly available dataset for this project work to train the models using Python programming language via the Spider IDE. The performance of the ANN and RF models was then evaluated and tested using the data.

2.1 Dataset

The dataset contains 101 records with fields; date, level and target. Data set was gotten from Kaggle by [21]. The frame of the dataset is summarized in TABLE 1. Dataset was split into 80% for training and 20% for testing sets. This dataset spans over 100 years from 1920 to 2020.

Table 1: Kaggle dataset for flood magnitude

	Date	**Level of the Flood**	**The Target**
0	1920-12-01	3	High
1	1921-12-01	1	Low
2	1922-12-01	2	Normal
3	1923-12-01	3	High
4	1924-12-01	1	Low
—-	—-	—-	—-
96	2016-12-01	2	Normal
97	2017-12-01	2	Normal
98	2018-12-01	1	Low
99	2019-12-01	2	Normal
100	2020-12-01	8	High

2.2 The Artificial Neural Network (ANN) Model

Stochastic Gradient Descent (SGD) is an optimization approach used by ANNs to guarantee that the least amount of error is produced. To reduce error, SGD instructs ANN on how to adjust the weight and bias parameters. The prediction process is facilitated by the built-in parameters and functions of ANN, such as trainlm, tansig, and purelin. These include epoch and aim. The parameters Epochs and Goal denote the quantity of training iterations and the intended accuracy level, respectively. The ANN was trained using the Levenberg-Marquardt algorithm trainlm function. The machine learning functions ”tansig” and ”purelin” were also employed. These transfer functions were applied. The ”gsubtract” function was used to obtain the R-Value, which inferred the prediction’s accuracy. The correctness of the made predictions was confirmed using the derived R-Value. These all guarantee appropriate learning and increased prediction accuracy in the model.

Runoff equation model developed by [2], and modified by [22], was used to develop our models. The dataset by [21], was integrated into the model.

The runoff equation is shown in equation 1.

$$\mathbf{Runoff} = ((\mathbf{1} - \mathbf{e}^{-\mathbf{0.65}})\mathbf{RF} * \mathbf{TP})/\mathbf{Max}(\mathbf{TP}) \tag{1}$$

Where:
RF = Rainfall
TP = Temperature

2.3 The Random Forest (RF) Model

The RF machine learning technique is a unique and powerful algorithm that is used for both regression and classification tasks. This technique builds various decision trees during training of the model and combines their output in order to enhance the accuracy of the model. RF was applied in this work to predict flood magnitude using variables like rainfall and temperature.

The RF model produces a collection of related decision trees, with each of the tree train differently, using different portions of the dataset. In order for the model to make predictions, the output of all the trees are combined through voting or computing the average for classification problem or regression problem respectively, improving the model's accuracy and overcoming overfitting.

3. RESULTS AND DISCUSSION

ROC graph, classification report, accuracy and confusion matrix are used to present the result of the models. The implementation was done with some fine-turned hyper-parameters values to obtain an optimal solution. FIGURE 1-FIGURE 3 show the total number of tested dataset, the confusion matrix of the ANN model, and the confusion matrix of the RF model respectively.

After training, the random forest created using the dataset is seen in FIGURE 4, where excellent detection accuracy metrics were achieved by combining the simplicity of several decision-trees. To do this, random samples were selected from the original dataset and replaced with variables to create trees, representing a random subset at each stage. As seen in FIGURE 4, it produced a diverse range of trees in the woodland area.

An analysis of ANN and RF classifiers' receiver operating characteristic (ROC) graph in FIGURE 5, illustrates the trade-off between sensitivity, or true positive rate, and specificity (1-FPR). A bit distant from the top x and y axis, the ANN model underperformed compared to the RF ROC curve, which is closer to the top-left corner of the graph. Points along the diagonal (True Positive Rate=False Positive Rate) were provided by the proposal, as anticipated.

TABLE 2 is the ANN classification report measured in terms of precision, recall and f1-score for predicting the target. The ANN recorded 0.94 level of precision in low cases of flood level and 0.87 for high cases of flood. For recall, it recorded 0.87 and 0.95 respectively.

