Sumerianz Journal of Scientific Research, 2024, Vol. 7, No. 2, pp. 7-19
ISSN(e): 2617-6955, ISSN(p): 2617-765X
Website: https://www.sumerianz.com
DOI: https://doi.org/10.47752/sjsr.72.7.19

Original Article Open Access

FPAS Model: A Case Study of Flood Prediction and Advisory System

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Article History

Received: 27 March, 2024

Revised: 8 June, 2024

Accepted: 19 June, 2024

Published: 23 June, 2024

How to Cite

Onwudebelu U., Ugah J. O. and Emewu B. M. et.al,. (2024). FPAS Model: A Case Study of Flood Prediction and Advisory System. *Sumerianz Journal of Scientific Research, Vol. 7, No. 2, pp. 7-19.*

Abstract

The increasing frequency of flood events worldwide is a significant concern, particularly for the United Nations (UN), as it impacts both economic stability and public safety. In recent decades, floods have caused extensive damage to lives and properties, and projections indicate this trend will continue. Rapid evacuation in the event of a flood relies on effective early warning systems that can predict floods and encourage residents to evacuate high-risk areas. Africa is the third most affected continent by floods, following Asia and Europe. However, the development and implementation of flood forecasting models in Africa are still in the early stages. The continent has only a few hydrological models for flood forecasting, and most of these need improvements to keep pace with changing conditions. The study aimed to enhance flood prediction and advisory systems by leveraging machine learning (ML). The objectives are to develop a predictive model, create dual subsystems for web and Android applications, disseminate predictions and advisories through multiple communication channels, and incorporate persuasive messages to prompt at-risk populations to evacuate. A survey was conducted in Cross River State to evaluate the impact of these persuasive messages and the overall support for the Flood Predictive and Advisory System (FPAS). The study utilized the NiMet dataset, preprocessed the data, and trained the model using SVM, Random Forest, and XGBoost algorithms. Subsequently, both the FPAS web and Android applications were developed and rigorously tested. The research methodology applied in this work was a hybrid approach, combining Object Oriented Analysis and Design Methodology (OOADM) and the Cross Industry Standard Process for Data Mining (CRISP-DM). OOADM was used to develop the mobile app for citizens' registration and a web app for administrative activities, while CRISP-DM was used to create a data-drive predictive model for the app. These applications facilitated citizen registration and administrative activities, providing feedback via websites, emails, and automated alerts. The survey results revealed that 76.56% of respondents had not experienced persuasive messages before, while 91.15% expressed strong support for the FPAS system incorporating these techniques. Finally, the study successfully developed an advanced flood prediction model and an integrated advisory system, demonstrating significant potential in enhancing disaster preparedness and response through innovative technology and strategic communication.

Keywords: Blockchain; Machine Learning; SVM; Random Forest; XGBoost; Disruptive Technology.

1. Introduction

Floods are among the most devastating natural disasters, causing significant loss of life, property damage, and disruption of livelihoods. There is an increasing risk of flooding in many areas around the world [1, 2]. Furthermore, flooding can spread contaminants like pesticides and fertilizers, which can have a negative impact on the environment [3]. All of this can lead to a loss of biodiversity and a decrease in the overall health of the ecosystem. Effective flood prediction and timely dissemination of advisories are critical for mitigating these impacts. Traditional flood prediction methods, while useful, often lack the precision and timeliness needed to protect vulnerable populations adequately. The integration of advanced technology such as machine learning can significantly enhance the accuracy and efficiency of flood prediction systems.

Some natural solutions have been suggested for flooding, and this natural solutions are designed to work with the natural environment to reduce the risk of flooding. One such example is restoring wetlands, which can help to absorb water and reduce flooding. Using green infrastructure is another solution, like rain gardens and bioswales, which are designed to slow down and absorb rainwater. These solutions can be cost-effective and can also have other benefits, like improving water quality and increasing biodiversity [4]. There are many different types of engineered solutions, which are typically constructed by humans to help reduce flooding such as floodwalls, which are built to protect areas from rising water levels. Also, storm-water detention basins, which are designed to temporarily hold and release water during heavy rainfall. There is also pumping, which is used to remove water from areas that are prone to flooding [3]. As flooding causes a lot of damages, home preparation for flooding is crucial. This includes things like elevating electrical equipment, installing check valves to prevent backflow, and sealing basement walls as well as creating an emergency kit with supplies like flashlights, batteries, and non-perishable food. Creating an evacuation plan is also important, so that users know what to do if they need to leave their home. It is also a good idea to make a digital backup of important documents, like insurance policies and financial records as well as certificates. Finally, it is important to stay informed about weather conditions and flood warnings.

The ability to predict and provide early warning of flooding is critical for public safety and disaster preparedness. However, traditional forecasting methods have their limitations. Disruptive technologies, such as big data, machine learning, and AI, offer the potential to significantly improve the accuracy and timeliness of flood prediction and advisory systems. By harnessing the power of disruptive technologies, we can save lives, protect property, and minimize the economic impact of flooding. One of the challenges of harnessing disruptive technologies for flood prediction and advisory is data quality and privacy [5]. Data from a variety of sources may be inaccurate, biased, or incomplete, which could lead to flawed predictions. Secondly, people may be concerned about the privacy of their data and the potential misuse of personal information. The third challenge is cost. While the cost of some disruptive technologies, like sensors and software, is decreasing, the cost of deploying and maintaining these technologies can be significant. Additionally, the cost of collecting and analyzing large amounts of data can be substantial. The fifth challenge is technical complexity. Deploying and maintaining disruptive technologies can require a high level of technical expertise. For example, collecting data from sensors and processing it using AI algorithms requires specialized knowledge and skills. Additionally, these technologies may require regular maintenance and updates to ensure they are working properly.

In this paper, we perform three different machine learning (ML) algorithms on flood data obtained from NiMet: support vector machines (SVM), random forest (RF), and extreme Gradient Boost (XGBoost). SVM is a supervised learning algorithm used for both classification and regression tasks. It is particularly effective in cases where the data is non-linearly separable. In the perspective of flood prediction, SVM is applied to predict the occurrence or severity of floods based on historical data. During the training phase, SVM identifies a subset of data points called support vectors, which are the data points closest to the hyper-plane [6]. SVMs can be used to classify data into different categories, such as "low risk" and "high risk" of flooding. SVMs work by finding a "hyperplane" that separates the data into two or more categories. A hyperplane is a mathematical concept that represents a line or a plane that divides a set of data into two or more categories. In the context of flood prediction, the weather data used in our prediction are minimum and maximum temperature (Celsius), rainfall (mm), relative humidity (%), visibility (meter), evapotranspiration (mm) and the categories could be "low risk or no flooding" and "high risk or flooding" of flooding. The RF algorithm is an ensemble learning method that combines multiple decision trees to make predictions and popular algorithm for both classification and regression tasks, including flood prediction. Just like SVMs, random forest is a supervised learning algorithm, but it works a bit differently. Instead of finding a single hyperplane, random forest creates a "forest" of decision trees. Each decision tree can classify the data into a category, and then the "forest" of trees can vote on the best classification for each data point. Extreme Gradient Boosting (XGBoost) is a powerful machine learning algorithm that belongs to the gradient boosting family. XGBoost is a boosting technique that is similar to random forest, but it has some key differences [7]. XGBoost uses a different approach to training the decision trees. It is widely used for both classification and regression tasks, including flood prediction. XGBoost is an ensemble learning method that combines multiple weak prediction models, typically decision trees, to create a strong predictive model. XGBoost uses a technique called gradient boosting to update the model in each iteration. Furthermore, XGBoost provides measures of feature importance, which is useful for understanding the factors that contribute to flood occurrence or severity [8].

