IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 29 February 2024, accepted 25 March 2024, date of publication 3 April 2024, date of current version 29 May 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3384473

RESEARCH ARTICLE

An Adaptive Hybrid (1D-2D) Convolution-Based ShuffleNetV2 Mechanism for Irrigation Levels Prediction in Agricultural Fields With Smart IoTs

XUEHUI XU[1], R. S. M. LAKSHMI PATIBANDLA[2], AMIT ARORA[3], MUNA AL-RAZGAN[4], EMAD MAHROUS AWWAD[5], AND VINCENT OMOLLO NYANGARESI[6,7]

[1]Electronic Information Engineering College, Wuhan Polytechnic, Wuhan, Hubei 430074, China
[2]Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Guntur, Andhra Pradesh 522006, India
[3]Department of Electrical, Electronics and Communication Engineering, Galgotias University, Greater Noida, Uttar Pradesh 203201, India
[4]Department of Software Engineering, College of Computer and Information Sciences, King Saud University, Riyadh 11345, Saudi Arabia
[5]Department of Electrical Engineering, College of Engineering, King Saud University, Riyadh 11421, Saudi Arabia
[6]Department of Computer Science and Software Engineering, Jaramogi Oginga Odinga Universtiy of Science and Technology, Bondo 210-40601, Kenya
[7]Department of Electronics and Communication Engineering, Saveetha School of Engineering, SIMATS, Chennai 602105, India

Corresponding author: Vincent Omollo Nyangaresi (vnyangaresi@jooust.ac.ke)

This work was supported by the King Saud University, Riyadh, Saudi Arabia, through Researchers Supporting Program under Grant RSP2024R206.

ABSTRACT Rich natural resources such as fertilizers, environment, groundwater, rivers, and land are abundant in many countries. Agriculture is the primary source of income for the people living in different countries. There have not been shortages of resources like river water and groundwater, in recent decades. But, the lack of knowledge on how to use those valuable resources is the main reason for resource wastage. The amount of water applied to crop fields in a variety of soil, weather, and crop growth stages can be managed and optimized using smart farming. The crop field's soil moisture can be measured using sensors positioned at various observation points, which will show how much water has been retained. Unfortunately, the smart farming system is not capable to receive the soil moisture data provided by the irrigation management due to issues with connectivity or sensor failure. Innovative agricultural approaches can be facilitated by the Internet of Things (IoT) technologies. These IoT nodes have encountered energy limitations and challenging routing techniques as a result of their low capacity. Therefore, it is imperative to resolve the issues by implementing an effective IoT-based irrigation system in the agricultural area. The major steps of the developed model are data collection and prediction. Initially, essential image and sensor data is attained from the benchmark resources. Next, the collected images are provided to the level of the irrigation prediction phase. This phase facilitates the farmers to maximize the crop yields and minimize the production cost. Here, effective irrigation prediction is performed using an Adaptive Hybrid (1D-2D) Convolution-based ShuffleNetV2 model (AHC-ShuffleNetV2). Moreover, the parameters of the suggested AHC-ShuffleNetV2 are optimized using a Fitness-based Piranha Foraging Optimization Algorithm (FPFOA). This increases the performance rates of the proposed model. Later, several experimental analyses are executed in the developed model over classical techniques to display their effectualness rate. When considering the sigmoid activation function, the implemented smart irrigation level prediction framework's RMSE was minimized by 73.15% of POA-ShuffleNetV2, 72.36% of RSA-ShuffleNetV2, 78.94% of MRS-ShuffleNetV2, and 79.47% of PFOA-ShuffleNetV2 respectively. Hence, it is revealed that the designed smart irrigation level prediction model attained low error rates and also achieved higher efficacy than the other baseline techniques.

INDEX TERMS Irrigation level prediction, agricultural fields, smart internet of things, fitness-based piranha foraging optimization algorithm, adaptive hybrid (1D-2D) convolution-based shufflenetV2 model.

I. INTRODUCTION

One of the main factors influencing precision agriculture is the control of water for irrigated crops. Crop stress is brought

The associate editor coordinating the review of this manuscript and approving it for publication was Stefano Scanzio.

on by insufficient irrigation with regard to water management and timing, which eventually lowers crop yield [9]. Because of this, there is a high demand for effective irrigation, which provides exact information regarding irrigation requirements instantly. Agriculture has highly benefited from the efficient use of irrigation systems [10]. Remote manual irrigation is an add-on demand in numerous situations including geographical region, crop health, and climatic change that is according to the experiential input of the farmers. The conventional works concentrate on either manual or automatic irrigations. But, the concept of recommending a complete device offering remote manual and automatic dynamic irrigation processes in the distinct growing crop stages is still far-fetched. In traditional irrigation systems, a large number of wires are needed to gather sensor data and send commands to the solenoid valves [11]. The entire system is costly and complex due to the high cost of cables and other accessories, which restricts the deployment's scope. Soil moisture can be collected at various soil depths in the agricultural land using positioned sensors at multiple monitoring locations. The amount of water retained in a crop field is indicated by analyzing the soil moisture [12]. It is difficult to determine the specific quantity of water needed by irrigation management as the smart farming system is unable to collect soil moisture data because of sensor malfunctions and connectivity issues [13]. Using various irrigation management data types from irrigation systems and crops, machine learning approaches can infer information about soil moisture. Consequently, irrigation water conservation can be enhanced by using forecasted soil moisture data [14].

By extending the conventional cloud computing architecture to the edge network and analyzing the monitored area, the fog computing paradigm also aids in addressing the connection issue in the farms [15]. As a result, fog computing reduces latency and bandwidth by processing sensor requests locally on the farms with the least amount of cloud computing involvement [16]. Nowadays, farmlands can have wireless coverage because of emerging communication technologies like Bluetooth, ZigBee, and General Packet Radio Service (GPRS) cellular networks [17]. These technologies also have certain restrictions. The GPRS-enabled devices require more power to maintain the burden associated with battery replacement [18]. Furthermore, they depend on telecom carriers' cellular networks, which can be unreliable in some rural locations [19]. Regarding ZigBee or Bluetooth solutions, the devices' low power performance can be ensured, but the communication range is insufficient to cover a significant amount of farmland [20]. A number of Low-Power Wide-Area Network (LPWAN) technologies, including Long Range (LoRa) radio technology, NB-IoT, and SigFox have been developed recently. Low cost, high capacity, low power consumption, and long-distance communication are the main characteristics of LPWAN technology. The LPWAN gets over traditional wireless technologies' drawbacks and its application in wireless irrigation systems seems quite promising [21].

Existing models employ machine learning approaches such as Gradient Boosting Regression Trees (GBRT), Random Forest (RF), and K-Nearest Neighbors (KNN) for irrigation level prediction. Nonetheless, Deep Neural Networks (DNN) has drawn interest in getting solutions for non-linear models [22]. These models involve deeper neural networks, which provide more significant learning capacities and, consequently, improved accuracy and performance [23]. Bi-directional Long Short-Term Memory (BLSTM) and LSTM are the two types of Recurrent Neural Networks (RNNs). These are specifically made to identify sequential features in input and then use those patterns to forecast future events. A number of IoT-enabled precision agriculture water management systems have been developed recently. The IoT is one of the promising technologies that can rectify the issues concurrently composed with environmental impact problems, time, and labor. The majority of them relies on sensing-based systems and predetermines the offline watering schedules. The solutions are generated by taking into account the user's background, level of expertise, and extended ambient factors [24]. The LSTM has many advantages related to the precision agriculture industry. The LSTM is a unique kind of neural network that is particularly useful for time series analysis. Furthermore, the customers' watering needs for the crops can be predicted by the collected models [25]. To increase water-saving efficiency, the data fusion models consider real-time sensor data, weather forecasts, irrigation records, and past local weather conditions. However, the conventional irrigation level prediction techniques didn't focus on the accuracy levels and system complexity. Moreover, the traditional techniques generate automatic models with big frameworks that increase the computational cost and also increase the processing time. Hence, an effective irrigation level prediction model is developed.

Some of the valuable contributions of the proposed deep learning-based irrigation level prediction model with smart IoTs are given below.

- To design a novel irrigation level prediction method in an agricultural field with smart IoTs by utilizing advanced deep learning mechanisms that facilitate to maximize the crop yields and minimize the production costs.
- To predict the irrigation level in the agricultural fields by developing the AHC-ShuffleNetV2 mechanism that integrates the hybrid 1D-2D convolution and ShuffleNetV2. In this network, the parameters such as epoch size, steps per epoch, and hidden neuron count are optimized using the proposed FPFOA to reduce the MAE and RMSE values. Moreover, with the help of this network, the efficiency of the implemented framework is enhanced and at the same time, the inefficient resource utilization and processing time are minimized.
- To propose a FPFOA by upgrading the random value in conventional PFOA that helps to progress the overall irrigation prediction capability of the developed network by optimizing the parameters.

- To check the efficacy of the offered deep learning-based irrigation level forecasting method by evaluating the suggested method with other heuristic approaches and deep learning networks.

The suggested irrigation level forecasting method using smart IoTs in the agricultural field is explained in the below sections. The literature regarding smart agriculture along with its shortcomings and merits are described in Sub-part II. In Sub-part III, the importance of deep learning in irrigation level prediction, existing challenges in irrigation level prediction, and finally the proposed irrigation level prediction model is explained.Sub-part IV provides the dataset details and describes about smart irrigation with IoT. Irrigation level prediction using deep learning is given in Sub-part V. The experimental findings are presented in Sub-part VI. The final

The final conclusion about the research is given in Sub-part VII.

