

A Comprehensive Review of Enhancing Flooding Prediction Accuracy Using Hybrid Deep Learning Algorithms

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ABSTRACT

Flood is one of the most disruptive natural hazards, responsible for loss of lives and damage to properties. A number of cities are subject to monsoon influences and hence face the disaster almost every year. Early notification of flood incidents could benefit the authorities and public in devising both short and long-term preventive measures, to prepare evacuation and rescue missions, and to relieve the flood victims. However, flood forecasting is often considered a regression problem, where the goal is to predict a continuous variable rather than classify events into discrete classes. This work is aimed at developing a model using hybrid Model using a shared MLP and LSTM algorithm combining the advantages of MLP and Long short-term memory (LSTM) to predict flooding with high accuracy. This research can assist decision makers in anticipating potential flooded areas and preemptively taking measures to mitigate socioeconomic disruptions caused by urban flooding, researchers and practitioners have focused on building accurate real-time flood prediction models. This work is based on the basic idea of hybridizing deep learning technique to correctly predict flooding. The propose model will make used of rainfall datasets collected from open-source repository portal collected from Nigerian data portal. The daily rainfall data for Kebbi state for eighteen years, from 2005 to 2022, was successfully acquired from the Nigerian data portal. The rainfall data consists of (12,053 data points at daily time steps). The research implementation is carried out in MATLAB 2021a.

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INTRODUCTION

Floods are one of nature's most catastrophic calamities which cause irreversible and immense damage to human life, agriculture, infrastructure, and socioeconomic system (Syed et al., 2022). Floods are one of the most significant natural disasters which often lead to loss of life and property. Therefore, correct and reliable flood forecasting is always an important task for flood hazard mitigation (Liu, Xu, & Yang, 2017). Several studies on flood catastrophe management and flood forecasting systems have been conducted (Syed et al., 2022). At present, two main approaches are employed in flood forecasting.

The first approach is based on physical modeling, which establishes the relationship between rainfall and runoff. However, it is difficult to develop a fully physically based forecasting model due to the complex nature of floods and the varied responses to them. The second approach is based on modeling statistical relationship between the hydrologic input and output. However, the relationship between rainfall and runoff is notoriously nonlinear during the storm events. Therefore, it is also difficult to construct a statistical model using conventional regression techniques (Liu et al., 2017).

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Machine learning-based data-driven models have achieved great success since their invention. Nowadays, the artificial neural network (ANN)-based machine learning methods have made great progress than ever before, such as the deep learning and reinforcement learning, etc (Kan et al., 2020). Flood prediction using machine learning models is an active area of research and has the potential to significantly improve our ability to predict and mitigate the impacts of floods. Machine learning models can be trained on historical flood data, as well as data from various sensors and weather stations, to learn patterns and relationships that can be used to predict the likelihood and severity of future floods. There are several machine learning algorithms that can be used for flood prediction, including decision trees, random forests, support vector machines, neural networks, and deep learning models such as convolutional neural networks and recurrent neural networks (Ghorpade et al., 2021). The choice of algorithm depends on the specific problem and the available data. In addition to selecting an appropriate algorithm, it is also important to carefully select and preprocess the input features. This may include variables such as rainfall, river flow rate, soil moisture, topography, and land use.

STATEMENT OF THE PROBLEM

Machine Learning (ML) models for flood prediction can be beneficial for flood alerts and flood reduction or prevention. To that end, machine learning (ML) techniques have gained popularity due to their low computational requirements and reliance mostly on observational data. The existing study by (Haribabu et al, 2021) proposes the prediction of flood by rainfall using a multilayer perceptron (MLP) classifier model. In the study, many algorithms are used for predicting the flood such as k-means clustering, support vector machine, and MLP classifier. Among them, MLP produces better accuracy, precision and recall. However, in regression tasks like flood forecasting using LSTM or other time series prediction models, precision, recall and F-score as used in the benchmark paper is not the most appropriate metric to

evaluate model performance. Instead, regression-specific metrics such as MSE, RMSE and MAPE are used. These metrics will provide a more meaningful measure of how well the model predicts continuous variables like rainfall, water levels or flow rates.

Additionally, MLP architecture as used in the existing study has drawbacks. The MLP does not have feedback connections, thus being unable to cope with temporal dependencies of nonlinear time series flood data. Additionally, the MLP algorithm generally does not provide gains in accuracy when compared to a recurrent neural network such as LSTM which has feedback connections. As seen in the literature, when predicting dynamic time series systems, an LSTM can achieve a 30% improvement in forecasting performance as against a conventional MLP. Therefore, these problems could be effectively mitigated by using a hybrid technique where the diverse errors from model misspecification and data uncertainty can cancel each other out through the aggregating progress. Here, hybrid technique is defined as a combination of several independent forecasters built with a given learning algorithm so as to improve the generalizability and robustness of a single forecaster. Hence, the research hybridized an LSTM algorithm with MLP so as to enhance the general performance of the MLP by leveraging its weakness in the context of flooding forecasting.

Aim and Objectives of the Study

The aim of this study is to enhance the prediction performance of flooding using hybrid deep learning algorithms. The specific objectives are:

The Objectives of the studies are;

1. To develop a hybrid model using MLP and LSTM algorithms for flood prediction by rainfall
2. To enhance the prediction accuracy against single model base predictor
3. To evaluate the performance of the model against state of the art using regression-specific metrics (MAE, RMSE and R2) and other decision support metrics (accuracy, precision, recall and F-score).

