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Flood Image Classification using Convolutional Neural Networks

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Abstract: *Flood disaster is a natural disaster that leads to loss of lives, properties damage, devastating effects on the economy and environment; therefore, there should be effective predictive measures to curb this problem. Between the years 2002- 2023, flood has caused death of over 200,000 people globally and occurred majorly in resource poor countries and communities. Different machine learning approaches have been developed for the prediction of floods. This study develops a novel model using convolutional neural networks (CNN) for the prediction of floods. Important parameters such as standard deviation and variance were incorporated in the parameters tuned CNN model that performed flood images feature extraction and classification for better predictive performance. The enhanced model was assessed with accuracy and loss measurement and compared with the existing model. The model leverage on the unique features of region of Interest aligns to resolve the issues of misalignments caused by the use of region of Interest pooling engaged in the traditional Faster-RCNN. The techniques and the developed system were implemented using a Python-based integrated development environment called "Anaconda Navigator" on Intel Core i5 with 8G Ram hardware of Window 10 operating system. The developed model achieved optimal accuracy at 200 epochs with 99.80% and corresponding loss of 0.0890. The results confirmed that predictive performance of a model can be improved by incorporating standard deviation and variance on model, coupled with its parameters tunning approach before classification.*

Keywords: *Convolutional neural networks, Flood, Machine learning, Prediction, Natural disasters*

1. INTRODUCTION

Rapid advancement in science and technology has been aided by different successful studies in computing. Data mining, machine learning, decision support system and artificial intelligence have been widely applied in different fields[1], [2] and one of such applications is the prediction of floods[3–6]. Data mining is a combination of algorithmic systems, discovering and extraction of patterns from data and it is applicable to many fields or disciplines in which data can be obtained, then such data can be mined [7]. For example, its applications in diseases diagnosis, drug testing, prediction of patient's response to prescription, cyber security, intrusion detection, fraudulent pattern detection, prediction of clients answering a mail, detection of associations in customer characteristics, logistics and decision making[8]. Artificial Intelligence (AI) is applied in the development of systems which can function intelligently and independently like human brain [9] and one of the fields of machine learning (ML) classification technique [10]. Machine learning aids computers to learn from data and recognize patterns with little human intervention[11]. It is often employed in artificial intelligence that are used for discovering of new properties by learning from training dataset [12]. Methods of machine learning classification techniques are sub divided into different categories; these classes include supervised learning, unsupervised learning, deep learning and dimensionality reduction[7, 72]. One of the application areas of machine learning is the deep learning, which is frequently adopted in core areas of mathematics, engineering and computer science [13]. Different studies had shown the impacts of machine learning and artificial intelligence in image processing, intelligent system development, natural language processing, security and signal processing [12, 71, 72]. Flooding is a condition in which surface water exceeds the retentive capacity of the dry land [7, 8, 14, 15]. Studies proved flood, as the most dangerous natural disaster which causes destruction to both non- structural and structural facilities [16]. The frequency of the flood occurrence has increased for the past few years [16]. Flooding can be caused by heavy rainfall, overflow of river in riverside areas, nature of soil, dam overflow and poor town planning[17, 18]. Floods have devastating effects on the economy, environment and people [19–21]. People that are mostly vulnerable to floods are those that live in floodplains with lack of flood warning systems or non-awareness of flooding hazard[22]. Therefore, there should be effective preventive measures such as proper drainage and waste management, planting of appropriate vegetation and flood alert system [23–25]. Flood menace between the year 2010 – 2020 has attributed to 3.6 billion residents being inundated woldwide, which estimated as 56% of the total world population[26]. It also affected over 50 countries in Africa between 2000 – 2019 [27]. The sum of 600, 000 people were affected in September, 2009 by torrential rains, flooding and the worst nations include Burkina Faso, Senegal, Niger and Ghana[28]. In Nigeria, flood killed 363 people between early July and November, 2021, displaced over 2.1 million people and also affected 30 states in Nigeria [27]. The flood disasters in the year 2021 caused approximately damages of $0.83 billion, $4.7 billion, $19.3 billion for Africa, Europe and Asia continents respectively[29].