TABLE 3 shows the classification report of RF model in terms of precision, recall and f1-score for detecting flood level. The precision value ranges from 0.97 to 0.98, and the recall value ranges from 0.98 to 0.97 and f-score value recorded 0.97 for low and high flood cases respectively.

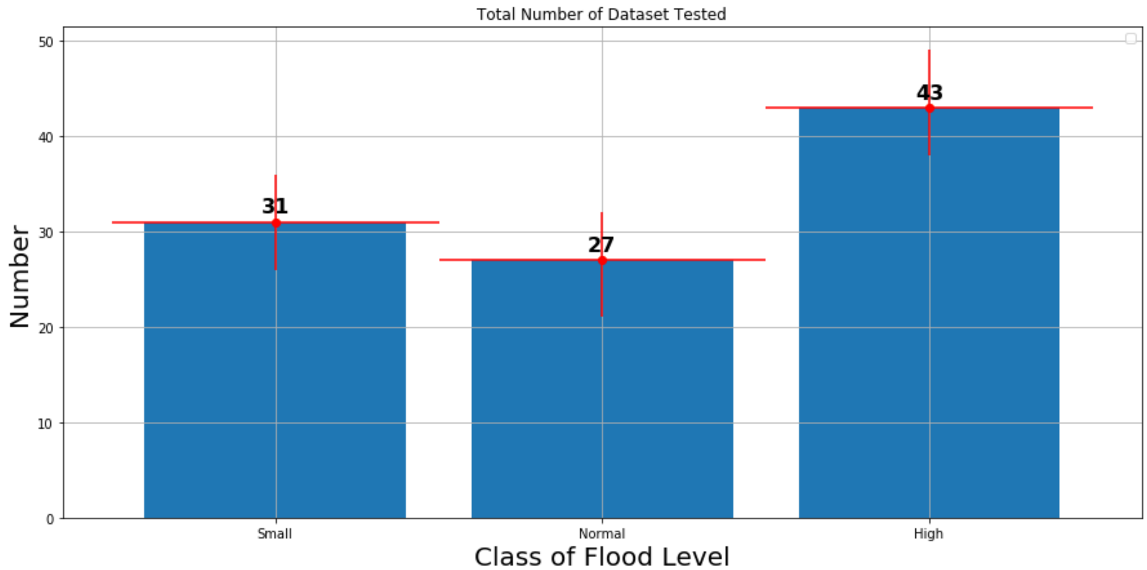

Figure 1: Total number of tested dataset

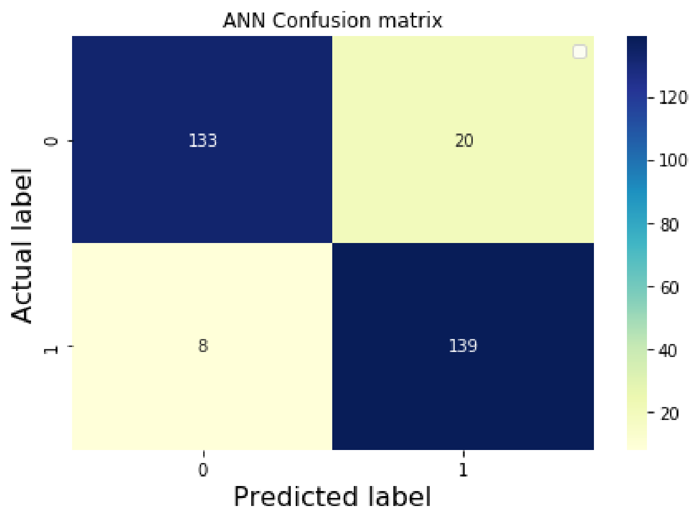

Figure 2: The confusion matrix of our ANN model

The success rate of the ANN and RF models are depicted in FIGURE 6. Note that the RF model produced 97.0% accuracy and performed better compared to the ANN model that produced 90.67% accuracy rate.