This paper focuses on predicting flood instances using dataset obtained from NiMet by developing the model that sooth the dataset using three ML algorithms. The followings are the summary of our key contributions:

i. We proposed a FPAS model that is based on machine learning in predicting flood instances using NiMet dataset.

ii. We evaluated the quality and performance of our model through experiments performed on model using accuracy, precision, recall and F1-score. Results showed that the proposed model was effective.

iii. We survey and evaluated the situation of flooding in Cross River State in Nigeria.

The remaining sections of this paper follows this pattern: *Section 2* focuses on a literature review of previous studies. *Section 3* presents the methodology and the FPAS model. The implementation and results of the FPAS model are presented in *Section 4*. Finally, the conclusion and future works are in *Section 5*.

2. The Theoretical Backgrounds

The increasing frequency and intensity of natural disasters, such as floods, have highlighted the need for accurate and secure prediction systems to mitigate the potential damages. This literature review aims to explore the existing research and literature on flood prediction and advisory system. A number of studies have been conducted on flood prediction and warning systems, and several traditional approaches have been proposed, including statistical models, artificial neural networks, and hydrological models.

In Munawar, *et al.* [9] the need to integrate disruptive technologies within smart cities to potentially deal with disasters as well as improve post-disaster management was raised, consequently, classification framework was developed which classifies the state-of-the-art technologies. This helps reduction in disaster risk as well as enhance the resilience of the cities. However, cities that are not smart cannot benefit from this. Cities in Nigeria are not smart. The researchers in Samikwa [10] pointed out the fact that Internet of Things (IoT) technologies and artificial neural network (ANN) cannot stop the occurrence of flood disasters. They iterated that there has been less focus on the utilization of edge computing for improved efficiency and reliability of such systems. Thus, a system for short-term flood prediction that uses IoT and ANN was developed, where the prediction computation is carried out on a low power edge computing device. The system monitors real-time rainfall and water level sensor data and predicts ahead of time flood water levels using long short-term memory. The results of evaluating the prototype of the system indicate a good performance in terms of flood prediction accuracy and response time. Two climatic parameters where used: water level and rainfall values. There is need to improve the performance of the model by using humidity, air pressure, temperature, etc. that affect rainfall which could be observed by sensors to improve the performance of the model when forecasting. Furthermore, there is lack for techniques of monitoring the system and detecting discrepancies in its behaviors resulting from the computation being carried out at the edge.

Assessing the post 2010 flood risk management and resilience building practices in District Layyah, Pakistan was carried out by Munawar, *et al.* [11]. The socioeconomic status of people living in the district of Layyah was found to be low and most people worked as laborers on the farms. The result shows that in Pakistan, disaster preparedness is higher for floods than other disaster events. Also, there was lack of technical skill and equipment by the authorities to deal with large-scale disaster events such as the 2010 floods. Furthermore, it was also discovered that education programs were not given to the people to prepare themselves for the disaster. A study of regular and frequent disasters like floods, cyclone storms, tidal surges, river bank erosion and earthquakes in Bangladesh was also carried out by Islam and Chik [12]. They used Internet, GIS, remote sensing, radar and satellite communications, and mobile communications in their study. Their results show the main reasons for disasters in Bangladesh which include: flat topography of its coastal areas, drainage congestion, low relief of floods, low river gradients, heavy monsoon rainfall, enormous discharge of sediments, funnel shapes and the relative shallowness of Bay of Bengal, etc. There is a need for more disaster preparedness, awareness, and proper management for effective mitigation against the impact of disasters. In our research, we evaluated the situation in a flood-prone area in Cross River state in Nigeria.

The questions whether or not resilience is simply a re-branding of the concept of mitigation which has previously been widely employed in the hazard and disaster management field were reviewed by Parker [13]. They surveyed six papers that discussed on disaster resilience. The discussion led to the conclusion that resilience is not a simple re-branding but is a concept that goes well beyond mitigation to embrace adaptation, change and transformation. Their work lack implementation. The impossibility of stopping flooding though difficult should not hinder the prevention of minimizing the serious damages caused by flood, this is the problem being addressed by [14]. Their research aims at evaluating the existing of machine learning approaches for flood prediction as well as evaluate parameters used for predicting flood, their evaluation was based on the review of previous research articles. They chose the hybridization of ML. Their results found out that various notable parameters were being used in model input and thus can assist researchers and/or flood managers as guideline in considering ML method for predicting results in early flood prediction. Their study compared and evaluated ML methods applied in flood prediction scenarios and parameters in the past 5 years, some insights and patterns might be discovered if it was done with dataset of more than 5 years. In our case we use the dataset of more than 30 years.

In Odiona, *et al.* [15] the authors tackled the problem of predicting age groups in humans using various biometric modalities by focusing on the use of transfer learning for sclera age group classification. 250 individuals of various ages were examined and 2000 Sclera images were collected from them and Otsu thresholding was used to segment the images using morphological processes. The experiment conducted was able to predict how accurately the age group of an individual can be classified from sclera images using pre-trained CNN architectures. The findings from the study showed that there is an aging template in the sclera that can be utilized to classify age.

Cat Swarm Optimizations (CSOs) have the problem of a low convergence rate and are easily trapped in local optima. To address this problem, [16] introduced new parameter which was added to the velocity for the tracing mode and the Opposition-Based Learning (OBL) technique was used to modify the CSO algorithm (ICSO-SVM). Thus, an Improved Cat Swarm Optimization (ICSO) was proposed for optimizing the parameters of SVM with the aim of enhancing its performance in Abdulraheem, *et al.* [16] . The proposed algorithm was verified using 15 datasets from the University of California Irvine (UCI) data repository and also six different performance metrics were used. The experimental results clearly indicate that the proposed method performs better than the other state-of-the-art methods. ML algorithms - Random Forest, XGBoost and TensorFlow Deep Neural Network (DNN) - were used by Udeze, *et al.* [17] for development of the models as well as for the detection of fraudulent credit card transactions. To develop an optimal models, four techniques were employed in their research to sample the datasets including the baseline train test split method, the class weighted hyper-parameter approach, the under-sampling and oversampling techniques. They observed that the DNN is more efficient than the other two algorithms in modelling the under-sampled dataset while overall, the three algorithms had a better performance in the oversampling technique than in the under-sampling technique. Nevertheless, the Random Forest performed better than the other algorithms in the baseline approach.