II. EXISTING WORKS

A. RELATED WORKS

In 2021, Roy et al. [1] have proposed AgriSens, an IoT-based dynamic irrigation scheduling system, to effectively manage water in irrigated crop areas. Using IoT, AgriSens offered manual, remote, automated, dynamic, and real-time irrigation treatment for various growth phases of a crop's life cycle. The amount of water in a field was measured by the developed low-cost water-level sensor. After that, an algorithm was created based on farmers' requirements for autonomous dynamic manual watering. With its user-friendly interface, AgriSens offered farmers a multimodal field information delivery via website, mobile app, and visual display.

In 2022, Jiménez et al. [2] have created a sophisticated IoT-multiagent precision irrigation method to increase irrigation systems' water consumption efficiency. An intelligent irrigation agent that independently prescribes and applies water amounts based on agronomical criteria was suggested in this research. This approach was expanded to eleven pump stations that serve water to 5911 fields, using both virtual and actual intelligent agents. A primary agent in each pump station receives information from hundreds of irrigation intelligent agents via an MQTT protocol regarding crop characteristics and water prescriptions. The primary agent created a regional irrigation map to manage geo-referenced field data and negotiate water resources among agents based on supply availability. Devices with internet access could be used to visualize intelligent irrigation agents and field maps. The fields' irrigation levels were applied correctly and it was proven by the results, which increased the fields' water use efficiency.

In 2022, Cordeiro et al. [3] have utilized Deep Neural Network (DNN) architecture to create a soil moisture prediction model. The created model addressed the issue of missing data in the dataset. Next, KNN data imputation was applied to fill in the missing values that guaranteed the requisite level of reliability. In order to assess the prediction models' performance based on RAM and CPU utilization, the proposed model was lastly implanted on a tiny single-board computer. Consequently, the models could be used to create fog architectures within an IoT environment. Their findings showed that the predictive model achieved high irrigation water without any wastage.

In 2021, Laphatphakkhanu et al. [4] have suggested an effective method to assess the water-use efficiency of three irrigation techniques: (1) basin irrigation, (2) Alternate Wetting and Drying (AWD), and (3) Modern Irrigation System (MIS), which used an IoT-based weather monitoring station. The water footprint was traced during the dry season of rice cultivation. According to the findings, the field's actual water usage for basin irrigation, AWD, and MIS was 7612, 5823, and 7461 m3/ha, respectively. Based on CROPWAT 8.0, the water demand was found to be close to the basin irrigation and MIS. For MIS, AWD, and basin irrigation, the corresponding rice productivity per area was calculated. The well-grained system was the MIS, with a high water footprint for the AWD, basin irrigation, and MIS, respectively, in the various rice-growing systems. Furthermore, when compared to AWD and basin irrigation, the MIS might lower the water footprint.

In 2022, Irshad et al. [5] have improved the system's energy management performance by introducing a revolutionary combination of optimal intelligent smart irrigation systems. Hierarchy Shuffled Shepherd Clustering (HSSC) was used here to form and choose the best cluster heads. Additionally, the Emperor Penguin Jellyfish Optimizer (EPJO) approach has been suggested for offering the best routing strategy and energy regulation. Network Simulator-2 (NS2) was the program used to simulate this operation. The suggested method's simulation results were verified and contrasted with traditional methods. As a result, the findings of the suggested technique showed better outcomes in comparison to the traditional works. Moreover, the produced model has substantially lower energy consumption and better network lifetime.

In 2022, Jani and Chaubey [6] have proposed a smart framework for agriculture that used the IoT to manage many kinds of inexpensive IoT sensors. They gather data from insects, water, air, and soil. Then, they analyze the data from sensors to make the right decisions. Their approach's unique contribution was to combine the scientific automation of pest identification, pesticide spraying, pest irrigation, and fertigation into a single framework, without the participation of farmers. The outcomes and comprehensive implementation instructions for the created framework's smart irrigation module were included in this work.

In 2022, Gong et al. [7] have proposed an intelligent irrigation system that optimized the watering schedule by integrating a LoRa network and a data fusion model. The data fusion model was presented in this work that integrated multi-source heterogeneous data, such as online monitoring sensor data, weather forecasts, user irrigation logs, and historical weather data. Then they used the LSTM network to simulate and predict the appropriate watering demands. Using LoRa, a self-powered wide-area network was established and made available to support various IoT application scenarios. It had a gateway as well as two different kinds of nodes: sensor and valve nodes. By using a water flow-based power generating strategy, the node achieved energy autonomy and maintenance-free operation over the course of its life cycle. The mobile application's interface, intelligent irrigation control, and network administration were all intended to be provided via a cloud platform. An analysis of the suggested system was conducted using a case study on landscape irrigation. Comparing the suggested system to the traditional manual setup options, the average water-saving efficiency was improved by the proposed framework.

In 2023, Behzadipour et al. [8] have suggested intelligent irrigation and modifying agricultural irrigation methods to regulate the amount of water needed by the plants. The primary data sources for this study were data from sensors including humidity of ambient and light and soil temperature. The MATLAB 2018 software and regression modeling in SPSS software were used to examine the data. With a combined model of images and sensors in genetic programming, the proposed model attained a smaller standard error and better R2 values. For the smart irrigation method, the microcontroller was adjusted by the proposed optimal model. By using this method more amount of water was saved in the crop fields. Finally, the accuracy and superiority of the model were estimated.

B. PROBLEM STATEMENT

In agriculture, water resources are the major sources for offering a better yield rate. Generally, effective irrigation systems are utilized to minimize the water utilization rate and also to enhance the productivity rate. Different advancements and complications presented in the classical irrigation system are presented in Table 1. AgriSens [1] implementation cost is minimal and also it has a higher reliability rate and has better accuracy rate in the system. Yet, it needs to overcome the issues in the packet delivery ratio and also it requires enhancing the lifetime of the system. MQTT Protocol [2] effectively schedules the irrigation time for the global and local level based on the field region. Moreover, it needs to minimize the overhead in the messages and needs processing power. DNN [3] reliability rate is high and it effectively fills the unknown values for the features and also it accurately predicts the soil moisture. Moreover, it requires enormous information for training and also its validation cost is higher. MIS [4] has a higher effectualness rate according to productivity and also it consumes minimal water and is an efficient technique. However, it requires time interval modification in every condition and also it didn't consider factors like wind speed, temperature, and rain. HSSC [5] consumes minimal energy and also enhances the lifetime of the network and it offers a finite routing path by resolving the delay and data failure issues. Moreover, its complexity rate is higher and also it requires overcoming the convergence issues in the system. IoT [6] initialization cost is lower than other techniques and also it automatically identifies the pests, fertilizers, and pesticide sprays. Yet, it needs to reduce the human interaction and also it needs to provide higher privacy and security rate. LSTM [7] didn't require replacing the battery as it utilizes the maintenance-free battery for the whole life cycle. Yet, it faces more complications when high-power features are utilized. The regression technique [8] effectively changes the microcontroller for better irrigation and also it has a superior accuracy rate. However, it needs to resolve the linearity and overfitting issues and also it requires improving the sensitivity rate. Thus, it is important to design an efficient IoT-based irrigation level prediction system by considering the several limitations of different techniques. The primary research gaps of the traditional models have been listed as follows.

- ➢ The traditional irrigation level prediction mechanisms demand more time, resources, and cost for its implementation. Yet, this is required minimal to enhance the performance rates of these models. Hence, this work designed a smart irrigation level prediction model with low cost and less resource utilization.
- ➢ The conventional irrigation level prediction techniques are prone to error rates. This tend to deduce the accuracy levels of the techniques. Hence, this work designed a new model that minimized the error rates and hence increased the accuracy levels.
- ➢ Since the traditional models have high computational complexity the work developed a new deep learning network with less complexity.

The conventional irrigation level prediction techniques fail to optimize the network parameters such as epoch size, steps per epoch, and hidden neuron count leading to overfitting. Hence, this work optimizes these parameters by introducing a new optimization algorithm.

III. SMART IoT- BASED IRRIGATION LEVEL PREDICTION IN AGRICULTURAL FIELDS USING HYBRID CONVOLUTION ADOPTED DEEP LEARNING ALGORITHM

A. IMPORTANCE OF DEEP LEARNING IN IRRIGATION LEVEL PREDICTION

The traditional machine learning techniques mostly need users' help to adjust the model parameters, but deep learning models learn the features directly from the training data, resulting in more accurate predictions. Since deep learning has been successfully applied in the domains of natural language processing and image classification methods, it is well suitable for deep learning technologies to address agricultural concerns [34]. Utilizing the exceptional processing capacity of modern computers is made possible by DCNN technology. Moreover, in numerous image analysis applications, deep learning techniques have demonstrated their ability to manage image noise and illumination variance. Furthermore, the studies discovered that deep learning models have the ability to analyze the consumption of water in irrigation fields and predict the irrigation conditions even in aerial images [35]. By using deep learning methods to analyze the condition of the field and monitoring the irrigation conditions, the farmers could able to take necessary measures to improve their crop

TABLE 1. Features and challenges of classical IoT-based irrigation level prediction system using different techniques.