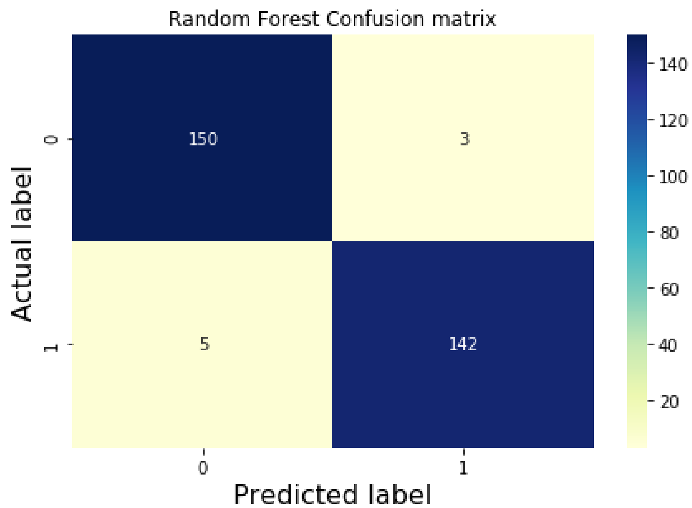

Figure 3: The confusion matrix of our random forest model

Table 2: The ANN Classification Report

	Precision	Recall	F1-score	support
0	0.94	0.87	0.90	153
1	0.87	0.95	0.91	147
Accuracy			0.91	300
Macro avg	0.91	0.91	0.91	300
Weighted avg	0.91	0.91	0.91	300

Table 3: The Random Forest Classification Report

	Precision	Recall	F1-score	support
0	0.97	0.98	0.97	153
1	0.98	0.97	0.97	147
Accuracy			0.97	300
Macro avg	0.97	0.97	0.97	300
Weighted avg	0.97	0.97	0.97	300

4. CONCLUSION

For this work, the authors focused on evaluating and comparing the performance and effectiveness of ANN and RF machine learning techniques in flood magnitude prediction. The authors used evaluation metrics like; ROC curves, confusion matrices, classification reports, and accuracy in percentage. Our findings reveal that the RF model outperformed the ANN model with a 07.0% and 90.67% accuracy respectively.