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LITERATURE REVIEW

In this section, a brief introduction on computational technique that are implored in the field of flood prediction are provided, specifically as discuss in the literature for proper understanding on how they operate, their weakness and limitations and how they have achieved their objectives.

Artificial Neural Network

Artificial neural Network model tries to simulate the structures and networks within human brain. The architecture of neural networks consists of nodes which generate a signal or remain silent as per a sigmoid activation function in most cases (Kang et al, 2018). Activation of each neuron is computed and the response is sent over output node of neurons. The traditional ANN is consisting of three main layers namely, the input, the hidden and output layers as shown in Fig. 1. These layers are interconnected. Each of these layers is comprise of multiple neurons with an activation function. There is no any systematic framework for chosen the numbers of hidden layers although three categories of parameters are implored to define ANN. This includes the connection style between different layers of neurons, the learning process of updating the weights of the interconnection and the activation (Z. Wang & Srinivasan, 2017). ANN has been applied in different areas because of their human intelligence performance e.g speech recognition, robotic control, image processing, data mining, and time series forecasting (Singh & Dwivedi, 2018).

Software metrics are measures of the success of a software process. In theory, metrics can help to improve the development process and provide companies with information that makes future projects more predictable, efficient. A number of software defect prediction techniques that use software metrics have been proposed. This can be divided into two types: supervised defect prediction approaches and unsupervised defect prediction approaches. Unsupervised defect prediction approaches can predict defect proneness without requiring a defect dataset (Yang et al., 2016). This approach can be used

when a training dataset is insufficient or is not available. For example (Yang et al., 2016) proposed an unsupervised approach that ranks the change metrics in descending order based on the reciprocal of the raw value of each change metric

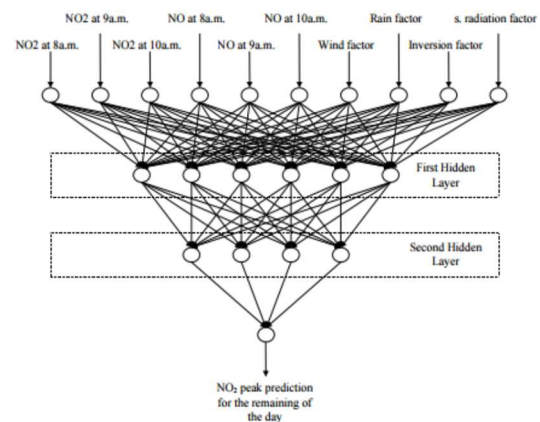


Figure 1: example of ANN model used for air quality prediction (Kang et al., 2018)

Long Short-term Memory LSTM

An artificial recurrent neural network (RNN) architecture called a long short-short term memory (LSTM) is utilized in deep learning. LSTM has feedback connections in contrast to traditional feed forward neural networks. It can analyze whole data sequences in addition to single data points (like photos) (such as speech or video). For instance, LSTM can be used for task like linked, unsegment handwriting identification, speech recognition, and network traffic anomaly detection, or IDSs (Abuzairu et al, 2022).

Support Vector Machine

Support Vector Machine (SVM) is a method used for classifying linear and non-linear data. It can easily solve problems such as small sample size, high dimension. It can be used for numeric prediction as well as classification. For this purpose, a model called Support Vector Regression (SVR) is used to solve the regression problems. SVR can also achieve both linear and nonlinear regression case.

Recurrent Neural Network and Deep Recurrent Neural Network (LSTM)

Recurrent neural network RNN is a family of neural networks for processing sequential data. RNN can be assumed as adding of loops to the basic feed forward neural network design. For instance, in a certain input layer, every neuron may pass its signal edgewise in adding forward to the subsequent layer. The output of the neural network may feedback as an input to the network with next input vector and it is continued in the similar fashion. The primary technique for training in feed forward neural networks is to back propagate error and update the neural network weights. Back propagation cannot be accommodated in RNN, because of the recurrent or loop connections. This problem is addressed with adjustment of back propagation technique called Back Propagation Trough Time (BPTT) Kaur et al, (2017) time series data may contain temporal dependencies.

Elman Neural Network

The Elman neural network was invented in 1990. This network introduces the principle of memory in order to process temporal information associated with the problem of working with historical data. It is important to store the past information because it may contain vital information (Ruiz et al, 2018). The structure in figure 4 is an Elman neural network which is one of the most popularly uses RNN. The network consists of a single hidden layer that is supported with feedback that is been delayed. It is also viewed as a special situation of feed forward network with more memory neurons and local feedback supporting it .The context unit is special units that store prior outputs of the hidden layer using a mechanism called positive feedback, for every hidden layer unit there is fully connected extra context unit with all hidden neurons in a forward mode. The connection between the state neurons is only to the internal nodes of the network (Ruiz et al., 2018).

