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Original Article

Parameter Tuned Hybrid Deep Learning Network with Improved Algorithm-Assisted Weighted Feature Selection for Yield Prediction Using IoT Sensor in Agricultural Field

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Abstract - *Crop yield prediction is inherently complex, determined by numerous issues including environment, genotype, and their interaction. Effective forecasting requires recognizing the functional criteria among interacting factors and yield, necessitating both robust algorithms and comprehensive datasets. Machine learning has become a crucial decision-making tool in agriculture, aiding in crop selection and cultivation management. Various machine learning techniques are employed to predict the crop yield. Among all these techniques, deep learning models offer improved accuracy in complex classes. In this work, applications of artificial intelligence techniques are explored with the Internet of Things (IoT) to enhance the prediction efficiency of crop yield. An automated and intelligent methodology, an adaptive classifier network, is employed. Data is collected from a benchmark database, and a Novel Parameter Wave Search Algorithm (NPWSA) optimizes and selects weighted features, which are then input into a Parameter-tuned Hybrid Network (PHNet). The PHNet model is built using a combination of a Pyramidal Dilated Convolutional Neural Network (PDCNN) and a Stacked Recurrent Neural Network (SRNN). The overall performance of the proposed technique is evaluated through several metrics. Experimental results demonstrate that NPWSA significantly improves prediction accuracy compared to conventional methods, contributing to enhanced crop productivity and improved economic outcomes for farmers.*

Keywords - *Internet of things, Novel parameter derived wave search algorithm, Pyramidal dilated convolutional neural network, Stacked recurrent neural network, Weighted features selection, Yield prediction.*

1. Introduction

Agriculture is one of the most effective and essential sources of food production, and farming delivers raw material for factories like wool, cotton, paper, wood, and leather products [9]. Efficient yield prediction aids in preserving food supply and prohibits drastic fluctuations [10]. Still, such high production of the crop is a complex task due to current climatic conditions and various other factors [11]. The majority of the agricultural fields are affected due to rain-fed conditions, and are highly vulnerable to climatic conditions and extreme weather conditions such as storms, droughts, and floods [12]. The deep learning techniques utilized in today's world require more knowledge about crops and soil, which makes it difficult to develop for different regions [13]. In some cases, crop yield predictions are affected by pest attack and crop diseases that badly affect the overall yield [14]. Some of the IoT-based innovations, like drones, robots, and remote sensors, make farmers' lives easier and have been used to monitor the productivity in agricultural fields [15]. IoT-assisted crop yield prediction allows farmers to improve productivity [16]. In the IoT-based smart farming, various sensors such as Humidity and temperature sensors (DHT11), potassium, nitrogen, phosphorus, and Total Organic Carbon (TOC) are used to monitor the agricultural field [17]. Various IoT-based yield prediction models have been proposed for better yield prediction, and these models have various drawbacks, such as false prediction, lower sustainability, high complexity, and computational expense [18]. It can be easily influenced by instability and high variance. In addition, technological issues and high costs are also the major issues to be seen in the traditional agricultural management models [19]. Deep Learning in smart agriculture can be utilized with IoT technology in order to improve agricultural production and quality by predicting crop yield [20]. The deep learning models are utilized for agricultural yield forecasting and have successfully adapted the deep learning approach for detecting weeds, irrigation water management, plant health, and evaluating yield, resulting in high-quality outcomes over different agricultural activities [21]. In addition, the data about the crop functionality under various climatic changes is offered by the deep learning classifiers [22]. Convolutional Neural Network (CNN) is a novel framework widely suggested to be used in disease detection, crop type prediction, and pest recognition [23]. In addition, CNNs require enormous training data, which makes the training process complicated and leads to slight variations [24]. Moreover, the Artificial Neural Network (ANN) uses various hidden layers to analyze the data. In some cases, the training process is complicated and also needs a novel optimization scheme for analyzing the higher-dimensional information [25]. Vanishing gradient issues need to be tackled in the deeper networks, which makes the training process complicated and also leads to poor convergence.

1.1. Motivation

In recent days, various crop yield prediction approaches have been used to maintain the crop yield with higher quality by considering the environmental constraints. Various deep learning and machine learning techniques are employed to execute the crop yield prediction procedures. Varun et al. used the Long Short-Term Memory (LSTM) model, which is efficient in handling the sequential information. But it leads to overfitting issues that make the training process complicated. Slower training takes place in the network, which leads to an interference issue. Akanksha et al. designed an Adaptive k-nearest Centroid Neighbour Classifier (AkNCN) for predicting the crop yield. Yet, their validation expense is higher and also leads to sensitivity issues while selecting the minimal values. In addition, these techniques need enormous data for validation, and handling the longer-range dependencies is a complicated task. In order to maintain the crop yield prediction more precisely and accurately, several issues presented in the classical framework need to be resolved. So, a novel deep learning-aided crop yield prediction scheme is suggested in this research work.

1.2. Contributions

The important contributions of the developed technique for predicting the crop yield are listed below:

- To demonstrate an IoT-based novel model for crop yield prediction with weighted feature selection using IoT sensors in the agriculture field. This assists in predicting the crop efficiently and thus exploring solutions that enable farmers to observe their crops from anywhere at a specific location. In addition, the deep learning network included in this work provides superior functional outcomes.
- To select weighted features for giving an effective prediction process using NPWSA. The weighted feature can be obtained by multiplying the features by the weight. Hence, by choosing this, the overfitting issues found in the model can be reduced, and the performance and efficacy of the system can be improved.
- To develop an NPWSA algorithm for evaluating the optimized factor that enhances the performance and efficacy of the proposed system. The NPWSA is the simplified optimizer from the conventional WSA.
- To generate a PHNet technique for performing the forecasting process of crop yield efficiently. This model is constructed with the integration of PDCNN and SRNN, which has the potential to resolve all the complexities and efficiently improve the model. On further development, the parameter optimization in both networks is accomplished by using the algorithm NPWSA.