Different machine learning models have been applied for the prediction of floods worldwide, such predictive models include Artificial neural network [30–35], support vector machine [6, 36, 37], coaxial correlation diagram hydrological and hydraulic models [39, 40] and Multilayer perception classifier[5, 41]. Different conditioning factors (CgFs) are considered for the prediction of floods, such factors include soil, curvature, stream index (SPI), distance to river and land use, Potential maximum retention, altitude, rainfall, slope degree, lithology, vegetation index, topographic wetness index, drainage density, Topographic position index, run off height, normalized vegetation difference [7, 14, 24, 42, 43]. Apart from these factors, Other variables are examined by [44, 45] in Kuala area of Malaysia, those variables include date, humidity, wind, rainfall (daily), rainfall (monthly), water level and flood class (either flood or no flood). Different researchers have compared the results obtained using these variables on different datasets in different parts of the world or studies area. Prediction of flood was done using decision tree [46–48]. The parameters used were temperature, water level and rainfall [46, 47]. The accuracy and sensitivity obtained was relatively high. The major drawback of these works is the inadequate data set. Artificial neural network model was adopted by [4, 49, 50] which accepts input features or parameters such as rainfall data, water level, hygrometric data, temperature and information on dam operation[48] The evaluation was done with accuracy and mean absolute percentage error of relatively good performance. The main drawback of these studies was high computational cost due to use of artificial neural network. Neuro – fuzzy techniques was employed for the prediction of flood by [51–53]. The input parameters used were rainfall, temperature level discharge[51, 52] and river sediments[52, 53]. The performance evaluation was done using accuracy, root mean square and error rate and relatively high performance was achieved. The drawback of this research works is the inadequate dataset (320 samples) and lack of similarity between the data used in the training. Bayesian network model was employed for the prediction of flood [54, 55]. The performance of the studies was done using mean absolute relative error[53] with value of less than 0.076. The drawback of these research works is that sample data is relatively small in this study (370 samples), cluster analysis cannot be achieved.