Author [citation]	Methodology	Features	Challenges
Roy et al. [1]	AgriSens	• Its implementation cost is minimal. • It has a higher reliability rate and also has a better accuracy rate in the system.	• It needs to overcome the issues in the packet delivery ratio. • It requires enhancing the lifetime of the system.
Jiménez et al. [2]	MQTT Protocol	• It effectively schedules the irrigation time for the global and local level based on the field region.	• It needs to minimize the overhead in the messages and needs processing power.
Cordeiroet al. [3]	DNN	• Its reliability rate is high and it effectively fills the unknown values for the features. • It accurately predicts the soil moisture.	• It requires enormous information for training. • Its validation cost is higher.
Laphatphakkhanutet al. [4]	MIS	• It has a higher effectualness rate according to productivity. • It consumes minimal water and is an efficient technique.	• It requires time interval modification in every condition. • It didn't consider factors like wind speed, temperature, and rain.
Irshadet al. [5]	HSSC	• It consumes minimal energy and also enhances the lifetime of the network. • It offers a finite routing path by resolving the delay and data failure issues.	• Its complexity rate is higher. • It requires overcoming the convergence issues in the system.
Jani and Chaubey [6]	IoT	• Its initialization cost is lower than other techniques. • It automatically identifies the pests, fertilizers, and pesticide sprays.	• It needs to reduce the human interaction. • It needs to provide higher privacy and security rates.
Gong et al. [7]	LSTM	• It didn't require replacing the battery as it utilizes the maintenance-free battery for the whole life cycle.	• It faces more complications when high-power features are utilized.
Behzadipouret al. [8]	Regression technique	• It effectively changes the microcontroller for better irrigation. • It has a superior accuracy rate.	• It needs to resolve the linearity and overfitting issues. • It requires improving the sensitivity rate.

yield. New deep learning-based techniques have been proposed in recent days to improve the agricultural sectors. Deep learning is useful in productivity prediction, crop disease detection, hyper-spectral imaging, and precision agriculture.

B. EXISTING CHALLENGES IN IRRIGATION LEVEL PREDICTION

The traditional methods utilized for irrigation level prediction take a lot of time for the calibration and the development process. The data requirements as well as the cost for predicting the irrigation level using neural networks are high. Most of the techniques do not provide optimum irrigation planning measures, which affects the quantity of soil nutrients as well as the quality of crops [36]. Processing soil moisture data in real-time dynamics is difficult. Based on the regions and weather conditions, the irrigation level should be provided. The soil moisture content should be analyzed before forecasting the irrigation level, but not all the methods are convenient to measure those data. The developing methods should be self-adaptable to different areas for predicting the irrigation level for various kinds of crops [37]. Correct data is needed to attain precise forecasting outcomes. But, some of the data collection processes in the existing methods are exposed to false data injection and privacy threats. Therefore, a deep learning-based irrigation level prediction in agricultural fields with smart IoTs is proposed.

C. SCHEMATIC VIEW OF PROPOSED IRRIGATION LEVEL PREDICTION MODEL

A deep learning-based technique for predicting the irrigation levels in agricultural fields with smart IoTs is proposed. The required image and sensor data for implementing this research are attained from the standard resources. Then, the collected images are passed to the irrigation level prediction phase. This process is accomplished by the developed AHC-ShuffleNetV2 model.

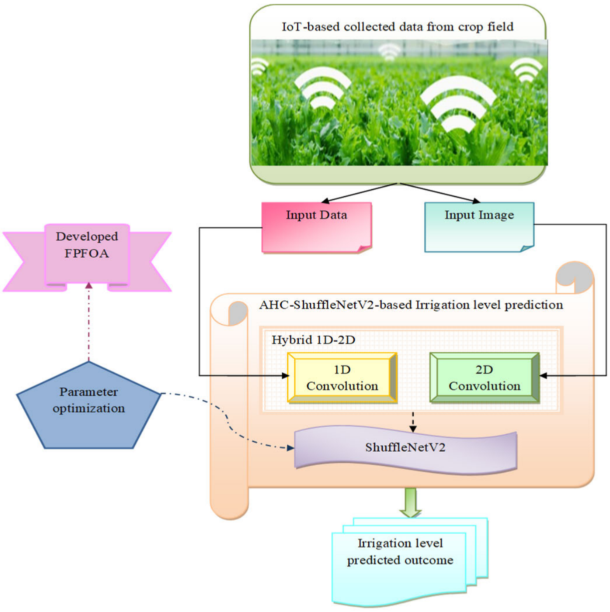


FIGURE 1. Visualization of the proposed mechanism for irrigation level prediction with smart IoTs.

It is developed by integrating two deep learning networks named hybrid 1D-2D and ShuffleNetV2. In order to further progress the prediction performance, a new heuristic approach FPFOA is recommended. It maximizes the prediction performance by optimizing steps per epoch, epoch size, and hidden neuron count in ShuffleNetV2 for decreasing the MAE and RMSE. Then different experimental analyses are conducted to demonstrate the efficacy of the designed irrigation levels prediction model using deep learning. The above Figure 1 visualizes the proposed mechanism for irrigation level prediction in agricultural fields with smart IoTs.

IV. IoT-BASED DATASET COLLECTION FOR PREDICTING IRRIGATION LEVEL AND DETAILED SUMMARIZATION OF PROPOSED OPTIMIZATION STRATEGY

A. SMART IRRIGATION WITH IoT

An innovative method for automating irrigation methods and reducing water consumption is the SMART irrigation system, which helps to improve the performance of crop growth by providing an adequate amount of water to crops. This method helps farmers to meet their demand for the correct amount of water for the irrigation process by adjusting the water level in agricultural fields based on actual weather and soil conditions. Numerous applications, such as irrigation decision assistance, crop selection and crop growth monitoring, are made possible by the IoT. In agriculture, different irrigation techniques are needed for each stage of a crop's growth. The agricultural fields' irrigation systems are being modernized with the application of IoT. A SMART irrigation system consists of wireless connection, data processing, fault detection, irrigation control, and data gathering using sensors. The water-level sensor, soil moisture, and daylight readings are employed in the crop field to take readings. The purpose of soil monitoring is to determine the amount of moisture in the soil by utilizing well-founded technologies in the SMART irrigation system. Two probes are put into the soil to form the soil moisture sensors. The soil moisture sensors are buried in the roots of turfs, shrubs, or trees allowing accurate measurement of the amount of moisture in soil. Low moisture soil offers reduced resistance and passes high current when the current goes through the probes. The variable resistance serves as a proxy for soil moisture content. A pictorial view of smart irrigation using IoT is depicted in Figure 2.

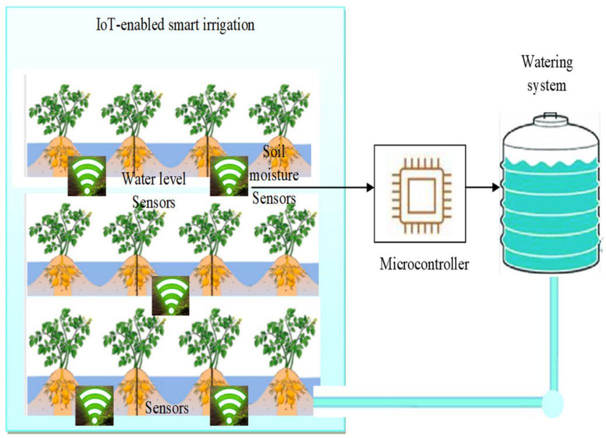


FIGURE 2. Pictorial view of smart irrigation using IoT.

B. DESCRIPTION OF AGRICULTURAL DATASET

From the below dataset, the images and data needed for this research are taken.

1) DATASET 1 AGRICULTURE CROP IMAGES

The agricultural crop images are accumulated from the link https://www.kaggle.com/datasets/aman2000jaiswal/agriculture-crop-images. Accessed on 2023-12-21, these images are collected. It consists of crop images including maize, jute, sugarcane, rice, and wheat. For all the above-mentioned crops, more than forty images are given in this database.

2) SOIL MOISTURE DATASET

The soil moisture content data are gathered from "https://www.kaggle.com/datasets/amirmohammdjalili/soil-moisture-dataset", accessed on 2023-12-21. From different layers of soil, the soil moisture content data is collected. The data is taken by considering seconds, hours, days, and months. Moreover, three different moisture content levels are given in this dataset.

3) DATASET 2 AGRICULTURAL CROP IMAGE CLASSIFICATION

The images for the proposed irrigation level prediction work are garnered from the data source link "https://www.kaggle.com/datasets/mdwaquarazam/agricultural-crops-image-classification: access date: 2024-02-23". This resource includes 30 distinct kinds of crops that are present in separate folders. Overall, this resource includes 829 images.

4) SOIL SENSOR READINGS

This data source is gathered through "https://discover.data.vic.gov.au/dataset/soil-sensor-readings-historical-data: access date:2024-02-23". It includes the historical readings for soil sensors. These readings are gathered from Melbourne City. The soil sensors take numerous readings like moisture, temperature, and salinity. The readings and units are presented within the data.

Some of the sample agricultural crop images for the proposed irrigation level prediction are given in Figure 3.

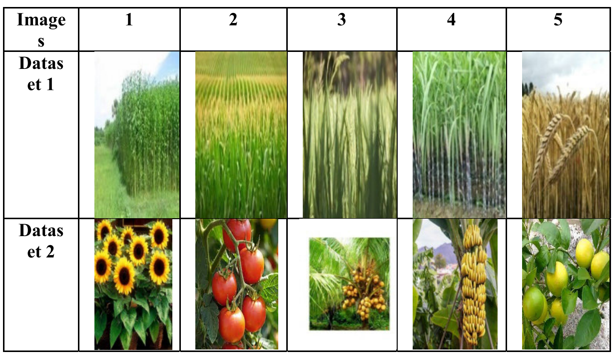


FIGURE 3. Sample agricultural crop images for the irrigation level prediction.

The gathered images are specified as IR_C^{LV} and the data are indicated as SL_I^{MO}. Here, the total amount of crop images and total soil moisture content are characterized as C and I, simultaneously.

C. PROPOSED FPFOA

The FPFOA is developed to maximize the irrigation levels prediction process by optimizing parameters. It optimizes steps per epoch, epoch size, and hidden neuron count in ShuffleNetV2 to reduce the MAE and RMSE. The conventional PFOA has the capacity to manage the time-varying randomization by traversing the search space effectively. However, it is not suitable for high dimensional optimization problems and it provides better solutions only with chosen test functions. Therefore, the random integer α_1 in the existing PFOA is updated to get the best optimal solution in the developed FPFOA. In order to update this value, the worst fitness and best fitness values are considered as shown in Eq. (1).

$$\alpha_1 = \left(\frac{NS}{ZF}\right) * 0.2 \tag{1}$$

Here, the random integer is characterized as α_1, and this value is upgraded in Eq. (2). The worst and best fitness values are termed as NS and ZF, simultaneously. By this updation in the traditional PFOA, the existing issues in PFOA are solved and the proposed FPFOA has the ability to offer better solutions with any kind of test functions.