1.3. Organization

The novel prediction model for crop yield, implemented in the following sections, is demonstrated. Section II outlines the related works, research gaps, and drawbacks. Section III shows the data collection lists and the proposed network details. Section IV elaborates on the proposed algorithm. Section V describes the various techniques used, including PDCNN and SRNN, as well as the tuned PHNet. Further, Section VI validates the results and discussion part, consisting of the simulation setup and the evaluation measures in it. The Finalized Section VII represents the conclusion and the future works of the crop yield prediction process.

2. Existing Works

2.1. Related Works

2.1.1. Existing Schemes for Crop Yield Prediction

In 2024, Varun and Rao [1] described a novel IoT-oriented smart agriculture farming technique that was executed in three distinct stages: crop detection, crop disease prediction, and crop yield prediction leveraging a Hybrid Attention-aimed Crop Type Detection Network (HA-CTDN). Here, the crop type classification processes were carried out using LSTM, and various experiments were then performed to verify the overall accuracy. In 2024, Ramzan et al. [2] implemented a model consisting of two modules, where the first one utilized static data and the second one used hybrid data collection along with the Ensemble learning algorithms to provide appropriate crops in the farm to improve the yield. This model also developed a low-cost solution and an intelligent method for farmers to compute data and forecast the optimal crop. The accuracy and the efficacy of the developed model were verified by the produced outcomes. In 2023, Gupta and Nahar [3] generated a new technique along with IoT for crop yield prediction. At first, data sources were preprocessed, and then the significant features were chosen through the Variance Inflation Factor Algorithm. Further, a hybridized machine learning process was considered to execute the crop yield prediction process. In the first step, soil quality was analyzed, and then crop yield was forecasted utilizing the Extreme Learning Machine algorithms (ELM), along with an ANN. Finally, several measures like RMSE, MAE, Explained Variance Score (EVS), accuracy, R2, MedAE, MAPE, MSLE, and MAE were used for the functionality estimation. In 2023, Talaat [4] introduced the

Crop Yield Prediction Algorithm (CYPA), which utilizes the IoT method in precision agriculture. Further, the big data datasets accumulated various features indefinitely in space and time, and can help to detect technology, plant species, meteorology, and soils. The developed CYPA included weather, chemical, agricultural field, and climate data to help anticipate annual crop yields by farmers and policymakers. Moreover, the experimenters proposed a novel optimizer related to active learning, which can improve CYPA's functionality.

In 2023, Ali et al. [5] demonstrated the advantage of using recent IoT models in the estimation of resource-use-effective and smart-farming systems. The present models not only helped in improving effective productivity, but also supported in capturing the climatic differences and water dynamics, helping in pest, insect, and disease management, and aiding data management in farming systems. Smart farming and IoT methods can assist in influencing and forecasting crop production and hence help in decision-making for several crop management practices, weedicide, and insecticide applications.

In 2024, Kuradusenge et al. [6] enhanced the design of the model for forecasting crop yields that combined ML and IoT. The model integrated historic crop yield data and current weather data to forecast seasonal crop yields. By applying the data for various agricultural seasons, the model enhances the favourable accuracy of the prediction along with the MAPE. These forecasting yield systems can diminish the food insecurity problems and improve the efficacy of the harvest by allowing early alert of the crop yield, promoting efficient procedures delivered between the stakeholders and the decision-makers.

In 2022, Hassan et al. [7] explored the application of artificial intelligence in the IoT for the prediction of crop in the agricultural field. AI-based anomaly detection assisted in finding out the challenges affecting crop yield, like weather conditions, pests, and diseases. Further, AI-oriented image recognition analyzes the early indication of diseases and pests, helping in accurate treatment in order to reduce crop losses.

The resource algorithm used fertilizers and water effectively, diminishing the environmental and water impact. Furthermore, the AI-based decision support method provided personalized recommendations for ideal planting crop rotations and schedules, improving the yield. In 2022, Liyakat et al. [8] suggested an integration architecture model in the agricultural outcome, where the scholars utilized IoT and agriculture applications. Initially, the soil collection strategy was to assemble the soil from each stem of the plants. Further, water was given to all the plants at a medium level, where every plant grew well after 110 days. Validation outcomes displayed that the suggested scheme was more efficient in enhancing the crop yield with good decision-making.

2.1.2. Recent Techniques for Crop Yield Prediction

In 2024, Cheng et al. [35] designed a new framework, Graph Neural Network-LSTM (GNN-LSTM), for the prediction of crop yield. In this framework, band selection procedures are carried out over dual channels that support predicting the crop yield under varying conditions. Here, the crop yield prediction efficiency was improved by adding the GNN layer, and also, the overall network efficiency was enhanced in all classes.

In 2025, Osibo et al. [36] implemented a novel Iterative Querying-based Gated Recurrent Unit (IQ-GRU) for yield prediction. The major goal of the developed scheme was to enhance the overall yield prediction performance over various iterations. Here, the Bayesian-optimized GRU was employed to collect the complicated temporal relationship over the targeted yield and crop variables. The IQ mechanism suggested the uncertainty-aided query strategy for refining the prediction outcomes.