Coaxial correlation diagrams were successfully applied on the rainfall-runoff predictions [56] and also, applied and compared with hydrological model (Xianjiang Xaj Model) for the reconstruction of flood series under human disturbances. [38, 56] Investigated eight gauged catchments located on semi-humid and semi-arid regions of China based on the topography, land cover and soil type parameters, [56] Investigated fifteen (15) catchments under Yangtze and Yellow River, China based on hydro-climatic attributes, topographic attributes and land cover. Coaxial correlation diagrams performed well with qualified rate (QR) of not less than 85%[56] and can only adjust the time series of total flood volumes[57]. The drawbacks of these works are: No statistical test to measure the strength of the correlation between the dependent and independent variables and also, no hint about the shape of likely flood hydrograph at forecast site. [58] Adopted Bayesian network model for the prediction of flood based on atmospheric ensemble forecasts. Flood peaks are estimated from atmospheric ensemble forecasts (AEF). The Bayesian network was trained to compute flood peak forecasts from atmospheric ensemble forecast and hydrological pre-conditions. Flood mapping models such as digital elevation model (DEM), hydrological engineering centre – hydrological modelling system (HEC-HMS), hydrological engineering centre – river analysis system (HEC-RAS), Sacramento soil moisture accounting (SAC-SMA), modèle du Génie Rural à 4 Paramètres journalier (GR4J), University hydrologiska byråns Vattenbal ansavdelning (MAC-HBVMcMaster) and University of waterloo flood forecasting system (WATFLOOD) models are applied on flood prediction[59], [60]. Digital elevation model (DEM) simulators was applied by [60] on the flood event of November 2019 and compared it using sentinel 2 images on lakes Njuwa, Gerio and also with River Benue water level. The results indicated that flood event occupied entire lake and also extended to 450% of the entire water conditions. [60] Employed five different hydrological models for waterford River watershed flood forecasting. It was observed that all the five models are capable of simulating stream flow both during validation and calibration periods, but it was clearly shown that both SAC-SMA and GR4J models performed better than the other three models (Mac-Hbvmcmaster, Watflood and HEC-HMS) for low, medium and peak flows. Synthetic minority oversampling technique (SMO) was adopted by [44, 45] to treat dataset imbalance. The same dataset format was used for the studies with eight (8) variables namely date, water level, monthly rainfall, daily rainfall, humidity, temperature, wind and class. Bayesian Network and other machine learning algorithms were used for classification[44, 45]. Different variants of Bayesian approaches namely Naïve Bayes, Bayesian Network, Tree Augmented Naïve Bayes were applied by [43]. Other machine learning algorithms applied include support vector machine (SVM), K–Nearest Neighbours (KNN) and Decision Tree [44]. A comparative analysis showed that smote tree augmented Naïve Bayes outperformed algorithms [43]. On the other side, Smote decision tree outperformed support vector machine and k-Nearest Neighbour. The authors suggested that further studies on the prediction of floods using time series since flood occurs with respect to time. Multilayer perception classifier, Adaptive Neuro Fuzzy Inference System, ANFIS-GA (Genetic Algorithm), ANFIS-DE (Differential Evolution), and ANFIS-PSO (Particle Swarm Optimization) were applied on the prediction of flood [5, 7] and compared with logistic regression, support vector machine, K-Nearest Neighbour algorithms and multilayer perception algorithm. It was observed that multilayer perception algorithm has the greatest accuracy of 97.40%, logistic regression, support vector machine and K-Nearest Neighbours have accuracy of 95.33%, 95.85% and 95.85% respectively [5]. ANFIS-GA (Genetic Algorithm) outperformed models with highest success rate and accuracy [7]. Different remote sensing technologies have been applied for the prediction of floods, such technologies includes active and passive methods [6]. Active remote sensing technology gained data from its own light on the earth surface, such as Radar (radio detection and ranging) and LIDAR (light detection and ranging) while passive technology depends on sunlight energy through imagery satellites to capture data. Examples of passive methods include multispectral remote sensing technology such as sentinel -2,MODIS, Landsat 7 and Landsat 8 [61] and hyper spectral. Flood mapping with digital elevation model (DEM) of high resolution is needed to improve