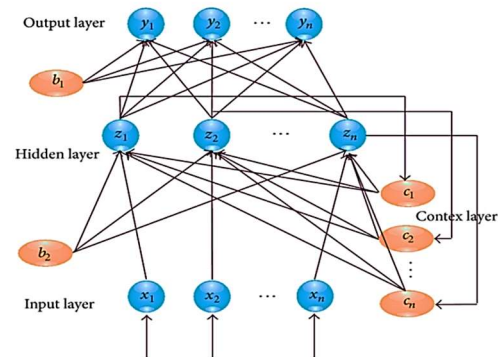


Figure 2: Structure of an Elman Neural network (Ruiz et al., 2018)

Convolutional Neural Network

A Convolutional Neural Network is included of one or more layers and then followed by one or more fully connected layers as in a standard multilayer neural network (Vahdatpour et al, 2018). Firstly, proposed Convolution neural networks (CNNs) for image processing, the architecture of a CNN is designed to take advantage of the 2D structure of an input image. This is achieved with local connections and tied weights followed by some form of pooling which results in translation invariant features (Aliyu et al., 2023). CNNs are easier to train and have many fewer parameters than fully connected networks with the same number of hidden units (Li et al. 2017). CNNs where widely applied in various computer application successfully including sequential data, processing of natural language, speech recognition and image classification (LeCun & Bengio, 1995).

Decision Tree

Decision tree model is a tree model in which each branch node represents a choice between several alternatives, and each leaf node represents a decision as shown in Figure 3. It is a supervised learning technique which uses a predictive model to map observations about an item (represented in the branches) to conclusions about the item's target value (represented in the leaves) (Kang et al., 2018).

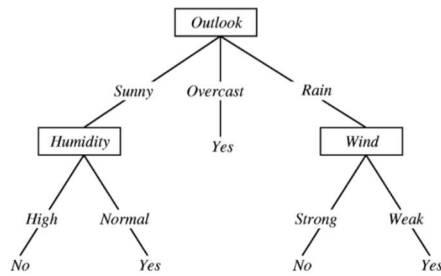


Figure 3: Decision tree algorithm (Kang et al., 2018)

Multilayered Perceptron

Multilayered perceptron (MLP) are special form feed-forward networks also known as universal approximators. MLPs are the most commonly used neural network architectures due to its simplicity (Hontoria et al, 2005). A feed forward network (MLP) has a layered structure, where each layer consists of units that receive their input from units from a directly connected layer below and transmit their output to units in a layer directly above the unit. There can exist multiple units in each layer and units of the neighboring layers are fully connected to each other, but no connections in the same layer. For a two-layer neural network, this is also known as multi-layer perceptron.

EMPIRICAL REVIEW

Several data-driven early flood prediction systems have been developed over the years. Machine learning is a popular branch of artificial intelligence that arose from the advancement of self-learning algorithms to extract knowledge from data in order to make predictions. In this section, we'll look at a few of these studies. Hayder et al. (2023) proposes an intelligent early flood forecasting and prediction leveraging machine and deep learning algorithms with advanced alert system and the experimental results showed that multi-layer perceptron classifier algorithm generates the best result with an accuracy of 93.3 percent, however multi-layer perceptron has some limitations in that it include too many parameters because it is fully connected. Each node is connected to another in

a very dense web resulting in redundancy and inefficiency. Liu et al. (2017) also proposes a flood forecasting model based on deep learning algorithm via integrated stacked autoencoders with BP neural network, and the findings of the research showed that the integrated algorithm-based SAE and BPN outperforms other approaches in terms of MSE and DC and has better line chart however, there is lack of full consideration of the imbalance of the data distribution.

Moreover, Gude, Corns and Long, (2020) proposes a flood prediction and uncertainty estimation using deep learning system and the experimental findings clearly points at the reduction of resistance in the urban environment as possibly effective flooding management alternative in Thailand, however, there is lack of studying there sources as an important key for planning of smart city adaptation measures and efficient operation of existing drainage infrastructure. Sahoo et al (2021) proposes a prediction of flood in Barrack River using hybrid machine learning approaches A case study where by the experimental results demonstrate that both RBF-FA and SVM-FA models gives more precise prediction outcomes compared to regular FFBN, RBFN and SVM models.

Assessment outcomes also revealed that both SVM-FA and SVM models performed better as of RBF-FA and RBF models in predicting river flood. Puttinaovarat and Horkaew (2020) also proposes a flood forecasting system based on integrated big crowdsource data using machine learning techniques and the findings showed that evaluation results on forecasted studied areas indicated that the system could forecast flood events highly accurately. Three best performing MLs were MPL ANN, SVM and RF respectively. It was elucidated empirically that the developed system could be used to alert the public and authorities alike of not only a current flood but also future ones however there is the limitations of lack of involving internet of things (IoT) in measuring actual meteorological data with preferred coverage.

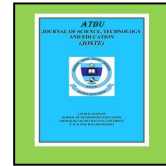
Widiasari et al (2018) proposes yet another Context based Hydrology time series data

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for a flood prediction model and the experimental results showed that LSTM yielded more accurate prediction of water elevation level in the downstream when compared to the multiple regression linear models that yielded MAPE prediction value of 10.55 percent, however the limitations are that LSTM are more complicated than traditional RNN and require more training data in order to learn effectively. (Fang et al., 2021) proposes a system called predicting flood susceptibility using long short-term memory (LSTM) neural network model where by the proposed LSS-LSTM method achieved a satisfactory prediction performance with the accuracy and AUC values of 93.75% and 0.965, respectively. Also, the LSS-LSTM method achieved better results than the benchmark methods of DNN, 1D-CNN, and 3D-CNN with several evaluation criteria. However, the prediction accuracy of LSS-LSTM can be effectively through the two manipulations of data augmentation and batch normalization. (Farooq et al., 2023) proposes a flood Forecasting Model Using Federated learning where by results showed that the proposed FFS predicted the historical floods with 84% accuracy however FFM can be expanded to predict floods in other regions of the world using their datasets.