Further, training was carried out to verify the overall crop yield efficiency of IQ-GRU. In 2024, Nejad et al. [37] proposed an ensemble crop yield prediction technique by considering Vision Transformer (ViT), Three-Dimensional CNN (3D-CNN), and Convolutional LSTM (ConvLSTM). Complicated patterns presented in the dataset were collected using an ensemble technique. In the experimental phase, temporal as well as spatial aspects of the samples were considered to advance the robustness while predicting the crop yield. In 2025, Yadav et al. [38] implemented a novel ensemble deep learning mechanism for predicting crop yield. In the collected data, segmentation procedures were executed through an adaptive concept. The Partial Least Squares Regression (PLSR) was employed to acquire the required features, and then the context-based attention scheme with Bidirectional GRU and Bidirectional LSTM (Bi-GRU-LSTM) was suggested to execute the prediction process. At last, highly robust outcomes were attained by the developed scheme over the classical techniques.

2.2. Research Gaps and Challenges

Smart farming, also sometimes referred to as smart agriculture, focuses on generating huge amounts of yield and improving the quality of food. IoT-oriented smart agriculture models have been employed to elevate trustworthy outcomes concerning food productivity. Today's modern technology has caused an increased utilization of IoT in order to enhance the productivity, cost-efficiency, and resource-use efficacy of agricultural production management, and faces enormous complexities that are elaborated below:

- Conventional agricultural prediction models face complexities such as the model being too expensive and time-consuming [1]. Hence, this leads to economic crisis and low yield of crops in the agricultural sector. Moreover, the models struggled with the inability to make sufficient decisions and insufficient resources. In order to tackle these problems, the developed framework utilized the required data from benchmark resources, and also deep learning schemes are suggested to offer better outcomes under different conditions.

- The existing approaches also face difficulties in lower sustainability, false prediction, and high complexity [2]. In addition, complex management and high cost are also found. Thus, to overcome these issues, a stacked network is considered, which helps to improve the scalability and also increases flexibility to use in various environments. Moreover, it reduces the false prediction errors, which helps to reduce the delay while predicting the crop yield.
- Conventional yield prediction schemes suffer from providing enough spatial information on small farms for optimizing crops. The processing period is long owing to the complex structure of the system. Thus, to collect the most significant spatial as well as multi-scale contextual information, a dilated layer is included. Using the dilated layer helps to minimize the spatial resolution loss and also enhances the overall crop yield prediction efficiency without any errors. The models cannot recover the refined feature specification. Moreover, the imbalance issue paves the way for overfitting that harms the stability of the system to verify the efficiency [6]. Hence, to overcome the imbalance as well as the overfitting issues, a novel optimization procedure is considered. Overcoming the overfitting supports speeding up the training in complex classes and also minimizes the validation expenses.

Several advancements and complications associated with the classical crop yield prediction model are tabulated in Table 1.

Table 1. Advancements and complications of yield prediction using IoT sensors in the agricultural field using deep learning approaches

Author [citation]	Techniques	Advancements	Complications
Kumar and Rao [1]	HA-CTDecNet	The proposed method improves the sustainability and the productivity. It attains reduced MAE while predicting the crop yield in complex classes.	During the detection process, this technique produces lower accuracy and efficacy rates. The complexity of this method is excessive, time-consuming, and results in inaccurate outcomes and insufficient data.
Ramzan et al [2]	EL	The accuracy and the effectiveness of crop yield prediction are improved by using this approach. It also introduced intelligent strategies to compute the data and then predict the appropriate crop yield.	It undergoes difficulties in computational tasks. It struggles to explain or interpret the model. These methods are too expensive and necessitate more resources.
Gupta and Nahar [3]	ELM and ANN	This model helps in enhancing the accuracy and functionality by reducing the error rates. It has the potential to handle huge amounts of data effectively.	The huge amount of data will result in more time consumption. It also commits many errors, even when the model undergoes accurate planning.
Talaat [4]	MR	The proposed algorithm has the ability to achieve the accuracy and efficacy rates of crop yield prediction. It offers higher accuracy under a dynamic environment without any misclassifications.	It uses more effort and time to predict the crop yield. When enormous amounts of data are assembled to train and work, the accuracy and precision rates will go down.
Ali et al. [5]	SVM	This technique gives accurate results to help the researchers and the farmers in the agricultural crop-yielding sector. It provides scalable outcomes in crop yield prediction.	Privacy issues, security concerns, and time consumption are some of the drawbacks to be seen.
Kuradusenge et al. [6]	Machine Learning	This predictive system can decrease food security struggles and improve harvest efficacy by allowing early consciousness of crop yield. It also provides efficient ideas for the enhancement of the model in crop yield prediction.	The major complexity is compiling data sources, which are required for the training of large data sets. It needs to tackle the class imbalance issues that arise in the network.
Hassan et al. [7]	AI	This model secures sensitive agricultural information from cyber threats, assuring the privacy of the data and data integrity.	This model struggles with underfitting and overfitting problems. The overfitting issues fail to produce new data, whereas the underfitting problems miss

			significant patterns that are required for crop yield prediction.
Liyakat [8]	AI	This network can deal with several types of data, both confidential and standardized. The significant quality of this network is that it provides high efficiency in data delivery for the computational task.	Often, this network meets technical problems in data gathering. It suffers from vulnerabilities and security risks.

3. Intelligent Model of IoT-aided Yield Prediction through a Hybridized Deep Learning Model

3.1. IoT-Assisted Data Collection

Advanced IoT sensors are deployed for agricultural yield prediction, like air pressure sensors, atmospheric sensors, temperature sensors, humidity sensors, and so on. Further, in this research, an IoT system is utilized to acquire the essential set of data, and the data are stored in the benchmark dataset. The data source is elucidated in the link as, "https://www.kaggle.com/datasets/patelris/crop-yield prediction-dataset Access Date: 2024-09-20".