PFOA [26]: The PFOA is designed based on the foraging behavior of piranhas. It is a type of fish and it is very aggressive in nature. These piranhas are mostly found in the Amazon Rivers. They can easily bite and eat animal flesh because of their serrated teeth. It has the ability to lay about 1000 eggs. For incubating the eggs, piranha uses plant leaves.

The attacking stage of piranha is divided into three types. In order to find better optimal solutions, three tactics including reverse evasion, population survival, and non-linear parameter control were employed in this algorithm.

Three kinds of foraging attacks take place in this algorithm. They are, scavenging foraging, bloodthirsty cluster attack, and localized group attacks. At first, the population of the piranha is initialized as in Eq. (2).

$$r_x = hu_x + \alpha_1 \times (bu_x - hu_x) \tag{2}$$

Here, the random parameter is denoted as α_1. Eq. (1) is used to update this random parameter. The lower and upper boundaries are stated as hu_x and bu_x, concurrently. The location of the x^{th} piranha is mentioned as r_x. Piranhas have a high ability to sense blood. In order to formulate this concept,

an intensity parameter B_x is employed. The intensity parameter represents the blood concentration level. Their movements will speed up according to the concentration level of blood.

The process of piranhas swimming towards the blood is formulated in the following Eq. (3)-Eq. (5).

$$B_x = \alpha_2 \times \frac{S_x}{4\pi t_x^2} \tag{3}$$

$$t_x = p_{yu} - p_x \tag{4}$$

$$S_x = [p_x(i) - p_{x+1}(i)]^2 \tag{5}$$

In the above expressions, the source intensity is indicated as S_x. The distance between the piranha and the prey is termed as t_x. The term p_{yu} refers to the prey. In order to handle premature convergence and time-varying randomized processes, the Non-linear parametric control strategies are adapted in this algorithm. A large value L is introduced to premature convergence and time-varying randomized processes, the Non-linear parametric control strategies are adapted in this algorithm. A large value L is introduced to prevent this algorithm from stucking in the local optimum. Based on the value L, the convergence of the algorithm will change.

$$L = G.\cos\left[\frac{\pi}{2} \otimes \left(\frac{i}{M\_i}\right)\right]^4 \tag{6}$$

In Eq. (6), the constant value is represented as G. Maximum counts of iterations are defined by the term M_i. To change the population direction, a flag value F is introduced and it is estimated using Eq. (7).

$$F = \begin{cases} 1 & \alpha_3 \leq 0.5 \\ -1 & \alpha_3 > 0.5 \end{cases} \tag{7}$$

Here, the random integer is defined by the term α_3. When piranhas are hungrier they even start to attack larger prey. If the prey is found near their habitat, the piranha calls other piranha using signals by splashing water. In this instance, group attacks will happen and it is formulated via Eq. (8).

$$p_x(i+1) = \mu_1 \sum_{m=1}^{rg} \frac{A_m(i) - p_x(i)}{rg} - p_{yu}(i) \tag{8}$$

In Eq. (8), the term rg specifies the random integer. A random value that lies in the range of $[-2, 2]$ is represented as μ_1. The fraction of the local population attack is defined as $A_m(i)$. The new position of the piranhas is symbolized as $p_x(i+1)$. When the concentration of blood is high, the piranhas start to swim faster to attack the wounded prey as it has a high sense of smell. This bloodthirsty attack of piranhas is modeled in the below Eq. (9).

$$\begin{aligned} p_x(i+1) = \mu_1 * f^{\mu_2} * p_{yu}(i) + E * p_{yu} * F * B_x \\ + F * \alpha_4 * L * B_x \end{aligned} \tag{9}$$

In the above expression, the hunting capacity of the piranhas is determined by the coefficient E. The updated position of the piranha population is termed as $p_x(i+1)$. Piranhas have less eyesight, so there is a high chance for the piranhas to be getting lost from the group. The lost piranha eats seeds to live. This scavenging hunting process is arithmetically expressed in Eq. (10).

$$p_x(i+1) = \frac{1}{2}\left[f^{\mu_2} * pH_1(i) - F * p_x(i)\right] \tag{10}$$

Here, the H_{1st} agent's position is denoted as pH_1. A survival rate UR category is adapted in this algorithm to maintain the piranha population. The new offspring are produced if $UR \leq \frac{1}{4}$. It is described in Eq. (11) and Eq. (12).

$$UR(x) = \frac{ft_M - ft(x)}{ft_M - ft_{MI}} \tag{11}$$

$$p_x(i+1) = p_{yu}(i) + \frac{1}{2}\left\{\begin{matrix} [pH_1(i) - F * pH_2(i)] - \\ [pH_2(i) - F * pH_3(i)] \end{matrix}\right\} \tag{12}$$

Here, the maximum and minimum fitness values are mentioned as ft_M and ft_{MI}, correspondingly. Algorithm 1 presents the pseudocode of the developed FPFOA.

Algorithm 1 FPFOA

Assign the parameters
Allocate the probability of piranha being hungry $A = 0.5$
Allocate the probability of blood concentration level $B = 0.5$
Update random parameter α in Eq. (1)
Create the population of piranha
While iteration $< M\_i$
If $\alpha < A$
    Upgrade nonlinear cosine factor L by Eq. (6)
        If $\alpha < B$
            Estimate the blood concentration level B_x via Eq. (7)
            Estimate group attack by Eq. (8)
        Else
            Perform bloodthirsty attack via Eq. (9)
        End if
    Perform scavenging hunting method in Eq. (10)
    Upgrade piranha survival strategy using Eq. (11)
    Compute P_{new}
    If $P_{new} < p_{yu}$ then
    Set $P_{new} = p_{yu}$
End while
Visualize the value of p_{yu}

V. INTELLIGENT DEEP LEARNING WITH HYBRID COVOLUTION MECHANISM FOR THE PREDICTION OF IRRIGATION LEVEL IN AGRICULTURE FIELDS

A. HYBRID (1D-2D) CONVOLUTION NETWORK

The 1D-2D Convolution Network [31] is used to forecast the irrigation level by taking input images as the input for 2D convolution and data are the input of 1D convolution. The goal of the hybrid1D and 2D convolution is to utilize different dimensional data to learn high-level features. The 2D convolution has the ability to learn high-level features and the 1D convolution has the capacity to learn deep features. The 1D convolution consists of a ReLU layer and a fully connected layer. Moreover, it has four batch normalization layers, max-pooling, and 1D convolution layers. There were 32 kernels are presented in this convolution layer. Processing of input by the 1D convolution is expressed in Eq. (13).

$$u(p) = v(p) * x(p) \tag{13}$$

Here, the convolution kernel is denoted as $x(p)$. The output and input of the convolutions are mentioned as $u(p)$ and $v(p)$, simultaneously. First convolution layer receives the 1D vector and generates features. The retrieved feature is mathematically expressed in Eq. (14).

$$v_m^k(p) = L(a_m^k + \sum_n v_n^{k-1} \times x_{mn}^k) \tag{14}$$

In the above expression, the ReLU function is represented as L. The bias of the nodes is indicated as a_m^k. The kernel parameters are represented as x^k_{mn}. The term k defines the layer and the m^{th} node is specified as v^k_m. For each parameter updation, the distribution of hidden units is changed. Following Eq. (15) and Eq. (19) give the computations for the batch normalization layers.

$$\eta^k = \frac{1}{C}\sum_m v^k_m \tag{15}$$

$$\left(\sigma^k\right)^2 = \frac{1}{C}\sum_m \left(v^k_m - \eta^k\right)^2 \tag{16}$$

$$v^k_{m\_norm} = \frac{v^k_m - \eta^k}{\sqrt{\left(\left(\sigma^k\right)^2 + \in\right)}} \tag{17}$$

$$v^k_{m\_norm} = \frac{v^k_m - \eta^k}{\sqrt{\left(\left(\sigma^k\right)^2 + \in\right)}} \tag{18}$$

$$\tilde{v} = \alpha^k v^k_{m\_norm} + \gamma^k \tag{19}$$

In the above expressions, the terms γ and α denotes the random parameters. A small positive number is termed as $\in$. The retrieved features are passed to the pooling layer. Then, the downsampling process takes place and it is expressed via Eq. (20).

$$v^k_m = \max_{\forall q \in \Omega_m} v^{k-1}_m \tag{20}$$

Totally, 64 features are produced by the third and fourth convolutional layers. The output attained from these layers is given to a fully connected layer and it is described in Eq. (21).

$$v^k = L\left(a^k + v^{k-1}.x^k\right) \tag{21}$$

Unlike 1D convolution, the2Dconvolution has two max-pooling layers. 32 feature maps are created from this first layer. The preceding layers form 64 features as output. The 1D-2D convolution layers are expressed in Eq. (22).

$$v^k = \left[v^{k-1}_{1D}\, v^{k-1}_{2D}\right] \tag{22}$$

The features learned by the fully connected layers of 1D-2D convolution are represented as v^{k-1}_{1D} and v^{k-1}_{2D}. The softmax function's input and softmax function can be described in Eq. (23) and Eq. (24).

$$v^m = \sum_n f_n X_{nm} \tag{23}$$

$$sft\,(v)_m = q_m \frac{\exp(v_i)}{\sum^p_n \exp(v_m)} \tag{24}$$

Here, the weighted connection is indicated as X_{nm}. The activation in the final layer is mentioned as q_m. A schematic depiction of hybrid 1D-2D convolution is given in Figure 4.