its accuracy of light detection and ranging, synthetic aperture ranging and interferometry SAR models [59] and images are processed using models such as sentinel application platform (SNAP) tools to enhance consistency in image properties. [62] Evaluated outcome of combination of sentinel 1 (S1) and sentinel 2 (S2) bands for flood mapping through the use of eleven (11) flood events of 446 flood mapping S1 images. It was observed that better accurate flood inundation maps were achieved by elevation of information which increased the F1 score from 0.62 to 0.73 using Sentinel 1 images without and with elevation of information respectively. [6] Compared the performance of change detection approach (CD) with support vector machine (SVM), random forest (RF) and maximum likehood classifier (MLC) on sentinel 1 images of San Diego, USA. Change detection (CD) approach which combines fuzzy rules, otsu algorithms, iso –clustering methods has least required data, computational time and also offers better performance with 0.81, 0.9, 0.85, 0.87 of precision, recall value, F1 score and accuracy respectively.Geographical information system based artificial neural network model was employed for the prediction of flood[31, 32, 62]. Image pre processing techniques coupled with Convolutional Neural Networks (CNN) are employed for object detection and semantic segmentation processes which are performed by [64]. Aspect ratio and canny edge dection are incorporated in the flood image classifiers. The flood image classifiers employed are fast R-CN (region based CNN), YOLOV3 (You look only once version 3), Mask R-CNN, SSD MobileNet (Single Shot MultuBox Detector MobileNet) and efficientDet. Fast Cnn model outperformed other models with accuracy of 91%. The study areas were Tehran province, Iran [32], Keelung City, Taiwan [63], Nigeria [31]. The dataset for the studies contained different conditioning factors (CgFs), such as rainfall, flow accumulation, slope aspect, drainage density, topographic wetness index, normalized difference vegetation index , land cover, distance to river, temperature and curvature. Performance evaluation comparison was made between artificial neural network model and soil conservation service curve model [32], with logistic regression model [31], with Sobek model[63]. However, the experimental results showed that artificial neural network outperformed logistic regression model with an accuracy of 87.5% [31], outperformed Sobek with an accuracy of 60.5% and with scsc model with accuracy of 84.5%. The studies recommended further evaluation through evolutionary computing algorithms. A modified artificial neural network was applied for the prediction of flood areas in Nigeria by [70]. The modified Artificial Neural Network performed better than the existing models with training and testing accuracies of 98.91% and 96.54% respectively. Convolutional neural networks (CNN) was combined with sorting algorithms for post flood disasters management by [65]. The level of severity of affected flood areas is determined and sorted out by the DenseNet and Inception v3 architecture. The research further demonstrated the performance of convolutional neural network integrated with sorting algorithms for decision making. The DenseNet and Inception v3 achieved the accuracy of 81% and 83% respectively. Limitations of these works are insufficient dataset, model over fitting and under fitting effects. Hence, this research incorporated standard deviation and variance on the parameter tuned convolutional neural network for feature extraction and classification. Sufficient dataset was employed with 3710 flood images. The flood images pre-processed techniques (feature extraction) coupled with parameters tuning enabled the optimal performance of the convolutional neural network. Problems caused as a result of flood occurrences can be minimized or prevented by either structural or non-structural approaches; structural approach include the development and construction of drainage system, proper waste management and design of alert system. Example of non-structural approach is the prediction of flood using data driven approach specifically, the introduction of machine learning algorithms. This research applied the data driven approach specifically convolution neural network model with incorporated standard deviation and variance for feature extraction and classification. Apart from the introductory part of this work, other sections are sub divided into section two which describes materials employed and method; section three analysed the results obtained and the last section (conclusion) gives the observed deductions from the research and recommendation appropriately.