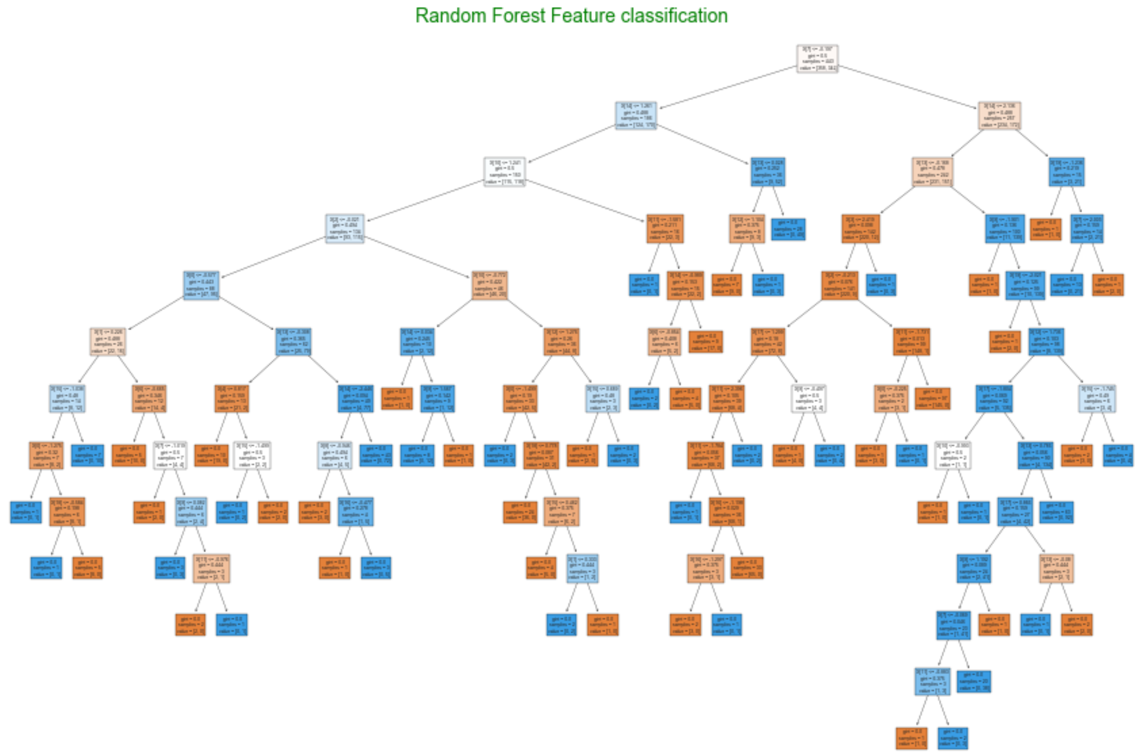

Figure 4: The random forest generated from dataset

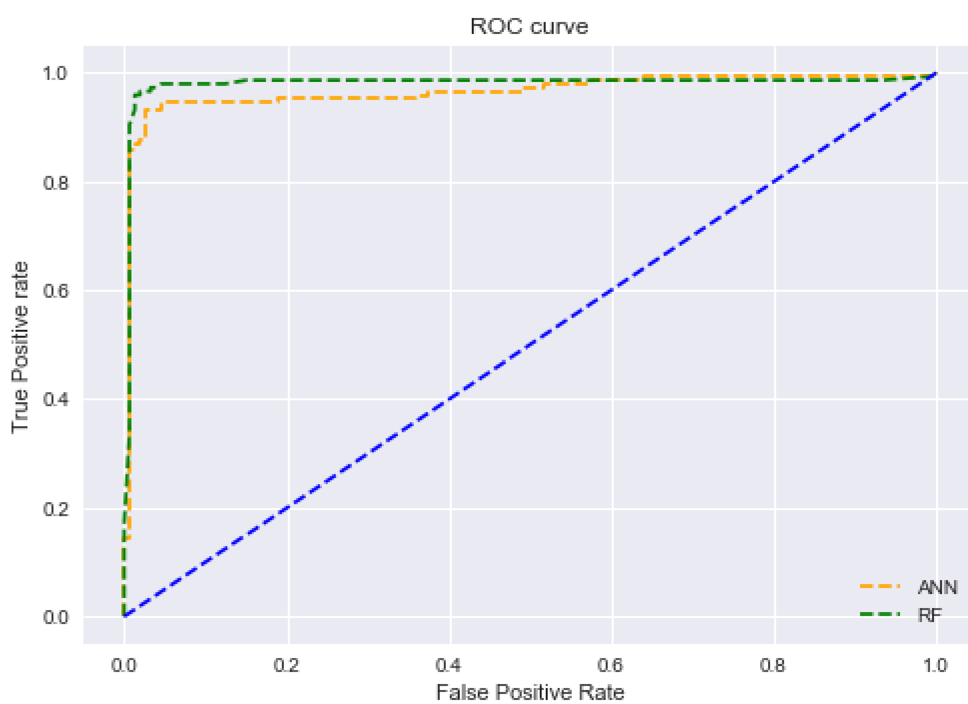

Figure 5: The ROC graph of ANN and RF

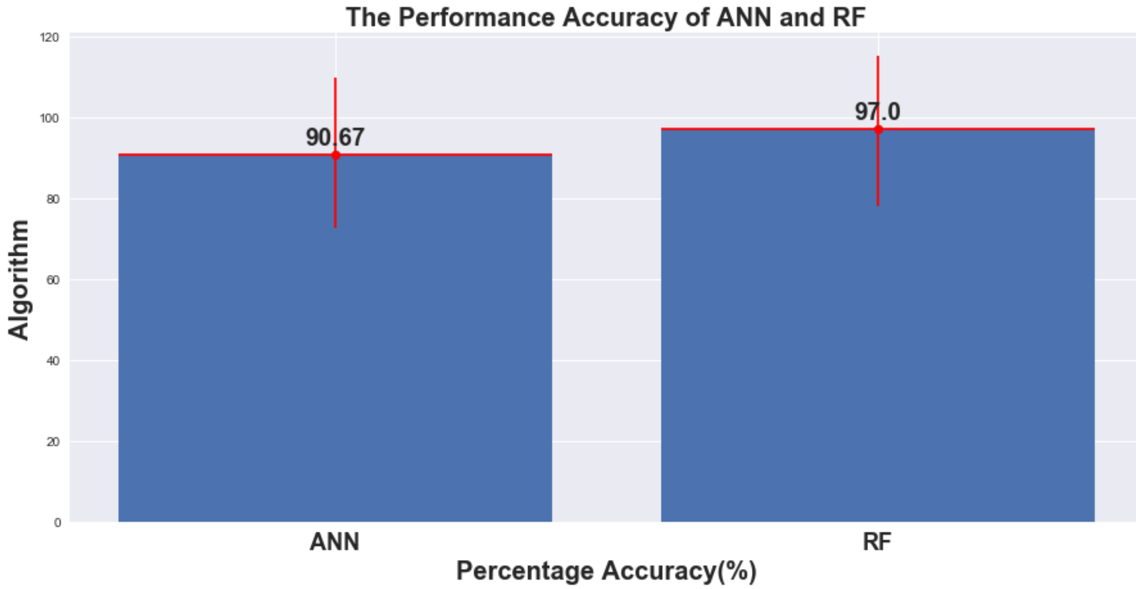

Figure 6: Performance accuracy of ANN and RF

The authors also note that the RF model had better recall F1-score for low flood and high flood situations, concluding the RF technique are better off than ANN technique for flood magnitude prediction.

The authors also noted that that RF technique had better specificity and sensitivity as the ROC curve of the RF model was closer to the top-left corner.

In conclusion, this work shows that Random Forest (RF) machine learning technique is a more reliable, robust and accurate for flood magnitude prediction, than Artificial Neural Network (ANN) technique. The author recommend exploitation of hyperparameters optimization, and addition of other hydrological variables apart from rainfall and temperature for future studies.

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APPENDIXES

Acronym Table

Acronym	Full Meaning
ANN	Artificial Neural Network
RF	Random Forest
FPM	Flood Prediction Models
NN	Neural Network
SVM	Support Vector Machine
ARIMA	AutoRegressive Integrated Moving Average
MLP	Multilayer Perceptron
NARX	Nonlinear Autoregressive Exogenous model