The given dataset consists of 250 records, and all the records are used in this work. Initially, the agricultural yield is based on weather changes like temperature, humidity, rain, etc., pesticides, and efficient details about the crop yield are a significant part of decision-making oriented to future forecasting and agricultural risk management. Moreover, the essential set of data collected using IoT sensors is depicted asCY_pfollows. The term CYdescribes the crop yield, and the variable $p$defines the prediction process, which varies from 1 to$p$.

3.2. Newly Developed Model: Yield Prediction using IoT Sensors

Usually, agriculture has a significant role in the Indian economy. The major crops produced in India are wheat, rice, maize, sugarcane, spices and pulses, tea, coffee, cotton, jute, and so on. Crop yield prediction is defined as evaluating how much a crop can produce food in a particular region during a specific season. Sustainable agriculture development can assist in saving watersheds, maintaining habitats, and enhancing water quality and soil health efficiently. On the other side, crop production losses occur because of the impact of diseases and pests, and weather changes in semi-arid changes. Nevertheless, unsustainable habitats can have powerful negative impacts on the people and the environment.

Therefore, in order to maintain and resolve the challenges caused, efficient detection and prediction techniques are followed. IoT applications in the field could be a life changer for the whole world. Using IoT, the system observes the crop field by adapting the sensors and controls the irrigation system. These deep learning techniques employed in the agricultural firm are utilized to enhance the quality and productivity of the crops.

Still, these techniques also result in high complexities in the model and need more computational power. These techniques cannot perform long sequences and can be difficult to train. Henceforth, a novel approach has been proposed for the prediction of crops. The pictorial presentation of the implemented work is provided in Figure 1. For predicting and feature selecting the crops from the agricultural field, enormous procedures related to deep learning models are generated. Primarily, the essential data is obtained from the benchmark data source.

Further, after collecting the required data, the weighted features are also chosen, where the weight is tuned and selected by utilizing the NPWSA. Feature selection assists deep learning techniques in concentrating on the most suitable data, which can provide more efficient and accurate outcomes. Furthermore, the resultant features are fed into the PHNet, in which the system is built with the PDCNN and SRNN. Further, the metrics and further evaluation give accurate results. At last, the classical techniques are compared with the modern approaches, where the developed methods succeed in the suitable prediction outcomes for improving the productivity of crops and the economic phase for the farmers.

3.3. Novel Parameter-Derived WSA

The newly developed NPWSA algorithm is introduced from the traditional WSA algorithm for achieving the positive components while predicting crop yield.

3.3.1. Purpose

The NPWSA-based technique is demonstrated by using the features of the standard WSA optimization [33]. It is utilized for optimizing weights. Hence, by optimizing the weight, the metrics like the relief score and the correlation coefficient are maximized using the NPWSA.

3.3.2. Novelty

While walking through the issues attained, it is observed that the WSA struggles with high-dimensional issues and fails to provide precise results. Thus, to solve these challenges, the NPWSA succeeds with high optimization accuracy over the standard WSA optimizer. Nevertheless, the WSA comprises a random value [0,1], respectively, and it is achieved by feeding a fitness-based random variable. Equation (1) below states the evaluation of a novel fitness-based arbitrary function.