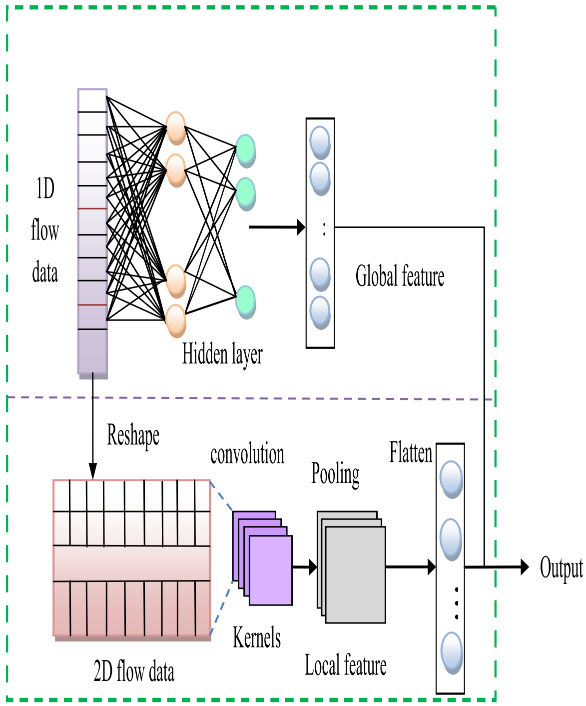


FIGURE 4. Schematic depiction of hybrid 1D-2D convolution.

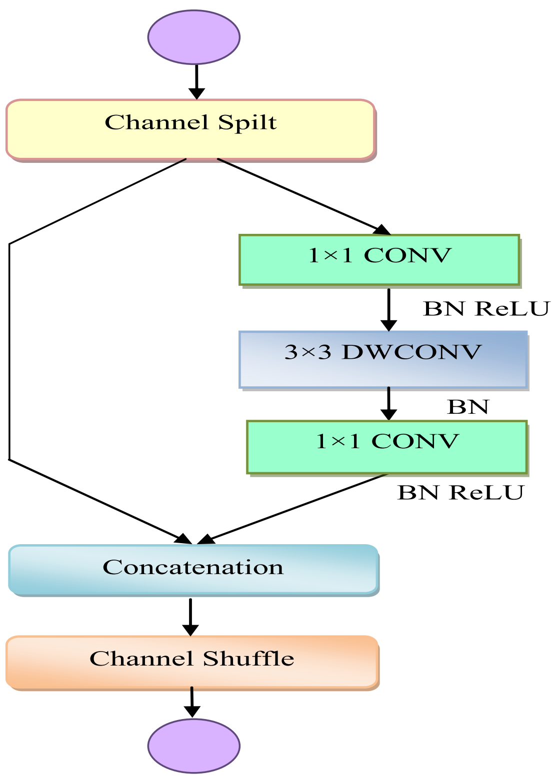


FIGURE 5. Diagrammatic representation of shuffleNetV2.

B. BASIC SHUFFLENETV2

The channel shuffle operation is performed by the ShuffleNetV2 [33] method. The architecture of ShuffleNetV2 consisted of two segments. Two groups are splitted from the feature channels in Segment 1. On the right side of the ShuffleNetV2, the ReLu, batch normalization, and convolution operations are performed. The left side of the network does not perform any functions in order to decrease

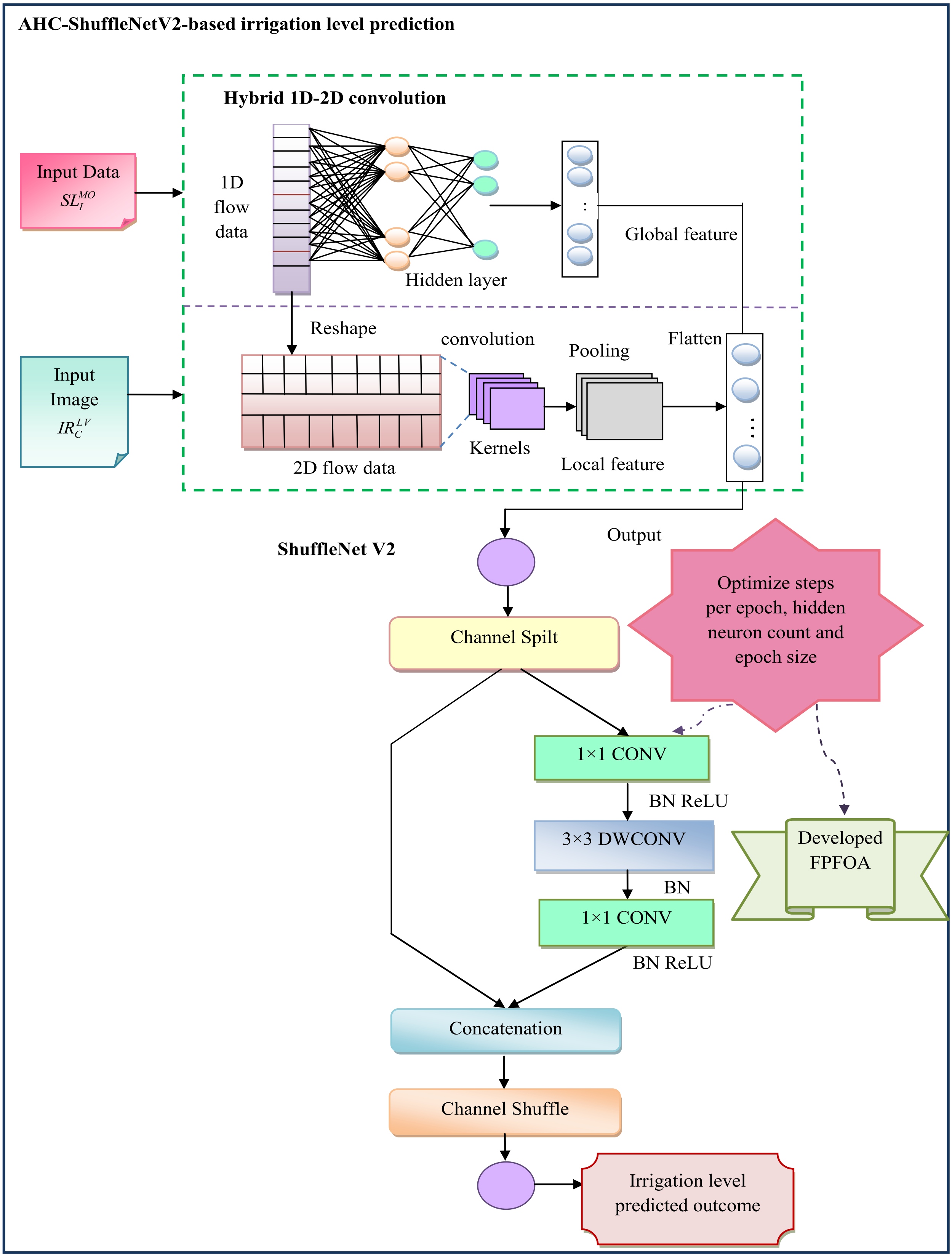


FIGURE 6. Architectural representation of the AHC-shuffleNetV2-based irrigation level prediction in agriculture fields.

the fragmentation of the model. The channels in the network are shuffled after connecting the output features from the right and left branches. In segment 2, operations like ReLu, batch normalization, and convolutions are performed