In recent years, there has been increasing interest in using blockchain technology [5, 18] to improve flood prediction and warning systems. A number of studies have been conducted on the use of blockchain technology in flood prediction and early warning systems, and they have shown promising results. Consequently, researchers are exploring ways through which this technology can be applied in flood prediction and early warning systems. It has been used in digital currencies, disaster relief aid distribution, e-governance, health science, environmental science, supply chain, etc. [19]. Blockchain technology in disaster management is being explored by researchers and so a blockchain-based disaster management approach using the deep learning algorithm has been developed to reduce energy usage and processing time [20]. Indeed, few researchers have dare to introduce this technology to enhance solutions flooding problems. For instance, [21] in his research used blockchain technology to simplify a decentralized network brainstorming as well as the generation of a simulated data stream. In a related work, [20] used monsoon-dominated catchment in Bangladesh as a case study and combining convolutional neural networks (CNN) with various machine learning techniques such as RF, SVM, XGBoost and long short-term memory (LSTM) to construct novel ensemble computational models (CNN-LSTM, CNN-XG, CNN-SVM, and CNN-RF) for flood hazard mapping.

3. Research Methods

In this research, different methods to gather information were utilized. Some of these methods are: (i) Review: different studies on flood prediction and early warning system as well as related topics were reviewed. (ii) Oral Interview: we discussed with stakeholders in Nigerian Meteorological Agency (NiMet). (iii) Dataset Collection Description: to evaluate the flood events and effects in the last 35 years, the dataset that was used for examining our research was obtained from NiMet. (iv.) Questionnaire: questionnaire was developed and distributed to inhabitants of flood-prone area in Cross River State. Upon completion of distributions and retrieval of the questionnaires, we analyzed and discussed the results of the 192 collected questionnaires.

The software methodology that we adopted to carry out this research is a combination of object oriented analysis and design methodology (OOADM) and cross industry standard process for data mining methodology (CRISP-DM). Firstly, we use OOADM to develop the interface because OOADM has the following benefits: (a.) It has capacity to tackle complex data and more challenging problem domains. (b.) It has the ability to improve communication among users, analysts, designers, and programmers. (c.) OOADM increases the robustness of systems, etc. Secondly, we used the CRISP-DM methodology because we are dealing with flood prediction which involves an aspect of Artificial Intelligence (AI). The CRISP-DM has a broader-focus and as such has the following advantages: (a.) Its process encourages data miners to focus on research goals, so as to ensure that the research goals remain at the center of the project throughout as well as that the project outputs provide tangible benefits to the institution. (b.) The CRISP-DM provides an iterative approach (Fig. 1). The iterative method minimizes the risk of getting to the end of the project and finding that the institution objectives have not really been addressed. Furthermore, it offers the frequent opportunities to evaluate the progress of the project against its original objectives indicating that the project stakeholders can adapt and change the objectives in the light of new findings.

In flood prediction, various parameters can be used in the prediction. In our research, we employed specifically six parameters: minimum and maximum temperature (Celsius), rainfall (mm), relative humidity (%), visibility (meter), evapotranspiration (mm). Data assimilation plays an important role in flood prediction and advisory system (FPAS). The source of data is derived from NiMet, this helps to improve the accuracy and the reliability of the flood predictions. SVM, Random forest, and XGBoost are all excellent choices for making flood predictions. They each have their own strengths and weaknesses, but they are all highly accurate and well-suited for this kind of task.

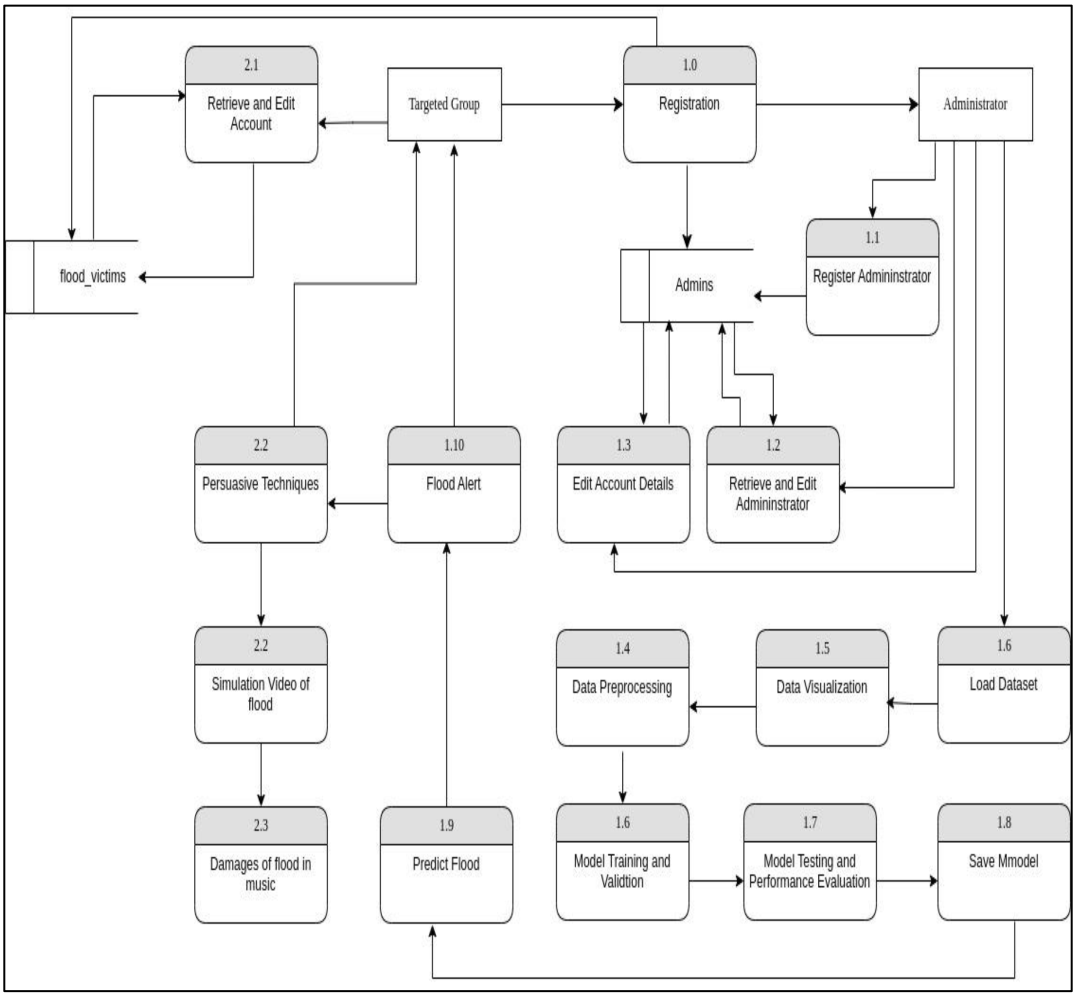

Figure-1. High Level Model of the FPAS System

4. The Results and Discussion

In this section, we discussed the evaluation of the performance of the FPAS model, the mobile application and the survey output.