2. METHODS AND MATERIALS

The developed model comprised image acquisition, image pre-processing and classification as drawn in the Figure 1. Each stage of the model was designed for specific purpose. The implementation of the developed model was done using python based integrated environment on Intel Core i5, 3.2 GHz CPU and 8 GB RAM of window 10 operating system. Acquired image datasets were acquired, classified and predicted on the developed model using standard deviation and variance incorporated in convolutional neural networks model for feature extraction and classification. The steps for the developed model include image acquisition, image pre-processing (scaling/normalization and feature extraction), tuned of the convolutional neural network models parameters and model evaluation using accuracy and percentage loss measurement. Table 1 depicts parameters tunned of the convolutional neural networks model.

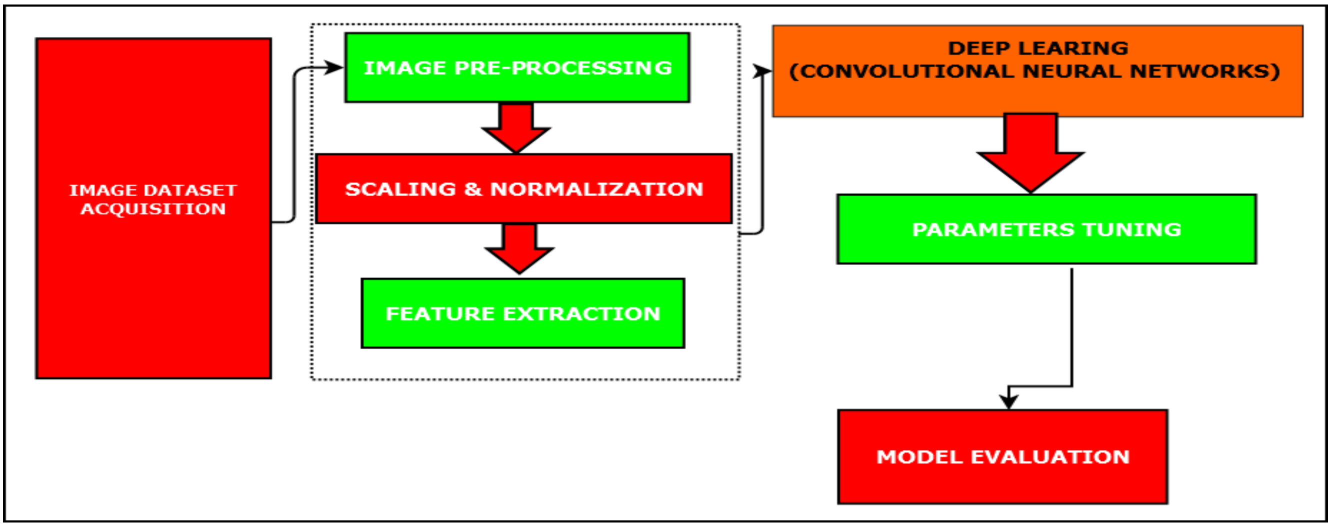

Figure 1: Developed model using parameters tuned convolutional neural networks

2.1 Image Data Acquisition

This is the process of obtaining data for classification process. Image datasets are employed for this study [66] and contained 3710 flood images. Samples of the image datasets are shown in the Figure 2.


Figure 2: Excerpt of flood image from dataset[66]

2.2 Image Pre-Processing

The acquired data are pre-processed by scaling the images to a specific size in order to enhance consistency and to speed up the rate of neural networks processing and computation. This process was further normalized by applying 240×240 pixel. Standard deviation and variance were also incorporated in the parameters tuned convolutional neural networks for the feature extraction and classification of flood image data.

2.3 Convolutional Neural Networks (CNN)

Convolutional neural networks (CNN) are regarded as one of impressive forms of artificial neural network (ANN) architecture which are capable tools for image pattern processing [67,73]. Convolutional neural network comprised convolutional layer, pooling layer and fully connected layer [68]. Convolutional layer is the main component and essential block of convolutional neural networks [69]. Equations 1 and 2 represent Feed forward nets and map of features respectively [67, 68] .

Considering the mathematical equation for the development of convolutional architectures.

Given the unknown function $d_0: X \rightarrow Y$ and the implementation of neural networks hypothesis, $d: X \rightarrow Y$ and decomposes the composition $f = d_1 \circ d_2 \cdots\cdots\cdots d_m$ where d_m is the layer. Feed forward nets (FFNs) produced an output of b^m of size k_m from input vector of T^{m-1} of size k_{m-1}.

Given the map form of:

$$T^{(m)} = c_m(E^{(m)} a^{(m-1)} + h^{(m)}) \tag{1}$$

Where $E^{(m)}$ is a matrix of $k_m \times k_{m-1}$, $h \in j^{k_m}$ and $c_m(.)$ as non-linear function. Input of $P^{(m-1)}$ is received and output $P^{(m)}$. The map of features is termed and expressed as output

$$P_0^{(m)} = c_m \sum_i E_{oi}^{(m)} * p_k^{(m-1)} + b_0^{(m)} \tag{2}$$

Where $*$ connotes 2D convolution operation

$$E_{oi} * p_k[s,t] = \sum_{p,q} A_k[s+p, t+q] e_{ok}\,[P-1-p, Q-1-q] \quad (3)$$

Where $e_{oi}^{(m)}$ with shape $p_m \times Q_m$, $b_0^{(m)} \in R$ and spatial filter with matrix $e_{oi}^{(m)}$.
Given $p^{(m-1)}$ image, a typical pooling layer of the pool sizes p_m, $Q_m \in N$ and strides $s_m, r_m \in U$ for channel wise operation of the:

$$p_0^{(m)}[s,t] = k.\sum_{p,q}(p_0^{m-1}[s_m g + p, r_m t + q])^{\rho 1/\rho} \quad (4)$$