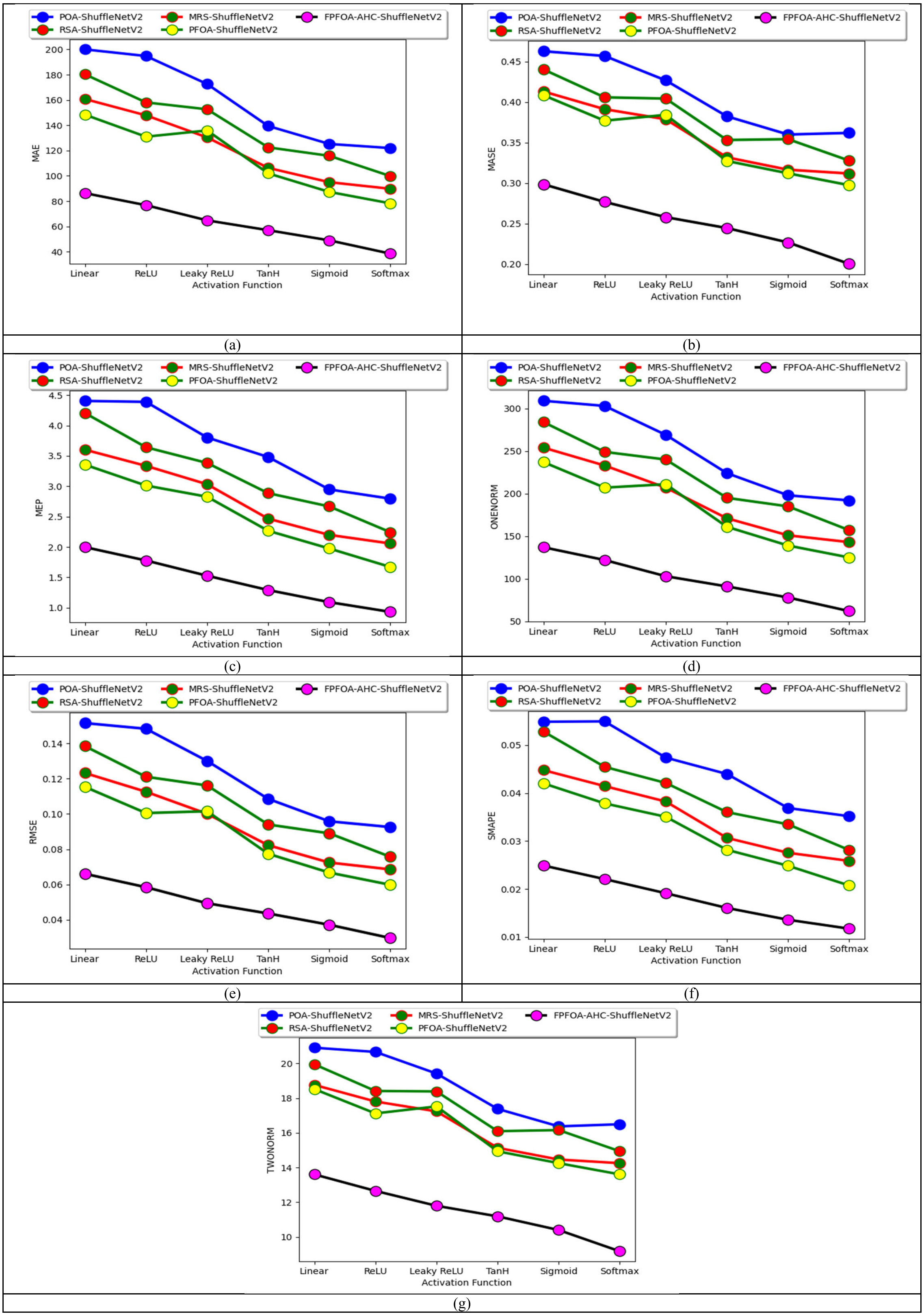


FIGURE 7. Irrigation level prediction performance analysis among different heuristic algorithms with regards to a) MAE, b) MASE, c) MEP, d) ONENORM, e) RMSE, f) SMAPE, and g) TWONORM.

afterdownsampling the right and left components. Channel shuffling and concreting both functions are performed by the ShuffleNetV2 model.The group convolutions are replaced by categorizing the input channels into two phases. The

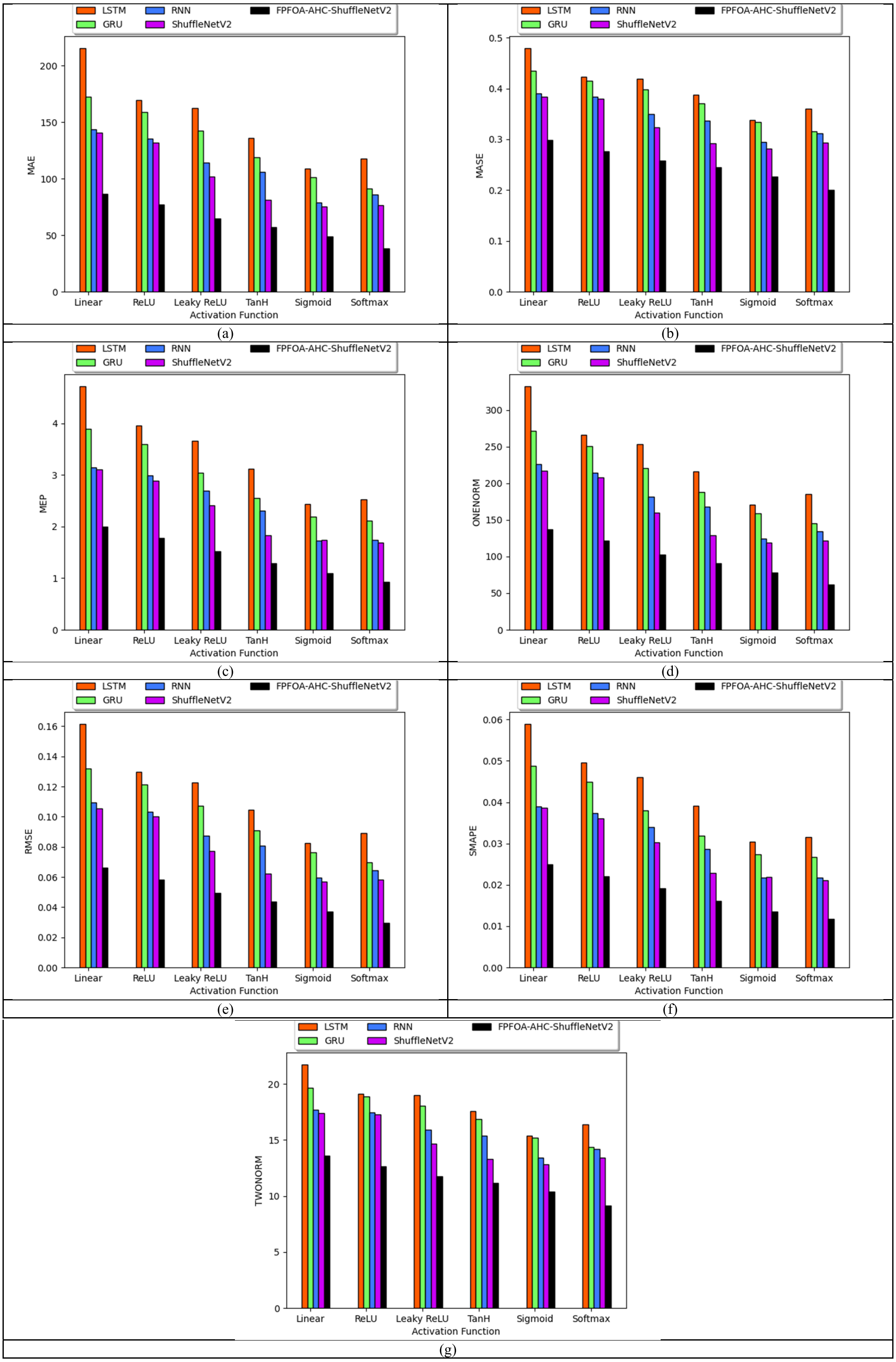


FIGURE 8. **Irrigation level prediction performance validation of the developed model over techniques by means of a) MAE, b) MASE, c) MEP, d) ONENORM, e) RMSE, f) SMAPE, and g) TWONORM.**

computations of the network are less as one branch of the network does not perform any operations. In the entire convolution, the number of channels is the same and it is maintained by the other branch. The totals of output

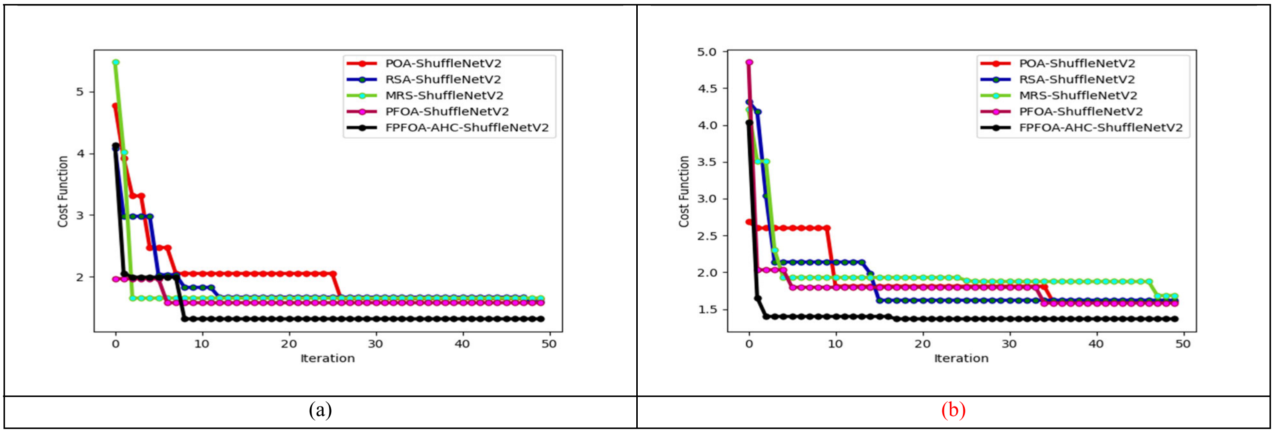


FIGURE 9. Convergence graph of the proposed irrigation level prediction model by comparing with other existing algorithms for (a) Dataset 1, and (b) Dataset 2".

channels are increased and the channel splits are eliminated by the shuffle unit employed in the ShuffleNetV2. The outputs attained from both the shuffle units are merged. Thus, improves the performance of the network and maximizes the information transmission among channels. A diagrammatic representation of shuffleNetV2 is shown in Figure 5.

C. PROPOSED AHC-SHUFFLENETV2-BASED IRRIGATION LEVEL PREDICTION

An AHC-ShuffleNetV2 network was created to predict the irrigation level. The input data SL_I^{MO} are sent to the 1D convolution as input and the gathered images IR_C^{LV} are processed by the 2D convolution. After the convolution process, the ShuffleNetV2 provides the predicted output. The AHC-ShuffleNetV2-based irrigation level prediction is useful for sewage disposal and control of dust in crop fields. Moreover, it prevents soil consolidation and the growth of weeds in irrigation fields by estimating the correct amount of water for appropriate crops. The objective of the AHC-ShuffleNetV2-based irrigation level prediction in the agriculture field is to minimize the MAE and RMSE. It is given in Eq. (25).

$$df = \underset{\{UI_Y^{SN}, ZF_P^{SN}, RE_F^{SN}\}}{\arg\min} (RMSE + MAE) \tag{25}$$

Here, the steps per epoch in shuffleNetV2 are defined by the term UI_Y^{SN} that is presented in the range of $[500 - 1000]$. The epoch size in the interval of $[5 - 50]$ is mentioned as ZF_P^{SN}. The objective function is symbolized as df. The hidden neuron count that lies in-between $[5 - 255]$ is represented as RE_F^{SN}. Below Eq. (26) and Eq. (27) present the computations for MAE and RMSE.

$$MAE = \frac{\sum_{w=1}^{D} |t_w - s_w|}{D} \tag{26}$$

$$RMSE = \sqrt{\frac{\sum_{w=1}^{D} \left(s_w - \hat{s}_w\right)^2}{D}} \tag{27}$$

In the above expressions, the total data point counts are referred as D. The true value and the predicted value are given as s_w and t_w, concurrently. The term w is the variable and the evaluated time series is represented as $\hat{s}_w$. Architectural representation of the developed AHC-ShuffleNetV2-based irrigation level prediction in agriculture fields is shown in Figure 6.