$$R = \frac{(CV+20*MV)}{(WV+40*MV)} \quad (1)$$

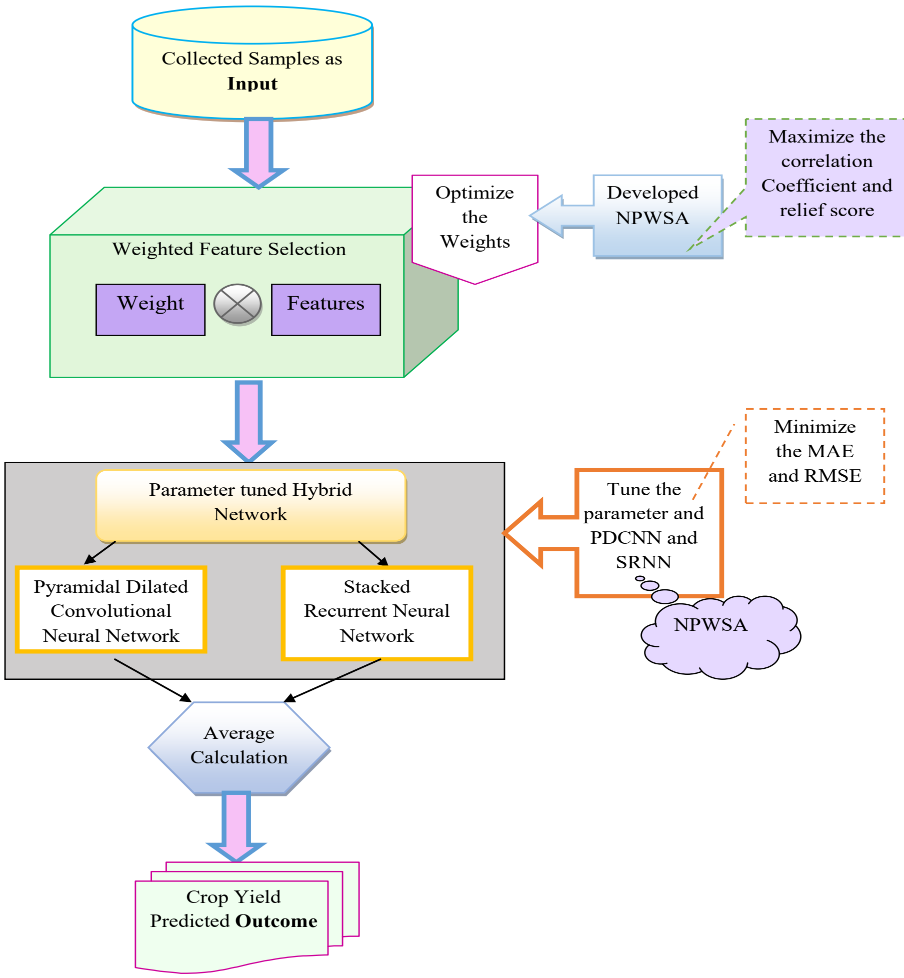


Fig. 1 Architectural view of the proposed crop yield prediction network

From Equation (1), the term states the random variable. Further, the terms CV MV represent the current fitness and the mean fitness function. Moreover, the term WV defines the worst function appropriately.

Here, the variable R is replaced in Equation (3). The notable steps followed for proposing the novel algorithm are expressed as follows:

Step 1 : To present a group of initialization preparations.
Step 2 : Further, the population coefficients and the fitness function value for the NPWSA are arbitrarily produced.
Step 3 : In the third step, initialization of population using Equation (2).

$$X = Lb + y * (Ub - Lb) \quad (2)$$

From Equation (2), the variable $y *$ is the arbitrary value in y, the terms Ub are the upper bound and Lb the lower bound in the search space.

Step 4: To calculate the fitness function and identify the best position of the current individual.
Step 5: In order to upgrade the position of the group using Equation (3).

$$X_j^{new} = Xminmax_{min} \quad (3)$$

Here, the term X_{min} is a factor encompassing the minimum values on each dimension of X, and X_{max} is the factor encompassing the maximum values on each dimension of X, respectively. The traditional algorithm has a random variable range of [0, 1].

As it is in this range, it suffers from premature convergence and is likely to fall easily into local optimal solutions for the difficult objective functions. Hence, a new random function is executed in this work, which is detailed in Equation (3).

Step 6 : Elevate the group position by deploying Equation (4) and Equation (5).

$$X_j^{new} = X_{best} + \frac{(X_{mj} - X_{best}).(1+n_j)}{\sigma} \quad (4)$$

$$X_j = X_j - \alpha . h_j \quad (5)$$

The variable $h$denotes the gradient; the factor αdefines the step coefficient.

Step 7 : The acquired solutions are secured for all iterations. At last, the tuned solutions are attained as an output for NPWSA.

The flowchart of the developed NPWSA is demonstrated in Figure 2.

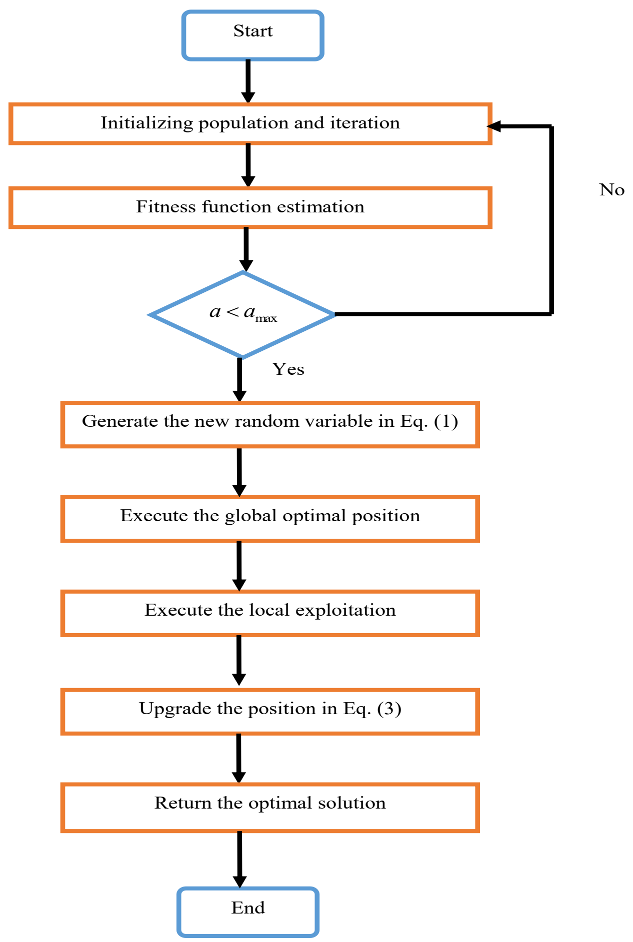


Fig. 2 Architectural flowchart of the NPWSA model

3.4. Weighted Feature Selection

In the beginning, the required raw data are sourced from the public dataset. The input data is described in termsCY_p. While the raw data is used for predicting the yield, it may consume more time and training speed, which can pave the way for performance degradation. To overcome such factors, the most pertinent features are to be selectedF_s. This feature information is suggested to be upgraded in a weighted manner, where it is easily processed under the learning classifier to provide the outcome. In order to update the feature, the weight factor is considered, and it is to be optimally selected by using the NPWSA. The tuned weight is representedW_t. Finally, weighted features are estimated through $WF = W_t \times F_s$From the input data, the essential features are only selected. The chosen features are multiplied by the weight to get weighted features. Further, the weight features are optimized using the NPWSA. Therefore, the important features are selected. Hence, it results in several benefits such as better model functionality, efficient handling with model interpretability, and so on. The weight is optimized using NPWSA. It is indicated as the termW_t. The feature is represented asF_s. Moreover, the weighted feature can be detailed as$W_{FS} = Weight \times FS$follows. The fitness function is estimated in Equation (6).

$$Obj(1) = \underset{\{W_t\}}{\arg\max} \left[RS + CC \right] \quad (6)$$

The term W_{FS} represents the tuned parameter weight, which ranges from [0.01-0.99]. Further, the terms RS CCdepict the relief score and the correlation coefficient, respectively.