Haribabu et al. (2021) proposes prediction of flood by rainfall using MLP classifier of neural network and the experimental results showed that MLP Classifier algorithm generated the best results with an accuracy of 93.3 percent. However, the MLP does not have feedback connection making it difficult to handled temporal dependencies in the time series flooding datasets. (Syed et al., 2022) proposes a flood Prediction Using Machine Learning Models and the findings indicate that the shorter timeline of data gives slightly better accuracy. the models gave higher accuracy with a shorter time range. Also, due to time constraint only the rainfall data along with flood occurrence was manageable however there are more factors related to flood like, river water level, temperature, humidity, other natural disasters etc, which are not considered in the research.

Hu et al (2019) proposes another system called rapid spatio-temporal flood prediction and uncertainty quantification using a deep learning method where promising results indicate that the use of LSTM-ROM can provide the flood prediction in seconds, enabling us to provide real-time predictions and inform the public in a timely manner, reducing injuries and fatalities. Comparing LSTM-ROM results with those from the full model, the LSTM-ROM exhibits a good agreement with the full model. However, further evaluation of LSTM-ROMs in flood forecast with different forecasting configurations including optimized training parameters, the predictive lead-time and the type of inputs was not taken into account. (Mitra et al., 2016) proposes research called a flood forecasting using Internet of things and Artificial Neural Networks and the experimental findings was that the WSN simulation results show that for higher number of nodes, the proposed scheme performs better than mesh, tree and star networks to a significant margin however Other QoS parameters, such as end-to-end delay, jitter, etc. need to be tested prior to implementation also more models need to be tested, by using different number of hidden layers or neurons in each layer.

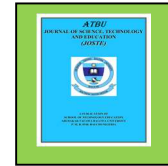
El-Magd et al (2021) proposes a system called Hybrid machine learning hydrological model for flood forecast purpose and the experimental findings indicate that t advantage of the proposed model over traditional neural network models is that it can predict discharge continuously without accuracy loss owed to its specially designed model structure however because of the real-world application of the HML hydrological model there is need for the possibility of the further application of the model in flood forecast problems. El-Magd et al. (2021) proposes a machine learning algorithm for flash flood prediction mapping in wadi el-laqeita and surroundings, central eastern desert, Egypt and based on the findings the XGBoost approach Based on the findings the XGBoost approach produced a little more precise result with ROC(AUC) accuracies of 90.2% and 80.7% however the distance from the stream network slope, topography and TWI conditioning factors

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was not considered as contributing factor in the modeling processes.

Motta, et al (2021) proposes a mixed approach for urban flood prediction using machine learning and GIS model in which the experimental results showed that from the ML stand point non-linear models were more capable of detecting floods and among those, the most performant model was random forest, yielding a Matthews correlation coefficient of 0.77. However, the paper did not consider a cost function for misclassification which needs to be developed to optimize the allocation of resources in the context of a flood management strategy. Ghaith et al (2022) proposes a synchronization enhanced Deep Learning Early Flood Risk Predictions: The Core of Data-Driven City Digital Twins for Climate Resilience Planning and the findings indicate that

the FPM efficiently reproduced the flood hazard characteristics with an efficiency of more than 95% for flood extent and more than 80% for inundation depth however, only fluvial flooding conditions were considered in the research.

Noymanee and Theeramunkong (2019) proposes a system called flood Forecasting with Machine Learning Technique on Hydrological Modeling and the results of the experiment showed that Heterogeneous Modelling find out the error in MIKE11 and reduce it, also the studies have shown that the easiest way is to minimize error in the NAM Model. However, Auto Calibration function not added more precision simulation result. MIKE 11 model can have computed the water level and discharges using the statistical technique in general situation.

Table 1. Summary of related works by Proposed System, algorithm compared with for evaluation, Findings and Weakness

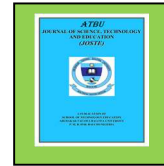
Authors	Proposed system	Findings	Weakness
(Hayder et al 2023)	An intelligent early flood forecasting and prediction leveraging machine and deep learning algorithms with advanced alert system.	Multi-layer perceptron classifier algorithm generates the best result with an accuracy of 93.3 percent.	Too many parameters because it is fully connected. Each node is connected to another in a very dense web resulting in redundancy and inefficiency.
(Liu, Xu, Yang 2017)	A flood forecasting model based on deep learning algorithm via integrated stacked autoencoders with BP neural network.	The experimental results show that the integrated algorithm-based SAE and BPN outperform other approaches in terms of MSE and DC and has better line chart.	Lack of full consideration of the imbalance of the data distribution.
(Gude, Corns, Long 2020)	Flood prediction and uncertainty estimation using deep learning.	Results clearly points at the reduction of resistance in the urban environment as possibly effective flooding management alternative in Thailand.	Lack of studying these sources as an important key for planning of smart city adaptation measures and efficient operation of existing drainage infrastructure.
(Sahoo, samantary, Ghose, 2021)	Prediction of flood in Barrack River using hybrid machine learning approaches A case study.	Results demonstrate that both RBF-FA and SVM-FA models gives more precise prediction outcomes compared to regular FFBN, RBFN and SVM models. Assessment	