2.4 Accuracy**:** The developed model is evaluated using accuracy and percentage loss measurement of the model. The accuracy is determined as the ratio of the correctly classified images to total number of the images [10, 70].

$$\text{Accuracy} = \frac{\text{Correctly classified image}}{\text{Total number of test images}} \quad (5)$$

2.5 Experimental Setup

Implementation of the model was done with python based integrated environment on Intel Core i5, 3.2 GHz CPU and 8 GB RAM of window 10 operating system. Image datasets were classified which contained 3710 flood images. The acquired images are scaled to enhance consistency to speed up the rate of computation. The cropping of the images was done with 240×240 pixel normalization of the images. Different libraries were imported for implementation with python based environment; such libraries include pandas, numpy, tensorflow, keras and sklearn. Parameters of the convolutional neural networks are tuned as illustrated with the Table 1 to enhance the predictive performance of the model and compared with the existing models using the same dataset.

Table 1: Parameter settings of the modified convolutional neural networks (CNN)

Parameters	Model Values
Optimizer	Rmsprop
Loss function	sparse_categorical_crossentropy
Activation Function	Relu
kernel size	3
Strides	2, 2
Filter	64
Epoch	10
Metrics	Accuracy, loss percentage
Learning rate	0.00001

3. RESULTS AND DISCUSSIONS

The developed convolutional neural network (CNN) gives better predictive performance than the existing model. The novel model has best fit accuracy at 10^{th} epoch with 99.80%- and with 0.0890 loss value and lowest value of 92.74% accuracy at the first epoch. The highest percentage loss measurement of 0.9325 was at the first epoch. The predictive performance of the novel model was compared with the results of the existing work of [66] as illustrated in Table 3. Developed model by [66] has an accuracy of 99.2% which is lower than the result obtained from the novel model. Figure 4 and Table 2 shows the results obtained with the novel model.

Table 2: Results obtained from novel model using convolutional neural networks

Epoch	Accuracy	Loss
1	0.9274	0.9325
2	0.9375	0.7250
3	0.9472	0. 5925
4	0.9611	0.5435
5	0.9725	0.4445

6	0.9795	0.1690
7	0.9878	0.1025
8	0.9893	0.1002
9	0.9925	0.0925
10	0.9980	0.0890

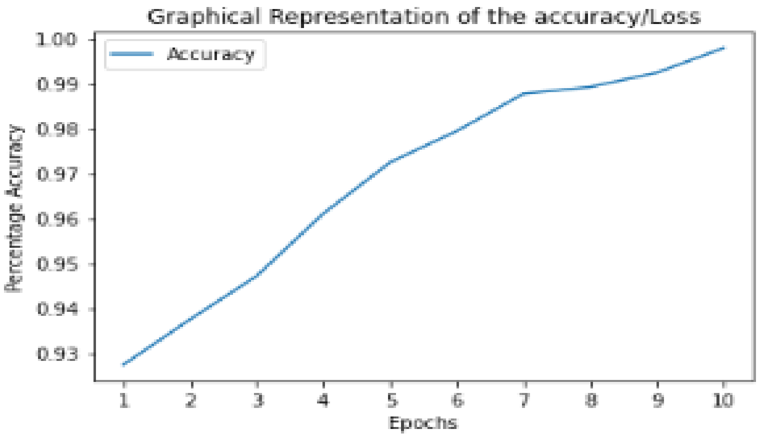

Figure 3: Graph of testing accuracy/loss against epochs

Table 3: Comparison of developed model and exiting model results

Author	Accuracy
[66]	99.20%
Developed Model	99.80%

4. CONCLUSION

In this study, a predictive model was developed using parameter tuned convolutional neural network. The system leverage on the unique features of Region of Interest Align to resolve the issues of misalignments caused by the use of Region of Interest Pooling engaged in the traditional Faster-RCNN. The techniques and the developed system were implemented using a Python-based integrated development environment called "Anaconda Navigator". The developed model achieved an accuracy of 99.80% during evaluation of the model. A robust system with the capacity to capture and process a wide range of area at a time may be included in future research.

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