VI. EXPERIMENTAL FINDINGS

A. EXPERIMENTAL SETUP

The proposed irrigation level prediction model using the deep learning mechanisms via smart IoTs was executed in Python. This research work was carried out with 3 numbers of chromosome lengths, iteration counts as 100, and total population as 10. Various deep learning methods as well as optimization algorithms were taken into account to estimate the performance of the suggested method. The deep learning networks including RNN [31], Gated Recurrent Unit (GRU) [30], LSTM [7], and shuffleNetV2 [33] were used to check the effectiveness of the implemented prediction method. Heuristic algorithms such as the Reptile Search Algorithm (RSA) [28], Pelican Optimization Algorithm (POA) [27], Mud Ring Algorithm (MRA) [29], and PFOA [26] were considered to verify the efficacy of the proposed algorithm.

B. EVALUATION METRICS

The developed irrigation level prediction method is estimated by some of the following measures given in Eq. (28)-Eq. (32).

$$|L|_1 = \sum_{m=1}^{r} |D_m| \tag{28}$$

$$MASE = \frac{1}{r} \sum_{m=1}^{f} |f\ (m)| \tag{29}$$

$$SMAPE = \frac{1}{r} \sum_{m=1}^{f} \frac{|C_m - D_m|}{(|C_m| + |D_m|)/2} \tag{30}$$

$$MD = \frac{\sum y - \bar{y}}{r} \tag{31}$$

TABLE 2. Statistical outcomes of the implemented deep learning-based irrigation level prediction method among other algorithms.

Statistical Report for Dataset 1					
TERMS	POA-ShuffleNetV2 [27]	RSA-ShuffleNetV2 [28]	MRS-ShuffleNetV2 [29]	PFOA-ShuffleNetV2 [26]	FPFOA-AHC-ShuffleNetV2C
Worst	4.778661	4.084858	5.474779	1.965489	4.134087
Best	1.641654	1.587351	1.651334	1.576056	1.314681
Mean	2.021962	1.850344	1.775158	1.622788	1.467027
Median	2.051252	1.665429	1.651334	1.576056	1.314681
Std	0.609727	0.480641	0.623831	0.126551	0.449002
Statistical Report for Dataset 2					
Worst	2.687104349	4.3201708	4.212295063	4.852967638	4.03766633
Best	1.600598016	1.620613628	1.684630483	1.583105108	1.366922258
Mean	1.90722241	1.875742919	2.007424753	1.808126933	1.436118568
Median	1.810360625	1.620613628	1.910774526	1.796302468	1.366922258
Std	0.362791267	0.56054577	0.453583306	0.453586938	0.373989795

TABLE 3. Irrigation level prediction results of the presented irrigation level forecasting model with smart IoTs.

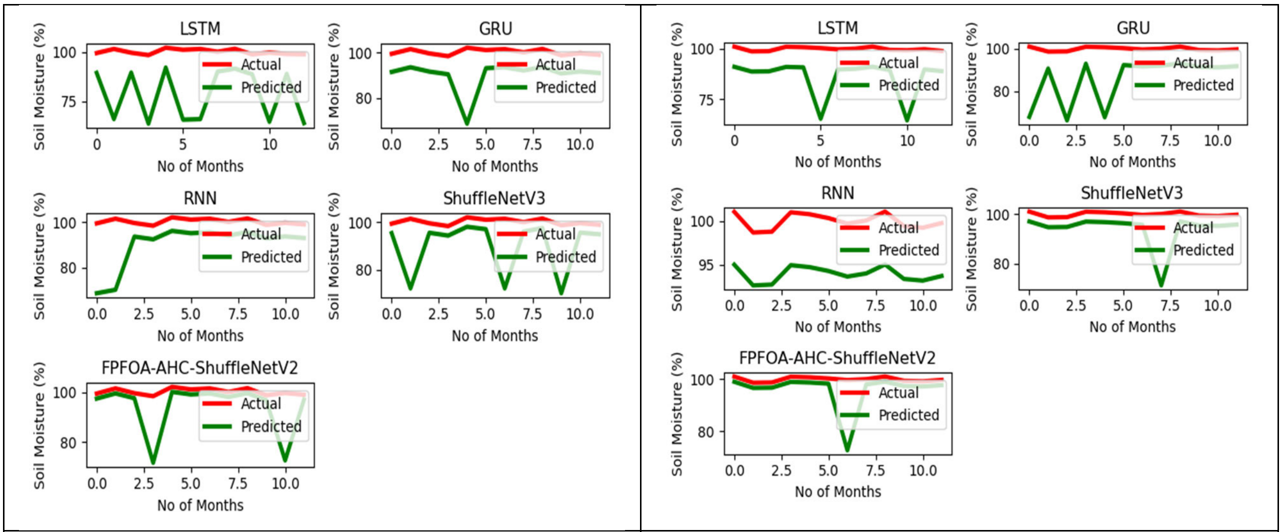
Algorithms Comparison for Dataset 1					
TERMS	POA-ShuffleNetV2 [27]	RSA-ShuffleNetV2 [28]	MRS-ShuffleNetV2 [29]	PFOA-ShuffleNetV2 [26]	FPFOA-AHC-ShuffleNetV2C
MEP	2.947105	2.667148	2.199041	1.974716	1.09179
SMAPE	0.036886	0.033482	0.027555	0.024845	0.013592
MASE	0.360078	0.354318	0.316607	0.312179	0.226833
MAE	125.2505	115.862	95.01329	87.32589	49.02457
RMSE	0.095791	0.088985	0.072422	0.066731	0.037161
ONENORM	198	185	151	139	78
TWONORM	16.37071	16.15549	14.45683	14.24781	10.3923
INFINITYNORM	2	2	2	2	2
Algorithm Comparison for Dataset 2					
MEP	2.621004566	2.22130998	1.894660502	1.606044155	0.944071588
SMAPE	0.033497717	0.028279511	0.024367691	0.020521173	0.01206264
MASE	0.25157041	0.233368517	0.211190855	0.197019044	0.151058902
MAE	261.5324232	228.3842287	187.1667184	163.4095563	96.94946401
RMSE	0.063287671	0.054460865	0.044601577	0.038816504	0.022818792
ONENORM	231	199	164	143	85
TWONORM	15.19868415	14.10673598	12.80624847	11.95826074	9.219544457
INFINITYNORM	1	1	1	1	1
Classifier Comparison for Dataset 1					
TERMS	LSTM [7]	GRU [30]	RNN [31]	ShuffleNetV2 [33]	FPFOA-AHC-ShuffleNetV2C
MEP	2.442404	2.189857	1.73253	1.73854	1.09179
SMAPE	0.030392	0.02731	0.021691	0.02182	0.013592
MASE	0.33845	0.333494	0.294528	0.281178	0.226833
MAE	108.7417	101.4395	78.69523	75.13136	49.02457
RMSE	0.082649	0.076553	0.059759	0.05702	0.037161
ONENORM	171	159	124	119	78
TWONORM	15.3948	15.19868	13.41641	12.84523	10.3923
INFINITYNORM	2	2	2	2	2
Classifier comparison for Dataset 2					
MEP	2.415393013	2.130462433	1.712297822	1.645033351	0.944071588
SMAPE	0.031113537	0.027255383	0.021939098	0.021020371	0.01206264
MASE	0.237688101	0.226362806	0.202317824	0.199377072	0.151058902
MAE	233.6644068	213.8244961	171.5084694	167.7860451	96.94946401
RMSE	0.056495633	0.05124012	0.040932502	0.039751217	0.022818792
ONENORM	207	188	151	147	85
TWONORM	14.38749457	13.7113092	12.28820573	12.12435565	9.219544457
INFINITYNORM	1	1	1	1	1

$$MEP = \frac{1}{r}\sum_{m=1}^{f}\frac{|C_m - D_m|}{C_m} \tag{32}$$

Here, the entire observation count is represented as r. The predicted and actual scores are specified as D_m and C_m. One norm is specified by the term D.

C. PREDICTION PERFORMANCE ANALYSIS AMONG HEURISTIC APPROACHES

The effectiveness of the irrigation level prediction in the crop field using the developed FPFOA-AHC-ShuffleNetV2 is validated among different algorithms by varying several activation functions including linear, ReLU, leaky ReLU,



(a) (b)

FIGURE 10. **Actual predicted analysis of the implemented smart IoTs-based irrigation level prediction over diverse deep learning techniques in terms of (a) Dataset 1, and (b) Dataset 2.**

TABLE 4. **Accuracy analysis of the implemented smart irrigation level prediction over multiple conventional algorithms.**

TERMS	POA-ShuffleNetV2 [27]	RSA-ShuffleNetV2 [28]	MRS-ShuffleNetV2 [29]	PFOA-ShuffleNetV2 [26]	FPFOA-AHC-ShuffleNetV2C
Dataset 1					
Accuracy	86.45030426	90.50709939	88.15415822	90.79107505	93.26572008
Dataset 2					
Accuracy	89.5320197	92.1182266	89.5320197	93.34975369	94.7044335

TABLE 5. **Accuracy analysis of the implemented smart irrigation level prediction over multiple conventional classifiers.**

TERMS	LSTM [7]	GRU [30]	RNN [31]	ShuffleNetV2 [33]	FPFOA-AHC-ShuffleNetV2C
Dataset 1					
Accuracy	87.99188641	89.85801217	89.20892495	92.77890467	93.26572008
Dataset 2					
Accuracy	88.91625616	92.36453202	91.00985222	94.08866995	94.7044335

TanH, Sigmoid, and Softmax. Moreover, in this, several standard error measures such as MAE, MASE, MEP, one norm, RMSE, SMAPE, and two norms are also considered for the performance analysis. Figure 7 presents the results of the proposed FPFOA-AHC-ShuffleNetV2 among different optimization approaches. When considering the ReLU activation function, the MAE of the proposed FPFOA-AHC-ShuffleNetV2 is minimized by 45.33%, 48.10%, 58.58%, and 39.92% than the conventional POA-ShuffleNetV2, RSA-ShuffleNetV2, MRS-ShuffleNetV2, and PFOA-ShuffleNetV2 correspondingly. This is the same for all the measures. Hence, it is revealed that the recommended FPFOA-AHC-ShuffleNetV2 attained more precise results than the other traditional models by reducing the error rate.