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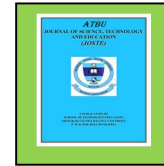
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(Puttinao, Varat, Horkaew, 2019)	Flood forecasting system based on integrated big crowdsource data using machine learning techniques.	outcomes also revealed that both SVM-FA and SVM models performed better as of RBF-FA and RBF models in predicting river flood. Evaluation results on forecasted studied areas indicated that the system could forecast flood events highly accurately. Three best performing MLs were MPL ANN, SVM and RF respectively. It was elucidated empirically that the developed system could be used to alert the public and authorities alike of not only a current flood but also future ones.	Lack of involving internet of things (IoT) in measuring actual meteorological data with preferred coverage.
Widiasari, Nugoho, Widyawan, Efendi, (2018)	Context based Hydrology time series data for a flood prediction model.	Results showed that LSTM yielded more accurate prediction of water elevation level in the downstream when compared to the multiple regression linear models that yielded MAPE prediction value of 10.55 percent.	LSTM are more complicated than traditional RNN and require more training data in order to learn effectively.
(fang, wang, peng, hong,)	Predicting flood susceptibility using long short-term memory (LSTM) neural network model	the proposed LSS-LSTM method achieved a satisfactory prediction performance with the accuracy and AUC values of 93.75% and 0.965, respectively. Also, the LSS-LSTM method achieved better results than the benchmark methods of DNN, 1D-CNN, and 3D-CNN with several evaluation criteria.	The prediction accuracy of LSS-LSTM can be effectively through the two manipulations of data augmentation and batch normalization.
(Farooq, et al 2023)	Flood Forecasting Model Using Federated Learning	Results showed that the proposed FFS predicted the historical floods with 84% accuracy.	FFM can be expanded to predict floods in other regions of the world using their datasets.
(Haribabu et al., 2021)	Prediction of flood by rainfall using MLP classifier of neural network model	The MLP Classifier algorithm generated the best results with an accuracy of 93.33 percent	MLP does not have feedback connection making it difficult to handled temporal dependencies in the



(Asif Syeed, et al)	Flood Prediction Using Machine Learning Models	The shorter timeline of data gives slightly better accuracy. the models gave higher accuracy with a shorter time range. Also, due to time constraint only the rainfall data along with flood occurrence was manageable.	time series flooding datasets There are more factors related to flood like, river water level, temperature, humidity, other natural disasters etc, which are not considered
(Hu, Fang, Pain, Navon, 2019)	Rapid spatio-temporal flood prediction and uncertainty quantification using a deep learning method	Promising results indicate that the use of LSTM-ROM can provide the flood prediction in seconds, enabling us to provide real-time predictions and inform the public in a timely manner, reducing injuries and fatalities. Comparing LSTM-ROM results with those from the full model, the LSTM-ROM exhibits a good agreement with the full model.	Further evaluation of LSTM-ROMs in flood forecast with different forecasting configurations including optimized training parameters, the predictive lead-time and the type of inputs was not considered.
(Mitra, et al 2016)	Flood forecasting using Internet of things and Artificial Neural Networks	The WSN simulation results show that for higher number of nodes, the proposed scheme performs better than mesh, tree and star networks to a significant margin.	Other QoS parameters, such as end-to-end delay, jitter, etc. need to be tested prior to implementation. More models need to be tested, by using different number of hidden layers or neurons in each layer.
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(El-magd, Pradhan, alamri 2021)	Machine learning algorithm for flash flood prediction mapping in wadi el-laqeita and	Based on the findings the XGBoost approach produced a little more precise result with ROC(AUC) accuracies of 90.2% and 80.7%	Distance from the stream network slope, topography and TWI conditioning factors was not considered as



(motta, neto, sarmiento, 2021)	surroundings, central eastern desert, Egypt A mixed approach for urban flood prediction using machine learning and GIS	Results showed that from the ML stand point non-linear models were more capable of detecting floods and among those, the most performant model was random forest, yielding a Matthews correlation coefficient of 0.77	contributing factor in the modeling processes. The paper did not consider a cost function for misclassification which need to be developed to optimize the allocation of resources in the context of a flood management strategy.
(Ghaith, Yosri, El-Dakhakhni, 2022)	Synchronization-Enhanced Deep Learning Early Flood Risk Predictions: The Core of Data-Driven City Digital Twins for Climate Resilience Planning	The FPM efficiently reproduced the flood hazard characteristics with an efficiency of more than 95% for flood extent and more than 80% for inundation depth.	Only fluvial flooding conditions were considered in the research.
(Noymanee, theeramunkong, 2019)	Flood Forecasting with Machine Learning Technique on Hydrological Modeling	Heterogeneous Modelling find out the error in MIKE11 and reduce it, also the studies have shown that the easiest way is to minimize error in the NAM Model.	Auto Calibration function not added more precision simulation result. MIKE 11 model can have computed the water level and discharges using the statistical technique in general situation.