NNARX	Neural System Autoregressive Model with Exogenous Feedback
RMSE	Root Mean Square Error
MAPE	Mean Absolute Percentage Error
LR	Logistic Regression
TLBO	Teaching Learning-Based Optimization
DBN	Deep Belief Network
SGD	Stochastic Gradient Descent
IDE	Integrated Development Environment
ROC	Receiver Operating Characteristic
AMF	Annual Maximum Flood
RBF	Radial Basis Function

Variables and Parameter Table

Variable / Parameter	Meaning / Description
RF	Rainfall (input variable in models)
TP	Temperature (input variable in models)
Epochs	Number of training iterations in ANN
Goal	Desired accuracy level in ANN
trainlm	Levenberg-Marquardt training function in ANN
tansig	Hyperbolic tangent sigmoid transfer function in ANN
purelin	Pure linear transfer function in ANN
gsubtract	Function used to calculate R-value (accuracy)
R-Value	Correlation coefficient used to determine prediction accuracy
Runoff	Estimated amount of flood runoff based on RF and TP
Date	Yearly time reference (1920–2020) in dataset
Level	Numeric flood level in dataset (1–8)
Target	Categorical flood magnitude (Low, Normal, High)
Dataset split	80% training, 20% testing
Confusion Matrix	Model evaluation matrix
Accuracy	Proportion of correctly predicted instances
ROC Graph	Receiver Operating Characteristic curve used to compare models