D. PREDICTION PERFORMANCE EVALUATION OVER DIFFERENT TECHNIQUES

The effectiveness of the irrigation level prediction in the crop field using the suggested FPFOA-AHC-ShuffleNetV2 is verified over other deep-learning techniques. The graphical representation of the results attained using the established FPFOA-AHC-ShuffleNetV2 by varying the activation function is depicted in Figure 8. When focusing the TanH activation function, the MEP of the recommended FPFOA-AHC-ShuffleNetV2 is reduced by 57.14%, 50%, 40%, and 25% than LSTM, GRU, RNN, and shuffleNetV2, concurrently. Therefore, it is highlighted that the capability of the irrigation level prediction using the suggested approach is improved by analyzing the above results. Moreover, the findings showed that the designed model outperformed the other conventional techniques.

E. CONVERGENCE ESTIMATION

The cost function valuation of the implemented irrigation level prediction in agricultural fields with smart IoTs is estimated by comparing the convergence outcomes of the proposed model with other algorithms. The convergence validation of the designed FPFOA-AHC-ShuffleNetV2 is given in Figure 9 for two datasets. At the 10th iteration, the convergence of the recommended FPFOA-AHC-ShuffleNetV2 based irrigation level prediction with smart IoTs is 61%, 75%, 77.27%, and 50% improved than POA-ShuffleNetV2, RSA-ShuffleNetV2, MRS-ShuffleNetV2, and PFOA-ShuffleNetV2, correspondingly in Figure 9 (a). Thus, the results proved that the investigated model is way better than existing algorithms. Also, it is shown that the designed FPFOA algorithm is more capable to optimize the network parameters than the other traditional algorithms.

F. STATISTICAL RESULTS OVER-OPTIMIZATION ALGORITHMS

The statistical results attained by the designed FPFOA-AHC-ShuffleNetV2C are visualized in below Table 2. The statistical results are estimated by comparing the proposed algorithm FPFOA with different heuristic approaches for two datasets. The superior performance of the recommended FPFOA is justified by the attained results that are given in the below table. The implemented FPFOA-AHC-ShuffleNetV2C technique is strengthened by 25.19% of POA-ShuffleNetV2, 20.61% of RSA-ShuffleNetV2, 25.95% of MRS-ShuffleNetV2, and 19.84% of PFOA-ShuffleNetV2 accordingly when considering the best factor in first dataset. Hence, it is ensured that the capability of the proposed algorithm FPFOA for improving the performance of irrigation level prediction is higher than traditional algorithms.

G. OVERALL PREDICTION PERFORMANCE EVALUATION

The irrigation level prediction by the proposed FPFOA-AHC-ShuffleNetV2 is compared with various techniques and heuristic algorithms. The prediction results of the designed FPFOA-AHC-ShuffleNetV2 are shown in Table 3.The SMAPE of the developed FPFOA-AHC-ShuffleNetV2 is 63.15%, 59.40%, 50.67% and 45.29% better than POA-ShuffleNetV2, RSA-ShuffleNetV2, MRS-ShuffleNetV2 and PFOA-ShuffleNetV2. Therefore, it is confirmed that the implemented FPFOA-AHC-ShuffleNetV2 model obtained more accurate irrigation level prediction than the other conventional techniques.

H. ACTUAL PREDICTED ANALYSIS

Figure 10 shows the actual predicted analysis of the proposed work concerning soil moisture. For the two data sources, this analysis is performed by utilizing several deep-learning techniques. From this analysis, it is shown that the suggested shuffleNetv3-based analysis attained better outcomes than the existing deep learning techniques.

I. ACCURACY ANALYSIS OF IMPLEMENTED MODEL

Table 4 and Table 5 depict the accuracy analysis of the designed irrigation level prediction framework for two datasets over several existing algorithms and prediction techniques. By using the sigmoid activation function, the accuracy is analyzed. For the second dataset, the accuracy is improved by 6.11% of LSTM, 2.47% of GRU, 3.9% of RNN, and 0.65% of shuffleNetV2 in Table 5. Hence, it is guaranteed that the designed smart IoTs-based irrigation level prediction framework achieved a higher level of accuracy than the other techniques.

VII. CONCLUSION

A technique for predicting the irrigation levels using deep learning by employing smart IoTs was developed. At first, the required crop field image and data regarding soil moisture were collected from online datasets. The data and images were given to the developed network AHC-ShuffleNetV2 for the irrigation level prediction. It was developed by integrating two deep learning networks such as hybrid 1D-2D and ShuffleNetV2. The images were given to the 2D convolution the data were given to the 1D convolution. In order to further enhance the prediction performance, a new heuristic approach FPFOA was suggested. It maximized the prediction performance by optimizing steps per epoch, epoch size, and hidden neuron count in ShuffleNetV2 for decreasing the MAE and RMSE. Then different experimental analyses were carried out to demonstrate the efficacy of the designed irrigation levels prediction model. The RMSE of the developed FPFOA-AHC-ShuffleNetV2 was 55.03%, 51.45%, 37.81%, and 34.82% superior to LSTM, GRU, RNN, and shuffleNetV2. Hence, the presented method accurately predicted the irrigation levels in crop fields, which was helpful for not consuming so much water by the crops. However, the implemented smart irrigation level prediction model cannot have the potential to analyze the effects of weather parameters such as temperature, UV ray, humidity, and wind on the field. In the near future work, this will be considered for rendering the better improvement by utilizing advanced deep-learning strategies.

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XUEHUI XU received the B.E. and M.E. degrees from Central China Normal University, Wuhan, China, in 2001 and in 2006, respectively. She is currently an Assistant Professor with the Electronic Information Engineering College, Wuhan Polytechnic University, Wuhan. Her research interests include the IoT, wireless sensor networks, electronic technology, and vocational education.

R. S. M. LAKSHMI PATIBANDLA received the Master of Technology degree in CSE from Acharya Nagarjuna University, in 2010. She has been an Assistant Professor with the Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur, Andhra Pradesh, India, since 2023. She has 22years of experience in industry and deemed to be university. She completed one DST funded project, in 2017. She has published more than 20 Scopus indexed publications and two SCIE papers. Her area of specialization is machine learning, deep learning, predictive analytics, and data mining.

AMIT ARORA received the B.E. degree in electronics engineering from Jiwaji University, Gwalior, India, in 2000, the M.Tech. degree in electronics and communication engineering from Rajiv Gandhi Proudyogiki Vishwavidyalaya, Bhopal, India, in 2008, and the Ph.D. degree in microwave engineering from IIT (BHU), Varanasi, India. Currently, he is an Associate Professor with Galgotias University, Greater Noida. His current research interests include real-time embedded systems, high frequency vacuum electron beam devices, and RF circuit design.

MUNA AL-RAZGAN received the Ph.D. degree in information technology from George Mason University, VA, USA. She is currently an Associate Professor of software engineering with the College of Computer and Information Sciences, King Saud University, Riyadh, Saudi Arabia. Her research interests include data mining, machine learning, artificial intelligence, educational data mining, and assistive technologies.

EMAD MAHROUS AWWAD was born in Menia, Egypt, in 1988. He received the degree in 2011, and the the M.Sc. degree in electrical engineering from the Electrical Engineering Department, King Saud University, in 2020. He is currently pursuing the Ph.D. degree with the Electrical Engineering Department, King Saud University. He was a Teaching Assistant with the Industrial Electronics and Control Engineering Department, Faculty of Electronic Engineering, Menofia University, Egypt, in 2012. He developed his research in the field of system design, control of linear and nonlinear systems, embedded system design, the Internet of Things (IoT), and implementation of autonomous mobile robots. He is interested in modeling, optimization, observer design, and model predictive controller of vehicle dynamics under the wheel-terrain interaction slippage phenomenon. He is also interested in artificial intelligent (AI), machine learning (ML), and deep learning (DL) related to the field of robotics and image processing.

VINCENT OMOLLO NYANGARESI received the B.Sc. degree in telecommunications and information technology and the M.Sc. and Ph.D. degrees in information technology security and audit. He is an experienced researcher in the areas of computer science and information technology. He has published over 120 research articles in peer-reviewed journals and conferences covering areas, such as communication systems, secure network communications, D2D, smart homes, internet of drones, smart grids, WSNs, cellular network security, VANETs, information systems acceptance modeling, TCP architecture and design, radio wave propagation, virtualization, and cloud computing. He is a renowned Reviewer for numerous IEEE, Taylor & Francis, MDPI, *PLOS One*, Elsevier, and Springer journals. In addition, he has served as a Technical Committee Member (TPC) for numerous international conferences and symposia, such as the International Conference on IoT as a Service (IoTaaS), Congress on Intelligent Systems (CIS), International Conference on Smart Grid and Energy Engineering (SGEE), and International Conference on Cloud, Big Data and IoT (CBIoT). Moreover, he serves as an Editor to some top journals, such as *PLOS One*.