RESEARCH GAPS

The existing study by Haribabu et al. (2021) proposes the prediction of flood by rainfall using a multilayer perceptron (MLP) classifier model. In the study, many algorithms are used for predicting the flood such as k-means clustering, support vector machine, and MLP classifier. Among them, MLP produces better accuracy. However, in regression tasks like flood forecasting using LSTM or other time series prediction models, precision, recall and F-score as used in the benchmark paper is not the most appropriate metric to evaluate model performance. Instead, regression-specific metrics such as MSE, RMSE and MAPE are used. These metrics will provide a more meaningful measure of how well the model predicts continuous variables like rainfall, water levels or flow rates. Additionally, MLP architecture

as used in the existing study has drawbacks. The MLP does not have feedback connections, thus being unable to cope with temporal dependencies of nonlinear time series flood data. Additionally, the MLP algorithm generally does not provide gains in accuracy when compared to a recurrent neural network such as LSTM which has feedback connections.

METHODOLOGY

The Proposed System

The major concern of this work is to improve on the prediction accuracy of the existing system by developing a model using a hybrid Model using a shared MLP and LSTM algorithm combining the advantages of MLP and Long short-term memory (LSTM) for the forecasting of

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flooding and evaluate the prediction performance with the existing model.

Analysis of the Existing System

There were just a few attempts at forecasting a Flash Flood with most Flood prediction using radar. Thus, the existing study by (Haribabu et al., 2021) proposes the prediction of flood by rainfall using a multilayer perceptron (MLP) classifier model. In the study, many algorithms are used for predicting the flood such as k-means clustering, support vector machine, and MLP classifier. Among them, MLP produces better accuracy. The architecture of the existing system is shown in Figure 5

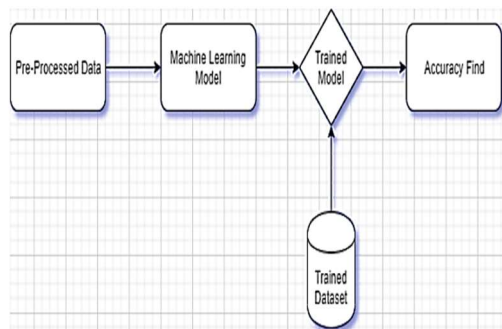


Figure 4: Architecture of the existing system (Haribabu et al., 2021)

The key aim of the project is to make predictions using neural networks (MLP). This was done using the analytical approach, which included data cleaning and processing, missing values, exploratory analysis, model building, and evaluation. Various modules were created to show how each of the analytical processes are used. Finally, various machine learning algorithms were used to forecast flash floods, each yielding different results. With an accuracy of 93.33 percent, the Multi-Layer Perceptron Classifier algorithm generated the best results. The following flood predictions are based on this information. The research is a Machine Learning based intensive model for flash flood predict.

Weakness of the Existing System

In regression tasks like flood forecasting using LSTM or other time series prediction

models, precision, recall and F-score as used in the benchmark paper is not the most appropriate metric to evaluate model performance. Instead, regression-specific metrics such as MSE, RMSE and MAPE are used. These metrics will provide a more meaningful measure of how well the model predicts continuous variables like rainfall, water levels or flow rates. Additionally, despite the promising performance of MLP as used in the base paper, the major drawback of MLP is its architecture. The MLP does not have feedback connections, thus being unable to cope with temporal dependencies of nonlinear time series flood data.

Additionally, the MLP algorithm generally does not provide gains in accuracy when compared to a recurrent neural network such as LSTM which has feedback connections. In many instances, the data depend not only on the total amount spent but also on other possible influence factors. In order to tackle this issue recurrent neural networks have proved to be a very helpful tool in time series environments (Cadenas et al, 2016). These models are a kind of recurrent system which is able to learn by itself, improving the approximation of the MLP by reducing the output error. Thus, Long Short-Term Memory (LSTM) is currently implored in the context of complex forecasting problem due to their abilities to model complex function with high accuracy. Potential improvement on prediction accuracy of the aforementioned MLP can be obtained using deep neural network where modeling of more complex functioning is allowed by the use of multiple layers of abstraction. Recurrent neural networks are known to improve time series prediction errors compare to their counterpart MLP as shown by Ashour and Abbas (2018).

Multilayered Perceptron Stage

The MLP Stage is the stage built on the Sequence Layer of the LSTM Stage. In this experiment, the normalized data set is fed as input to the MLP input layer which is the top most layer of the MLP network. A sequence input layer inputs sequence data to a network for processing and training to achieve the desired forecast accuracy.

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The MLP network is composed of three layers which are the input, hidden and output layer.

LSTM Stage

The output of the MLP output layer is fed to the sequence input layer of the LSTM network which then produces our forecast output. In this experiment, The LSTM network is composed of three layers which are the sequence input layer, LSTM layer and fully connected layer and the LSTM output layer. The next layer in this experiment after the Sequence Layer is the LSTM Layer. The LSTM layer here is the intermediate layer in a LSTM Recurrent Neural Network. The LSTM layer in our work learns long-term dependencies between time steps of sequence data. This layer also models the time series and sequence data in the network and perform additive interactions, which can help improve gradient flow over long sequences during training.