The correlation coefficient is the process of finding the similarities between the features. The relief score is known as the distance between the actual and the target values.

The formulation for the correlation coefficient is specified in Equation (7).

$$cc = \frac{\Sigma(y_i - y_j)(z_i - z_j)}{\sqrt{\Sigma(y_i - y_j)^2 \Sigma(z_i - z_j)^2}} \tag{7}$$

From Equation (7), the variable cc means the correlation coefficient. The terms y_i $y_j$denote the values of $i$the -feature and the mean of the j -feature. In additionz_i, it z_j describes the values of i -feature and the mean of the j -feature.

The elaboration for the relief score is expressed in Equation (8).

$$R_e = M\left(e\left(X_g^J\right) - D\right) - M\left(e\left(X_g^J\right) - E\right) \tag{8}$$

From Equation (8), the attribute $X_g^J$is depicted as$\left(e\left(X_g^J\right) - D\right)$, the variable Dstates the nearest distance of a different class, and the factor Edefines the nearest instance of the same class. Further, the variable $M$is the objective function. The output of the weighted feature can be depicted asW_F. The illustration of the weighted feature is provided in Figure 3.

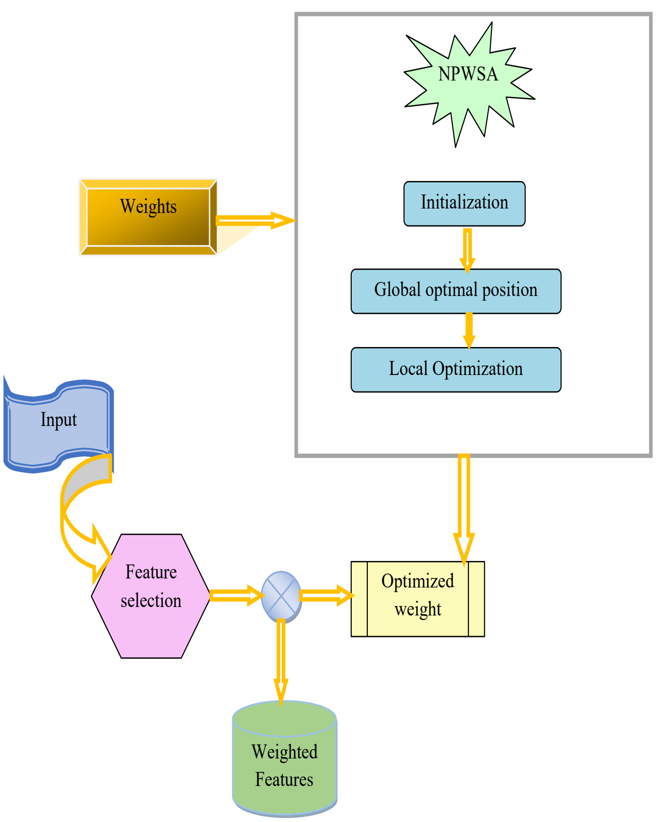


Fig. 3 Structural view of weighted feature selection

4. Yield Prediction in Agriculture using Parameter-Tuned Hybrid Deep Learning Network

4.1. Pyramidal Dilated CNN

The developed PDCNN is utilized for predicting crop yields, where the pyramidal dilated convolution operation is enforced in the CNN to achieve better performance. CNN [33] is one of the fundamental networks under deep learning techniques that are mainly used for image processing, data processing, and computer vision. This network is a division of a neural network for processing data, which has a grid-like topology. CNN is known as a neural networks that deploy convolution in place of common matrix multiplication in at least one of its layers. It undergoes certain drawbacks, such as requiring computational power to train, a huge volume of training data, a lot of memory, high cost to train, being easily prone to overfitting, and so on. Hence, to overcome the challenges, the pyramidal dilated operation is advised.

4.1.1. Dilation

In the CNN, a dilation layer is included as it has the efficiency to improve the respective fields. This layer uses minimal parameters in the feature map and also processes minimal samples. Here, the dilation rate refers to the up-sampling filter presented with the weights of successive filters. Receptive scales in the dilated convolution are monitored to attain various sampling rates, and they are also efficient in protecting the actual feature map.

4.1.2. Pyramid Dilated Module [33]

The PDCNN [33] consists of 5 different branches. The primary branch is offered with a 1x1 convolution that is initially utilized for functioning channel-wise pooling for dimensionality elimination. In some cases, the dilated convolution is presented with higher sampling efficiency, which is equal to the size of the feature maps. Here, a simple filter is used with a size of 1x1. Various branches presented in the middle layer employ the dilated convolution in the size 3x3 along with different sampling rates in order to enhance the information presented in multiple scales. If parallel dilated convolutions are developed imperfectly, the gridding phenomenon will appear. Based on the saw tooth wave-like heuristic method and various dilation rates (2, 3, and 5) in the pyramid, dilated modules are assumed. Further, the average pooling layer for the local region is considered as the final branch using a kernel size of 3x3. In the feature map, the average value of the kernel 3x3 is analyzed to increase the robustness over common modifications. Finally, the outcomes of all these branches are combined over multiple scales and move towards a 1x1 convolution. Hence, in this case, PDCNN is considered as it provides high benefits for data processing, consumes less time and power, and solves the overfitting-related issues. The PDC layer is comprised of dilated convolution layers, and their values are expressed in Equation (9).

$$O = o_1^1 \wedge o_2^2 \wedge o_3^4 \wedge \ldots \wedge o_m^e \quad (9)$$

Here, the terms O_m and o_m^e states are the PDC layer, and $\wedge$ they estimate the stacking on the sub-dilated convolutional layers. In this phase, the skip connections are widely dependent on different dilation values. The benefit of the PDCNN framework is attaining the spatial information presented in the higher ranges, and also eliminating the hidden space in the receptive field. The structural representation of PDCNN is provided in Figure 4.