4.1. The Evaluation of the Performance of the FPAS Model

There are different metrics used to evaluate the performance of a machine learning model. A common way to visualize the results of a machine learning model is called a *confusion matrix*. A confusion matrix shows how many predictions were correct and how many were incorrect. It also shows the different types of errors the model is making, like "false positives (FP)" and "false negatives (FN)." For Instance, let say our flood prediction model makes a prediction of "no flood" for a location where there actually is a flood. That would be a "false negative." In this case, the model was "confused" about whether there was a flood or not. On the other hand, if our model predicts a "flood" when there is not one, that is, a "false positive." Furthermore, in our flood prediction model, a "true positive (TP)" is when the model correctly predicts that a flood will occur, while a "true negative (TN)" is when the model correctly predicts that a flood will not occur. These terms: TP, TN, FP and FN are important for evaluating the four performance metrics: accuracy, precision, recall, and F-measure used in machine learning performance of the flood prediction model. The formula derived from these terms are shown in equations (1) to (4) and they are used to compute the four performance metrics stated:

(i.) Accuracy: Equation (1) measures the accuracy as the percentage of correct predictions made by the model. It is the proportion of correct instances of predictions over the entire test dataset, which is expressed mathematically as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (1)$$

(ii.) Precision: It is a metric that measures how many of the predicted positive outcomes are actually correct. Equation (2) is used to calculate the precision.

$$Precision = \frac{TP}{TP + FP} \qquad (2)$$

(iii.) Recall: Equation (3) is the definition of recall instances. It is a metric that measures how many of the actual positive outcomes or instances of flooding were correctly predicted.

$$Recall = \frac{TP}{TP + PN} \quad (3)$$

(iv.) F-measure: The harmonic mean of the recall and accuracy which is used to calculate the F-measure (also called F1-score) is shown in Equation (4).

$$F - measure = 2 * \left(\frac{precision * Recall}{Precision + Recall}\right) \quad (4)$$

The SVM confusion matrix is shown in Fig. 2. It indicates that the SVM model successfully classifies 84 instances of flood prediction out of which TP = 23, FP = 6, TN = 54 and FN = 1.

$$Accuracy = \frac{23 + 54}{23 + 54 + 6 + 1} = \frac{77}{84} = 0.916667$$

$$Precision = \frac{23}{23 + 6} = \frac{23}{29} = 0.793144$$

$$Recall = \frac{23}{23 + 1} = \frac{23}{24} = 0.958333$$

$$F - measure = 2 * \left(\frac{0.793144 * 0.958333}{0.793144 + 0.958333}\right) = 2 * \frac{(0.760096)}{(1.751477)} = 2 * 0.433974 = 0.867948$$

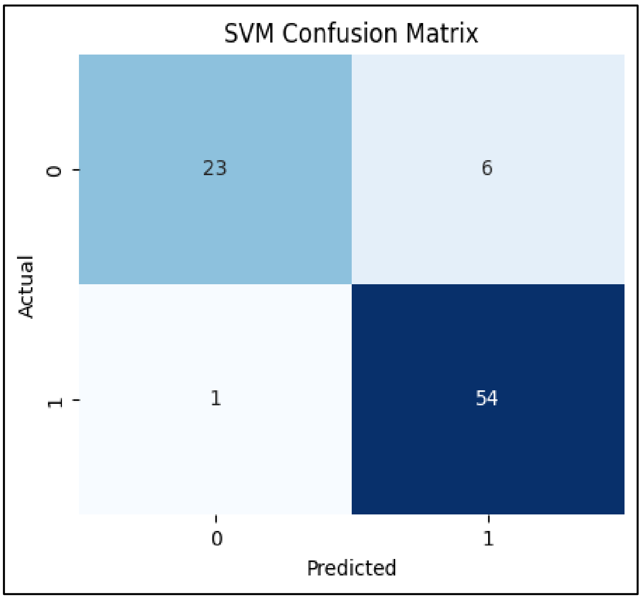

Figure-2. Confusion Matrix of SVM Model

What can be deduced from a model using SVM with a performance metrics of accuracy = 91.67%, precision = 79.31%, Recall = 95.83% and F-measure of 86.79%? Those metrics suggest that the SVM model is performing very well. The high accuracy and recall values mean that the model is correctly identifying both positive and negative cases, and the high precision and F-measure values mean that the model is identifying positive cases with high confidence. The Ransom Forest confusion matrix is shown in Fig. 3. It indicates that the Ransom Forest model successfully classifies 84 instances of flood prediction out of which TP = 55, FP = 0, TN = 29 and FN = 0.

$$Accuracy = \frac{23 + 54}{23 + 54 + 0 + 0} = \frac{84}{84} = 1$$

$$Precision = \frac{23}{23 + 0} = \frac{23}{23} = 1$$

$$Recall = \frac{23}{23 + 0} = \frac{23}{23} = 1$$

$$F - measure = 2 * \left(\frac{1 * 1}{1 + 1}\right) = 2 * \frac{(1)}{(2)} = \frac{2}{2} = 1$$

What can be deduced from a model using random forest with a performance metrics of accuracy = 100%, precision = 100%, Recall = 100% and F-measure of 100%? These are impressive metrics. The XGBoost confusion matrix is shown in Fig. 4. It indicates that the XGBoost model successfully classifies 84 instances of flood prediction out of which TP = 55, FP = 0, TN = 29 and FN = 0. Surprisingly, it follows the same pattern as observed in the Random forest model.