Evaluation Parameters and Performance Metrics

The experiments are evaluated in the MATLAB platform. Performances are compared with three existing techniques like MLP, RF and LR. Finally, performances are evaluated regarding various quality measure such as accuracy, precision, recall and F-score of each of the model. These metrics can be mathematically express as:

i. Accuracy: this performance metric deals with the correct prediction made by the model and this metric can be expressed as:

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

ii. Precision: precisions provide information about how precise/accurate your model is out of those predicted positives, how many of them are actual positives. Precisions is a good measure to determine when cost of false positives is high. It is mathematically expressed as:

$$\text{Precision} = \frac{TP}{TP+} \dots (2)$$

iii. Recall attempts to answer what proportion of actual positives was identified correctly. It is expressed mathematically as:

$$\text{Recall} = TP / (TP + FN) \dots (3)$$

iv. F-Measure is a function of precision and recall, it might be better to use when we seek to balance between precision and recall and there is an even class distribution (large number of actual negatives). It is mathematically express as:

$$F1 = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall}) \dots (4)$$

Where TP (True Positive) = Are the cases when the actual class of the data point was 1 (true) and the predicted is also 1 (true).

TN (True Negative) = Are the cases when the actual class of the data point was 0 (false) and the predicted is also 0 (false).

FP (False Positive) = Are the cases when the actual class of the data point was 0 (false) and the predicted is 1 (true).

FN (False Negative) = Are the cases when the actual class of the data point was 1 (true) and the predicted is 0 (false).

Furthermore, the developed network is tested and evaluated by using predictive accuracy like the Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and the correlation Error (R²) in the MATLAB Neural Network (NN-tools) package to ensure a more generalize evaluation across all the models. The three error measures are defined as follows:

Implementation of the System

The system will be implemented using MATLAB version 2021a on HP laptop System Corei (TM) i7-4200U, 1.7GHz CPU and 6GB RAM. The system is experimented using the dataset specified in the design.

Data Collection

This research work uses a journal published by Haribabu et al, (2021) as a primary source of data collected. Many other journals and websites were also consulted during the data collection. The daily rainfall data for Kebbi state for eighteen years, from 2005 to 2022, was successfully acquired from the Nigerian data portal accessible in the link (Kebbi Annual Rainfall, 2005-2022 (opendataforafrica.org)). The rainfall



data consists of (12,053 data points at daily time steps).

CONCLUSIONS AND FUTURE RESEARCH DIRECTION

In this study, we focus on regression assessment measures such as MAE, RMSE, MAPE, and R-squared to evaluate the accuracy and performance of the proposed MPL-LSTM-based flood forecasting model. These measures will provide a more relevant measure of the model's ability to predict continuous variables such as water levels, rainfall, and flow rates. The goal of this research is to create a model that predicts floods with high accuracy using a shared hybrid MLP and LSTM algorithm that combines the benefits of MLP and Long short-term memory (LSTM). The MATLAB platform is used to evaluate the experiments. In the future, we advocate creating a long-term forecasting model based on the unique transfer learning method based on the LSTM algorithm. This can predict floods over a long time horizon by tracking future changes and modeling the complicated pattern of flood data.

REFERENCES

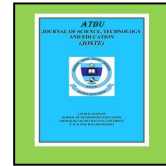
- Ahmad, A., Musa, K. I., Zambuk, F. U., & Lawal, M. A. (2022). Optimizing Connection Weights in a Long Short-Term Memory (LSTM) Using Whale Optimization Algorithm (WOA): A Review. *ATBU Journal of Science, Technology and Education*, 10(3), 362-373.
- Aliyu, M. A., Boukari, S., Gamsha, A. M., Abdurrahman, M. L., & Gital, A. Y. (2023). Toward a Better Model for the Semantic Segmentation of Remote Sensing Imagery. Paper presented at the Proceedings of 3rd International Conference on Artificial Intelligence: Advances and Applications: ICAIAA 2022.
- Ashour, M. A. H., & Abbas, R. A. (2018). Improving Time Series' Forecast Errors by Using Recurrent Neural Networks. Paper presented at the Proceedings of the 2018 7th International Conference on Software and Computer Applications.
- El-Magd, S. A. A., Pradhan, B., & Alamri, A. (2021). Machine learning algorithm for flash flood prediction mapping in Wadi El-Laqeita and surroundings, Central Eastern Desert, Egypt. *Arabian Journal of Geosciences*, 14, 1-14.
- Fang, Z., Wang, Y., Peng, L., & Hong, H. (2021). Predicting flood susceptibility using LSTM neural networks. *Journal of Hydrology*, 594, 125734.
- Farooq, M. S., Tehseen, R., Qureshi, J. N., Omer, U., Yaqoob, R., Tanweer, H. A., & Atal, Z. (2023). FFM: Flood forecasting model using federated learning. *IEEE Access*, 11, 24472-24483.
- Ghaith, M., Yosri, A., & El-Dakhkhni, W. (2022). Synchronization-Enhanced Deep Learning Early Flood Risk Predictions: The Core of Data-Driven City Digital Twins for Climate Resilience Planning. *Water*, 14(22), 3619.
- Ghorpade, P., Gadge, A., Lende, A., Chordiya, H., Gosavi, G., Mishra, A., . . . Shaikh, N. (2021). Flood forecasting using machine learning: a review. Paper presented at the 2021 8th International Conference on Smart Computing and Communications (ICSCC).
- Gude, V., Corns, S., & Long, S. (2020). Flood prediction and uncertainty estimation using deep learning. *Water*, 12(3), 884.
- Haribabu, S., Gupta, G. S., Kumar, P. N., & Rajendran, P. S. (2021). Prediction of Flood by Rainfall Using MLP Classifier of Neural Network Model. Paper presented at the 2021 6th International Conference on Communication and Electronics Systems (ICES).
- Hayder, I. M., Al-Amiedy, T. A., Ghaban, W., Saeed, F., Nasser, M., Al-Ali, G. A., & Younis, H. A. (2023). An Intelligent Early Flood Forecasting and Prediction Leveraging Machine and Deep Learning Algorithms with Advanced Alert System. *Processes*, 11(2), 481.