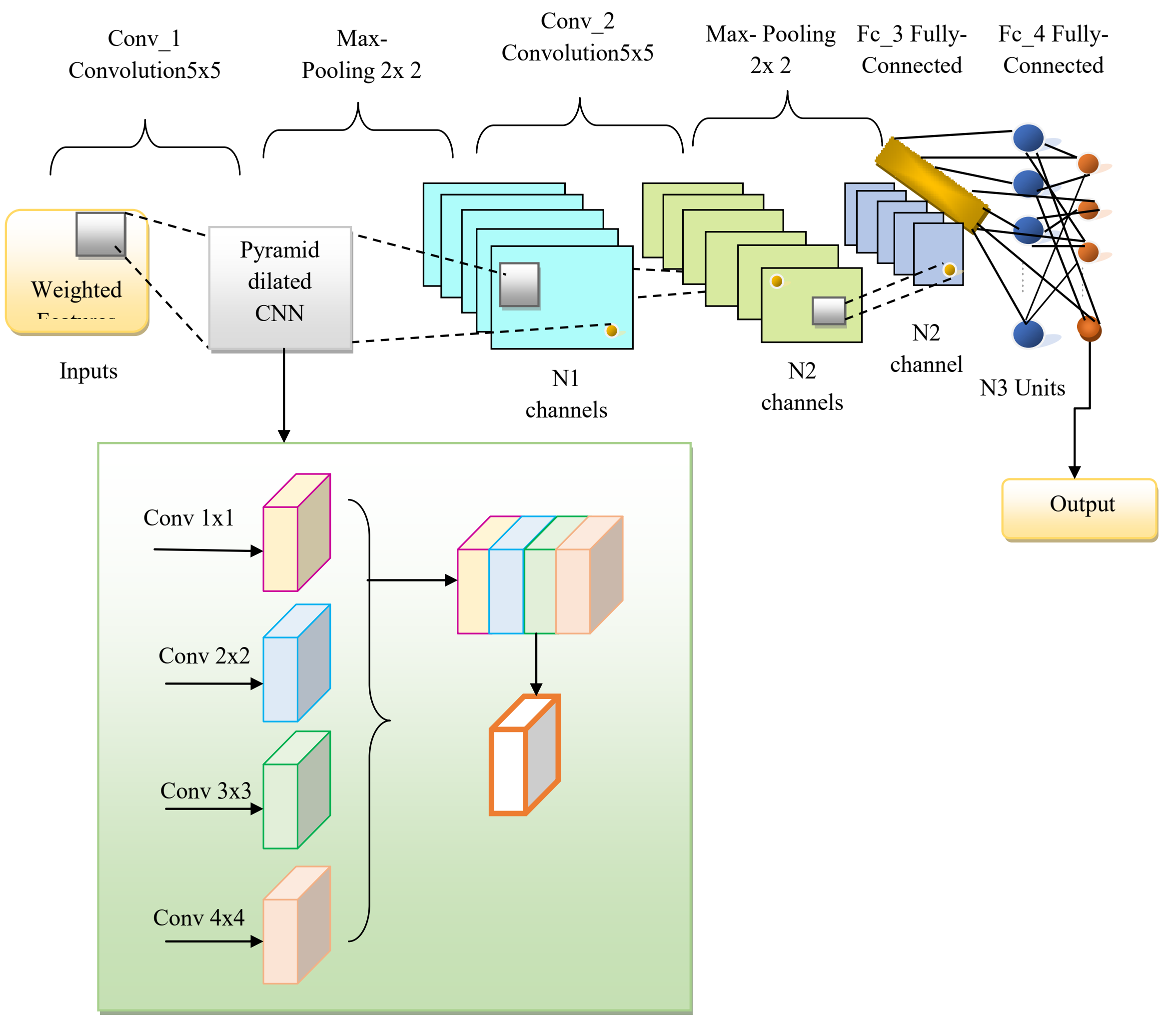


Fig. 4 Diagrammatic view of the PDCNN

4.2. Stacked RNN

The designed SRNN is used for the prediction process in crop yields, where the stacked operation is employed in the RNN to elevate the functional outcomes. RNN [34] comes under the deep learning network with a recurrent feedback framework. A standard framework of an RNN has an input layer, an output layer, and a hidden layer. Every neuron in the hidden layer comprises a feedback layer, which allows the RNN to learn prior details transmitted from the input of the data. Hence, the RNN is highly apt to handle the sequential information. Moreover, a significant characteristic of RNNs is that, because of their recurrent framework, it has the potential to perform sequences with distinct lengths.

RNN historical state expressed in Equation (10).

$$t^{(u)} = g\left(Vy^{(u)} + Xt^{(u-1)} + c_t{}^{(u)}\right) \quad (10)$$

From the above-mentioned Equation (10), the network input at a time u is $y^{(u)}$ and the hidden layer outcomes are given as $t^{(u)}$. Finally, the system evaluation $\hat{z}^{(u)}$ is acquired by the linear mapping related to the weighted sum of states that is estimated in Equation (11).

$$\hat{z}^{(u)} = g(Wt^{(u)} + c_z^{(u)}) \quad (11)$$

Rather than the ordinary RNN with an individual hidden layer, extra $(e-1)$ RNN layers are stacked with the first RNN layers to process the hierarchical characteristic learning and enhance the SRNN [32] functionality.