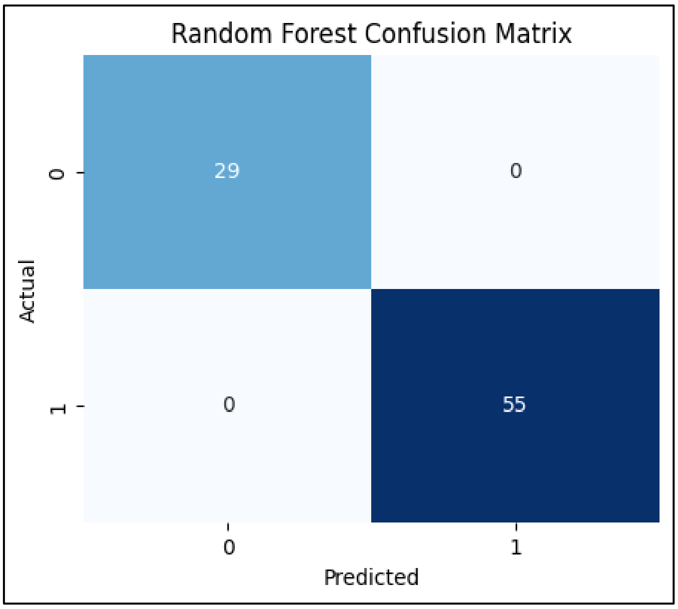

Figure-3. Confusion Matrix for Ransom Forest Model

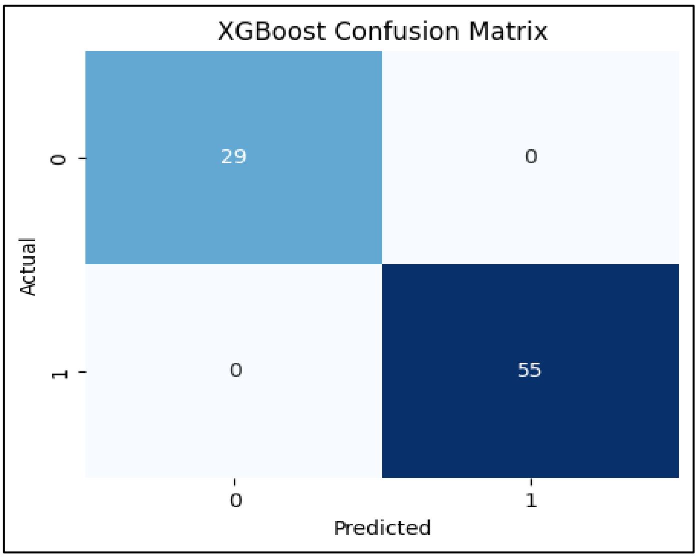

Figure-4. Confusion Matrix for XGBoost Model

Table-1. The Evaluation of the Performance of the FPAS Model

Classifier	Accuracy	Precision	Recall	F1-Score
SVM	92%	79%	96%	87%
Random Forest	100%	100%	100%	100%
XGBoost	100%	100%	100%	100%

From Table 1 we can understand the performance of the models, random forest and XGBoost outperformed SVM.

4.2. Application Layer Implementation

The application layer in the FPAS model (see Fig. 5 and Fig. 6) provides an easy-to-use interface based on user registration and it processes are generally based on interacting directly with applications and providing an easy-to-use interface for end users to record, store and access their data as well as for the admin to do the predictions and manage the public users' information concerning the flooding.

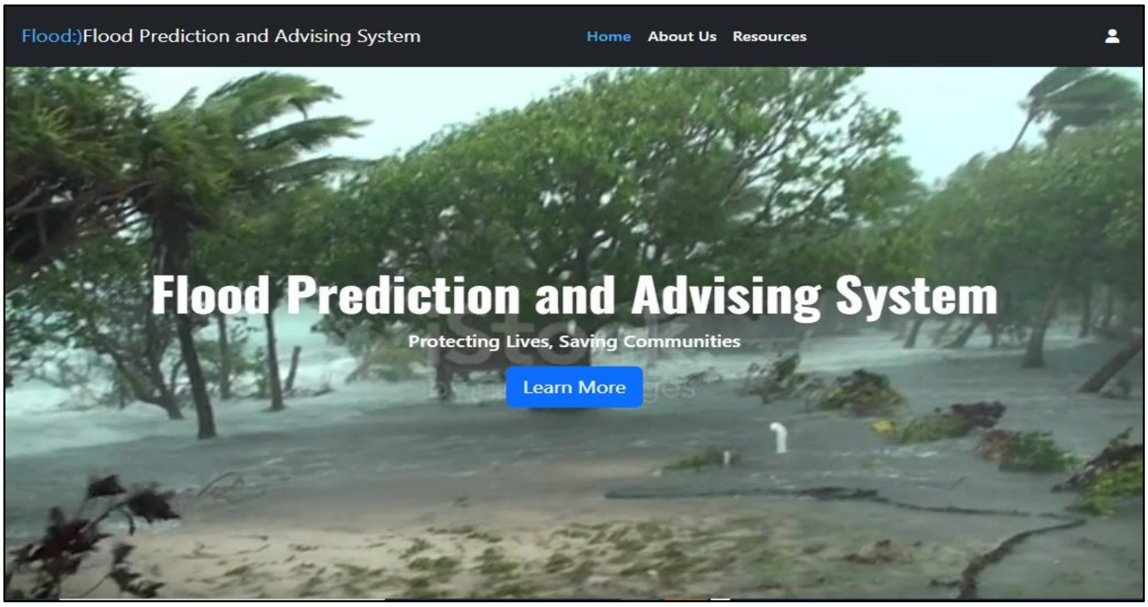

Figure-5. Home Page for FPAS

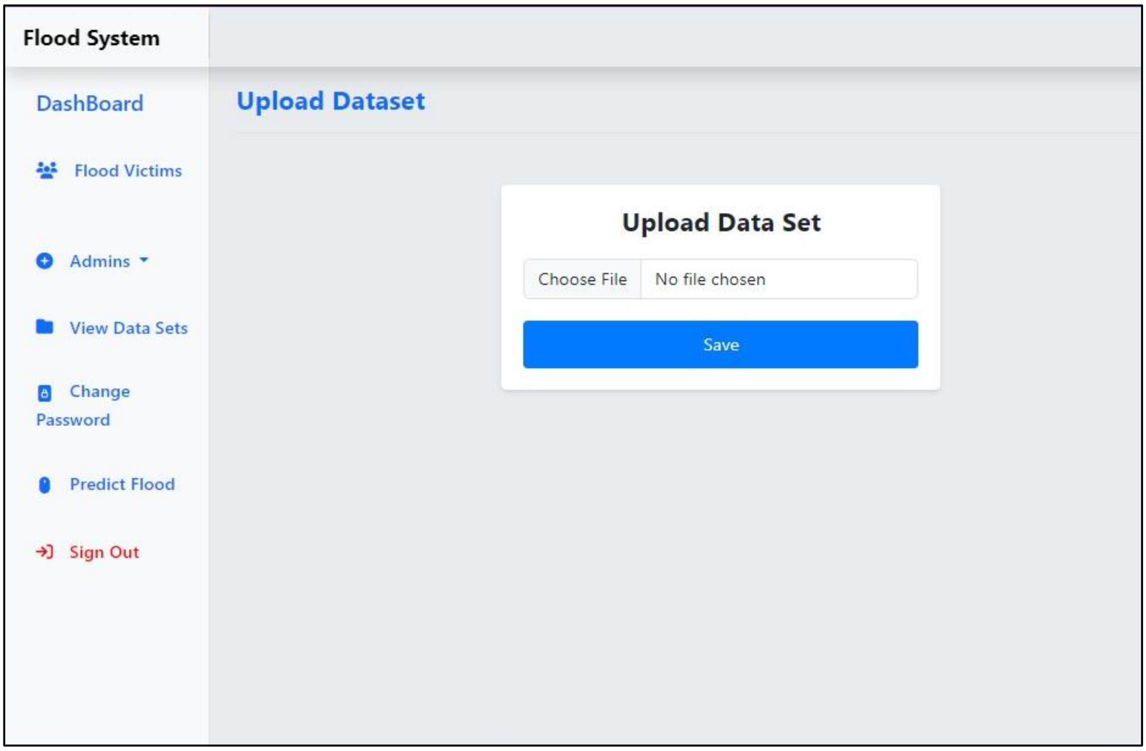

Figure-6. The FPAS Model Interface

4.2.1. User Registration Process

Through the user interface shown in Fig. 7, the user can register to the app and be added to the registered new user list. In the case of our FPAS model, we have two options to register: Register flood victim or Administrator. In the *sign-up module*, the public will use this module to sign-up and register their details on the platform (see Fig. 8). They submit their details including a username, email. Phone number, address, age and gender. The sign-up module also provide a log in or sign-in access, where access to the platform using a username and password. The system validates their login criteria and allows them access and if authentication fails an error message is displayed. The registered users will get alert messages through their phones (see Fig. 9). The admin login module grants admin access to the platform using their username and password. When given access successfully, the admin will carry out the predictions specified parameter to inform the general public if they will be flooding or not.