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- Hontoria, L., Aguilera, J., & Zufiria, P. (2005). An application of the multilayer perceptron: solar radiation maps in Spain. *Solar energy*, 79(5), 523-530.
- Hu, R., Fang, F., Pain, C., & Navon, I. (2019). Rapid spatio-temporal flood prediction and uncertainty quantification using a deep learning method. *Journal of Hydrology*, 575, 911-920.
- Kan, G., Liang, K., Yu, H., Sun, B., Ding, L., Li, J., . . . Shen, C. (2020). Hybrid machine learning hydrological model for flood forecast purpose. *Open Geosciences*, 12(1), 813-820.
- Kang, G. K., Gao, J. Z., Chiao, S., Lu, S., & Xie, G. (2018). Air quality prediction: Big data and machine learning approaches. *International Journal of Environmental Science and Development*, 9(1), 8-16.
- Kaur, A., Bansal, D., & Singla, S. (2017). A review on estimating the effects of inhaling airborne pollutants and air quality monitoring. Paper presented at the 2017 8th international conference on computing, communication and networking technologies (ICCCNT).
- LeCun, Y., & Bengio, Y. (1995). Convolutional networks for images, speech, and time series. *The handbook of brain theory and neural networks*, 3361(10), 1995.
- Liu, F., Xu, F., & Yang, S. (2017). A flood forecasting model based on deep learning algorithm via integrating stacked autoencoders with BP neural network. Paper presented at the 2017 IEEE third International conference on multimedia big data (BigMM).
- Mitra, P., Ray, R., Chatterjee, R., Basu, R., Saha, P., Raha, S., . . . Saha, S. (2016). Flood forecasting using Internet of things and artificial neural networks. Paper presented at the 2016 IEEE 7th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON).
- Motta, M., de Castro Neto, M., & Sarmiento, P. (2021). A mixed approach for urban flood prediction using Machine Learning and GIS. *International journal of disaster risk reduction*, 56, 102154.
- Noymanee, J., & Theeramunkong, T. (2019). Flood forecasting with machine learning technique on hydrological modeling. *Procedia Computer Science*, 156, 377-386.
- Puttinaovarat, S., & Horkaew, P. (2020). Flood forecasting system based on integrated big and crowdsourced data by using machine learning techniques. *IEEE Access*, 8, 5885-5905.
- Ruiz, L. G. B., Rueda, R., Cuéllar, M. P., & Pegalajar, M. (2018). Energy consumption forecasting based on Elman neural networks with evolutive optimization. *Expert Systems with Applications*, 92, 380-389.
- Sahoo, A., Samantaray, S., & Ghose, D. K. (2021). Prediction of flood in Barak River using hybrid machine learning approaches: a case study. *Journal of the Geological Society of India*, 97, 186-198.
- Singh, P., & Dwivedi, P. (2018). Integration of new evolutionary approach with artificial neural network for solving short term load forecast problem. *Applied energy*, 217, 537-549.
- Syeed, M. M. A., Farzana, M., Namir, I., Ishrar, I., Nushra, M. H., & Rahman, T. (2022). Flood prediction using machine learning models. Paper presented at the 2022 International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA).
- Vahdatpour, M. S., Sajedi, H., & Ramezani, F. (2018). Air pollution forecasting from sky images with shallow and deep classifiers. *Earth Science Informatics*, 11(3), 413-422.
- Wang, H., Wang, G., Li, G., Peng, J., & Liu, Y. (2016). Deep belief network based deterministic and probabilistic wind speed forecasting approach. *Applied energy*, 182, 80-93.

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- Wang, Z., & Srinivasan, R. S. (2017). A review of artificial intelligence based building energy use prediction: Contrasting the capabilities of single and ensemble prediction models. *Renewable and sustainable energy reviews*, 75, 796-808.
- Widiasari, I. R., Nugoho, L. E., & Efendi, R. (2018). Context-based hydrology time series data for a flood prediction model using LSTM. Paper presented at the 2018 5th International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE).
- Y. Liu, H. Zheng, X. Feng, and Z. Chen, "Short-term traffic flow prediction with Conv-LSTM," in 2017 9th International Conference on Wireless Communications and Signal Processing (WCSP), 2017: IEEE, pp. 1-6.
- Zuhairi, A. H., Yakub, F., Zaki, S. A., & Ali, M. S. M. (2022, November). Review of flood prediction hybrid machine learning models using datasets. In *IOP Conference Series: Earth and Environmental Science* (Vol. 1091, No. 1, p. 012040). IOP Publish