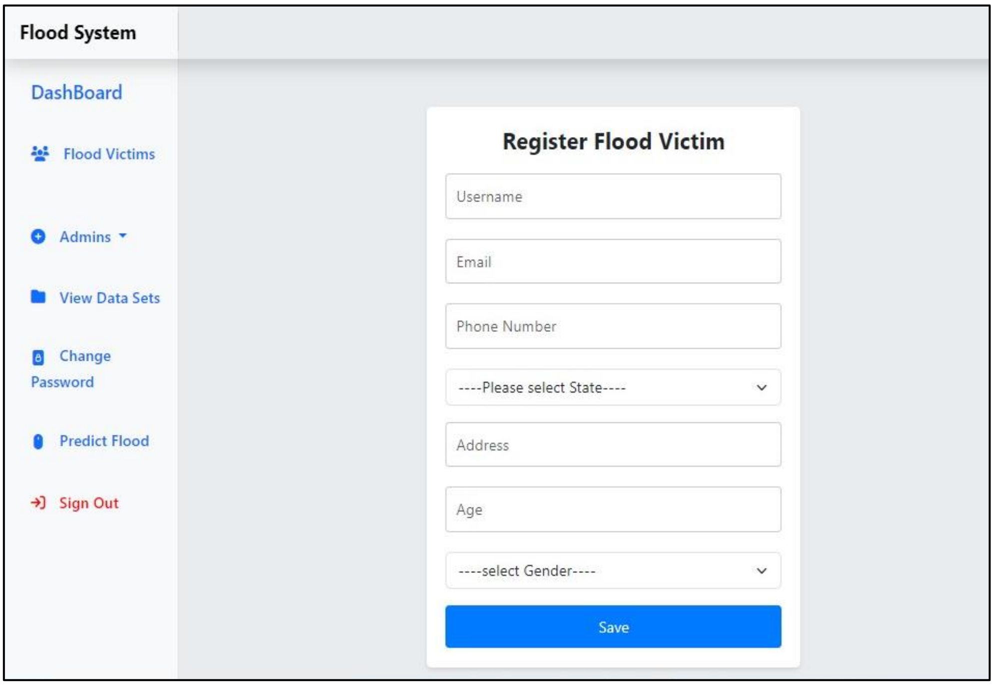

Figure-7. User Registration Interface

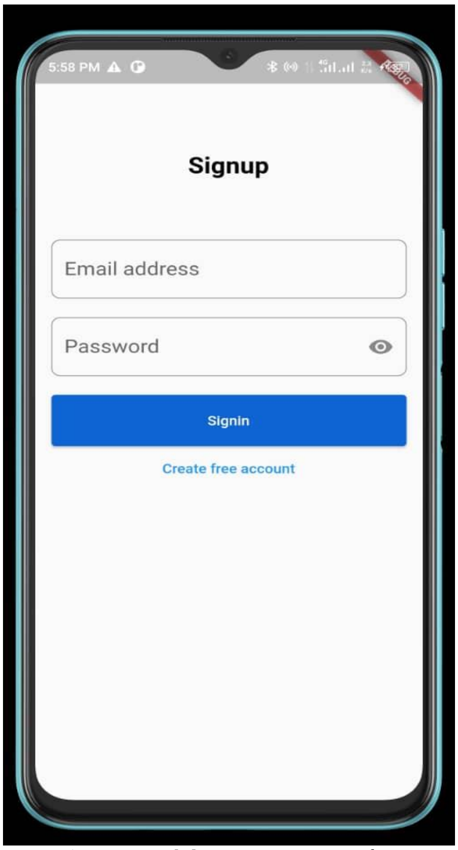

Figure-8. Mobile App Sign-up Interface

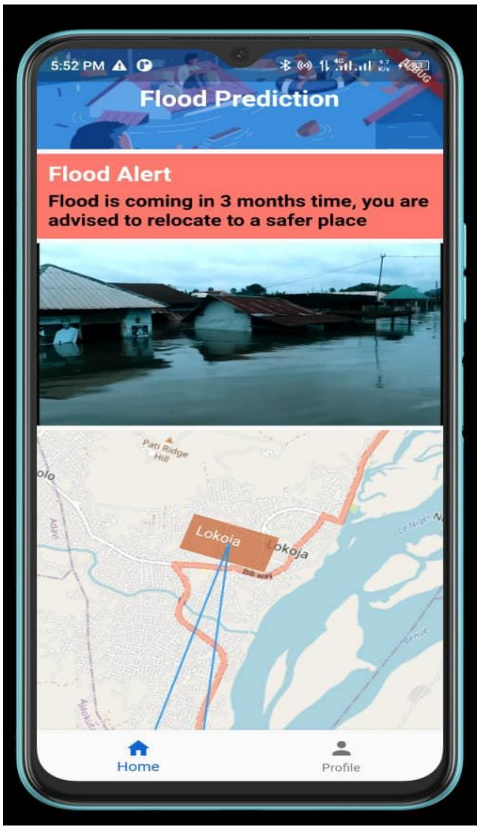

Figure-9. Mobile App Flood Prediction Alert

4.2.2. Flood Prediction Parameters

Our predictions were made with the meteorological data derived from NiMet using the following parameters: minimum and maximum temperature, rainfall, relative humidity, visibility, and evapotranspiration. The interface for inputting the parameter is shown in Fig. 10. With parameters of minimum temperature = 10 ^{o}C, maximum temperature = 25 ^{o}C, rainfall = 90mm, relative humidity = 50%, visibility = 100m, and evapotranspiration = 10mm, the model gave us a result of "*no flood*" (see Fig. 11). However, using the following parameters: minimum temperature = 20 ^{o}C, maximum temperature = 30 ^{o}C, Celsius, rainfall = 100mm, relative humidity = 600%, visibility = 2000m, and evapotranspiration = 10mm, the model gave us a result of *"flood predicted"* (see Fig. 12).

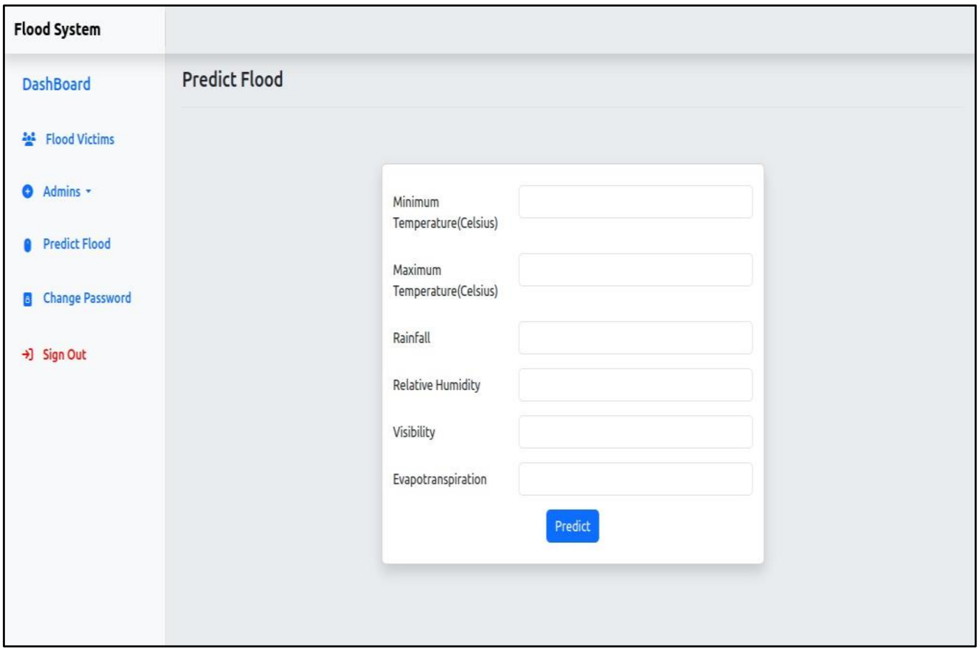

Figure-10. Flood Prediction Parameter Interface

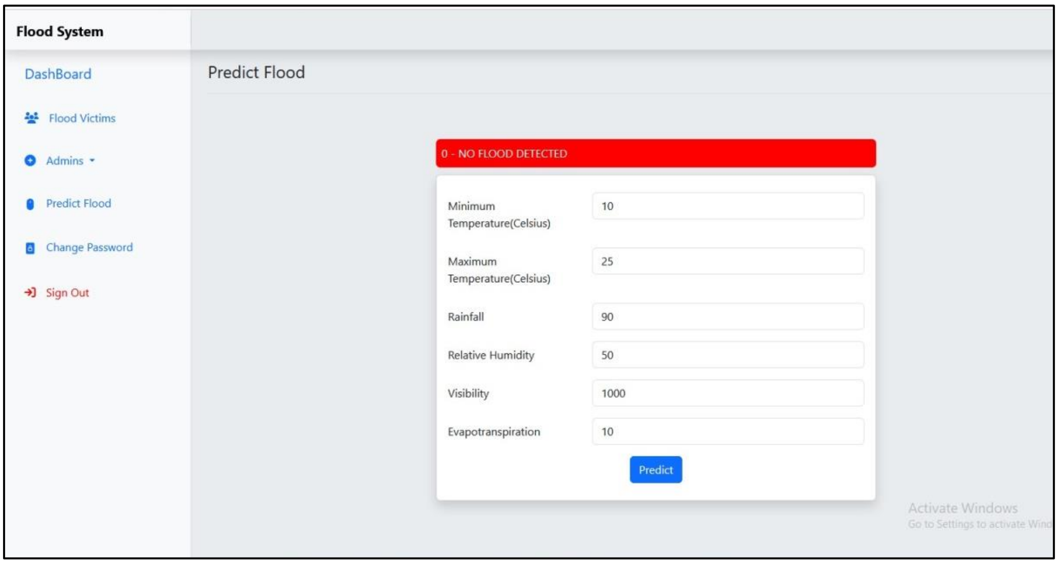

Figure-11. No Flood Predicted

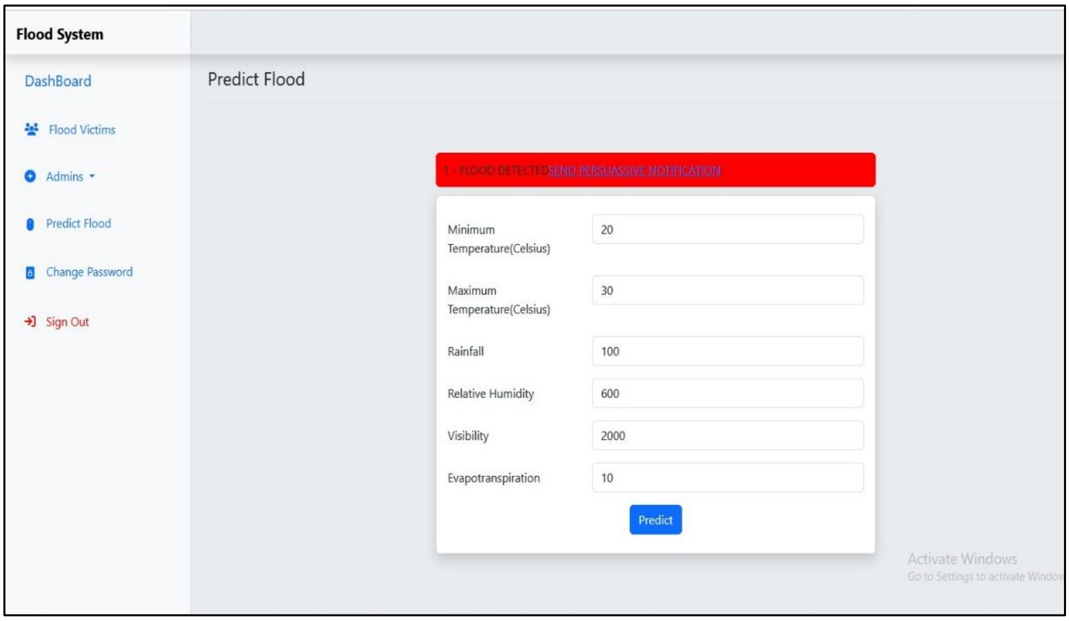

Figure-12. Flood Predicted

4.3. Analysis of the Survey

A total of 200 questionnaires were distributed in Isobo Otaka and Isobo Bikobiko, Obubra Local Government Area (L. G. A.), Cross River State (CRS) and 192 questionnaires were retrieved at the end of the exercise that lasted from Friday, 3rd November 2023 to Monday, 6th November 2023. Table 2 represents the socio-demographic characteristics of the study participants. It could be clearly seen that greater percentage of the study participants in CRS are male 57.29% while 42.71% are female.

Table-2. Social-Demographic Characteristics of the Study Participants

Variable	Frequency CRS (N=192)
	Gender
Male	110
Female	82
	Age Group (Year)
10 – 15	8
16 – 20	106
21 – 25	22
26 – 30	24
31 & Above	32
	Education Qualification
FSLC	8
SSCE	106
NCE	22
B. Sc.	24
Postgraduate	32

The result further shows that only 17.19% of the respondent have tertiary education while significant proportion of them, that is, 53.13% have secondary education and 29.69% (3.09%) reported to have primary education. In Table 3, when asked how many times they have been warned of an impending flood disaster, 91.67% says that they were not often informed, 1.04% says they were always, 6.25% they have been informed just ones while 1.04% says they have never been informed. Consequently, there is a need for the population at risk to be informed on time by the appropriate authorities using advisory.

Furthermore, in Table 3, 69.58% of the respondents declared that they were informed of the impending flood disaster by the government, 4.17% says they were informed by friends, and 2.60% says they were informed by their relatives while 3.65% says others. In Table 4, 91.15% of the target users opined that they FPAS system with modern technology should be embedded into it. Finally, when the respondents were asked about the persuasive nature of the messages sent to them, 76.56% declared that the warning messages were not persuasive while 18.23% says they were (see Table 5). Thus, the need to include persuasive messages.

Table-3. Response on Being Warned of Impending Flood Disaster in CRS

Question	Response category	CRS (N=192)
How many times have you been warned of an impending flood disaster?	None	2 (1.04%)
	Ones	12 (6.25%)
	Always	2 (1.04%)
	Not Often	176 (91.67%)
Who warned you?	Government	172 (69.58%)
	Friends	8 (4.17%)
	Relatives	5 (2.60%)
	Others	7 (3.65%)

Table-4. Response on Opinion of Target users concerning Flood Prediction and Advisory System using Modern Technology

Question	Response category	CRS (N=192)
Did you think flood prediction and advisory system using modern technology is necessary?	Yes	175 (91.15%)
	No	2 (1.04%)
	Not very Necessary	9 (4.69%)
	Somehow Necessary	6 (3.13%)

Table-5. Response on whether the means through which the Warning is given Persuasive

Question	Response category	CRS (N=192)
Is the means through which the warning is given persuasive?	Yes	35 (18.23%)
	No	142 (76.56%)
	Sometimes	10 (5.21%)

5. Conclusions and Prospects for Further Research

This study addresses the need for a comprehensive flood prediction and advisory system by leveraging machine learning algorithms. This paper presents the methodology, implementation, and evaluation of the FPAS model, highlighting its potential to revolutionize flood preparedness and response through innovative technological solutions. We used three machine learning algorithms – SVM, Random forest, XGBoost - for making predictions on flood dataset obtained from NiMet. The research methodology applied in this work was a hybrid approach, combining OOADM and CRISP-DM. OOADM was used to develop the mobile app for citizens' registration and a web app for administrative activities, while CRISP-DM was used to create a data-drive predictive model for the app using the NiMet flood dataset. The Random Forest and XGBoost achieved a precision of 100% while the SVM gets 79%. In future work, we seek to develop, test and improve the FPAS model by implementing the model embedding persuasive techniques – audio, personalization, and story - that will persuade those in flood-prone areas to leave and move to safety areas.

References

[1] Terti, G., Ruin, I., Anquetin, S., and Gourley, J. J., 2015. "Dynamic vulnerability factors for impact-based flash flood prediction." *Natural Hazards,* vol. 79, pp. 1481–1497.

[2] Madhuri, R., Sistla, S., and Raju, K. S., 2021. "Application of machine learning algorithms for flood susceptibility assessment and risk management." *J. Water Climate Change,* vol. 12, pp. 2608–2623.

[3] World Meteorological Organization WMO, 2011. "Manual on flood forecasting and warning, WMO. No. 1072."

[4] La Rocca, M., Miliani, S., and Prestininzi, P., 2020. "Discrete boltzmann numerical simulation of simplified urban flooding configurations caused by dam break." *Front. Earth Sci.,* vol. 8, p. 346. Available: https://doi.org/10.3389/feart.2020.00346

[5] Ugah, J. O. and Onwudebelu, U., 2023. "Blockchain-based flood prediction and advisory system: Ensuring accuracy, scalability and security." In *the conference proceedings of Society for the Advancement of ICT & Comparative knowledge (SOCTHADICKconf'23).* pp. 109 –130.

[6] Cristianini, N. and Shawe-Taylor, J., 2000. *An introduction to support vector machines and other kernel-based learning methods*. Cambridge University Press.

[7] Chen, T. and Guestrin, C., 2016. "Xgboost: A scalable tree boosting system." In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining.* pp. 785-794.

[8] Chen, T. and He, T., 2021. "Xgboost: Scalable gpu accelerated learning. arxiv preprint arxiv:2106.13371."

[9] Munawar, H. S., Mojtahedi, M., Hammad, A. W. A., Kouzani, A., and Mahmud, M. A. P., 2021. "Disruptive technologies as a solution for disaster risk management: A review." *Science of the Total Environment,* vol. 806, p. 151351. Available: https://doi:10.1016/j.scitotenv.2021.151351

[10] Samikwa, E., 2020. *Flood prediction system using iot and artificial neural networks with edge computing, M. Sc. Degree project in computer science and engineering, second cycle*. Credits Stockholm, Sweden.

[11] Munawar, H. S., Khan, S. I., Anum, N., Qadir, Z., Kouzani, A. Z., and Parvez-Mahmud, M. A., 2021. "Post-flood risk management and resilience building practices: A case study." *Applied Sciences,* vol. 11, p. 4823.

[12] Islam, S. and Chik, Z., 2011. "Disaster in Bangladesh and management with advanced Information system." *Disaster Prevention and Management,* vol. 20, pp. 521-530.

[13] Parker, D. J., 2020. "Disaster resilience – a challenged science." *Environmental Hazards,* vol. 19, pp. 1-9. Available: https://doi.org/10.1080/17477891.2019.1694857

[14] Nur-Adib, M., 2019. "Evaluation of machine learning approach in flood prediction scenarios and its input parameters: A systematic review, iop conference series: Earth and environment science. The 7th aun/seed-net regional conference on natural disaster (rcnd 2019)." Available: https://www.doi:10.1088/1755-1315/479/1/012038

[15] Odiona, P. O., Musab, M. N., and Shuaibua, S. U., 2022. "Age Prediction from Sclera Images using Deep Learning." *Journal of the Nigerian Society of Physical Sciences,* vol. 4, p. 787. Available: https://doi.org/10.46481/jnsps.2022.787

[16] Abdulraheem, S. A., Aliyu, S., and Abdullahi, F. B., 2023. "Hyper-parameter tuning for support vector machine using an improved cat swarm optimization algorithm." *Journal of the Nigerian Society of Physical Sciences,* vol. 5, p. 1007. Available: https://doi.org/10.46481/jnsps.2023.1007

[17] Udeze, C. L., Eteng, I. E., and Ibor, A. E., 2022. "Application of machine learning and resampling techniques to credit card fraud detection." *Journal of the Nigerian Society of Physical Sciences,* vol. 4, p. 787. Available: https://doi.org/10.46481/jnsps.2022.769

[18] Ugah, J. O. and Onwudebelu, U., 2023. "FPAS system: The new frontier in flood prediction and the lifesaver for flood-prone communities." *African Journal of Management Information System Afr. J. MIS,* vol. 5, Available: https://afrjmis.net/

[19] Sheela, K. and Priya, C., 2021. *Enhancement of iot security solutions blockchain technology. In: Blockchain applications for secure iot frameworks: Technologies shaping the future* vol. 1. India: Bentham Science Publishers. p. 131.

[20] Mia, M. M. U., Rahman, A., Elbeltagi, M., Abdullah-Al-Mahbub, G., Sharma, H. M., Islam, S. C., Pal, R., Costache, A. R., Islam, M. M., *et al.*, 2022. "Sustainable flood risk assessment using deep learning-based algorithms with a blockchain technology." *Geocarto International,* Available: https://doi.org/10.1080/10106049.2022.2112982

[21] Swan, M., 2015. "Blockchain thinking: The brain as a decentralized autonomous corporation [commentary]." *IEEE Technology and Society Magazine,* vol. 34, pp. 41–52.