This network consists of two or more RNN layers, like SRNN.

An entirely linked dense output layer was utilized to categorize the outcome of n^{th} the layer in SRNN, as given in Equation (12).

$$\hat{z}_l = \sigma_z(X_{iw}i_{nl} + c_w) \tag{12}$$

Here, the term X_{iw}defines the kernel weight matrix deployed for the linear transformationi_{nl}. SRNN is learned to process multi-class and binary categorization phases for various algorithms. Training loss(M) in the SRNN is reduced by employing the cross-entropy loss(θ) function. The multi-class classification and binary functionality of SRNN are tuned utilizing the optimization technique. The pictorial model of SRNN techniques is shown in Figure 5.

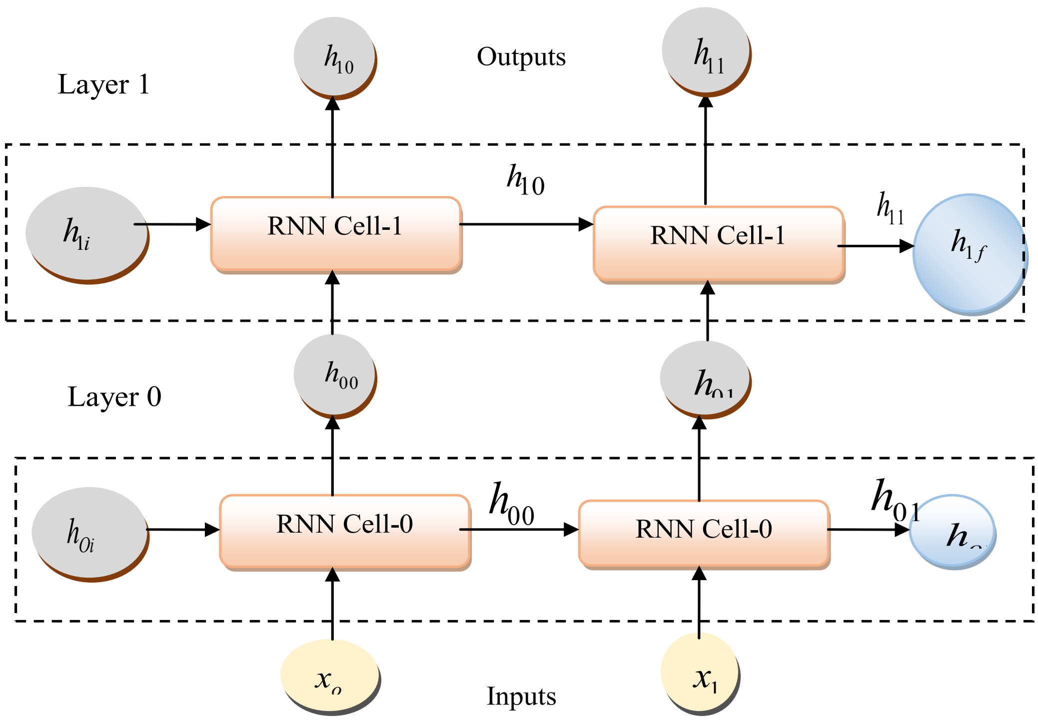


Fig. 5 Illustration of SRNN

4.3. Recommended PHNet for Prediction

The weighted feature $W_f$is given as an input for the prediction model. The PHNet is newly implemented for predicting the crop yield, where it is the combination of PDCNN and SRNN. The PDCNN is constructed by using the idea of dilated convolution, whereas the SRNN is constructed by the concept of RNN. This new model is mainly used for predicting crop yield.

The PDCNN can observe the diversity and variability of images and perform well on the new data. Moreover, this network can easily find the spatial layouts. SRNN produces more accurate values to develop a model. This network is more suitable for detecting the sequential and the temporal data. Henceforth, these two networks are selected. Thus, PDCNN and SRNN are integrated and used to develop this model. In order to overcome the issues affected, the hidden neuron count and the epoch count are added for each of these networks. Further, these parameters are optimized using the NPWSA. The parameters that are tuned are the hidden neuron count and epoch count in SRNN and PDNN, respectively.

Henceforth, the developed WSA is deployed to elevate the prediction phase effectively. Hence, by optimizing these parameters, the values of MAE and RMSE are minimized. Thus, this minimization can be depicted in the fitness function that is elaborated in Equation (13).

$$Obj(2) = \underset{\{hid^{SRNN}, epo^{SRNN}, hid^{PDCNN}, epo^{PDCNN}\}}{\arg\min} \left[MA_E + RMS_E \right] \tag{13}$$

From Equation (13), the terms hid^{SRNN} epo^{SRNN}define the hidden and epoch count in SRNN, whereas the terms epo^{PDCNN} hid^{PDCNN}describe the epoch and hidden count in PDCNN. Further, the term MA_E expresses the Mean Absolute Error, and the term RMS_Estates the Root Mean Squared Error, respectively. The output delivered by the PDCNN is taken as the predicted score S1. Similarly, the output from the SRNN is represented as S2. These two predicted values are further taken into the average calculation. The further performance is highly functionalized and efficient. Hence, the final predicted outcome of crop yield is received. The diagrammatic illustration of the recommended PHNet is offered in Figure 6.

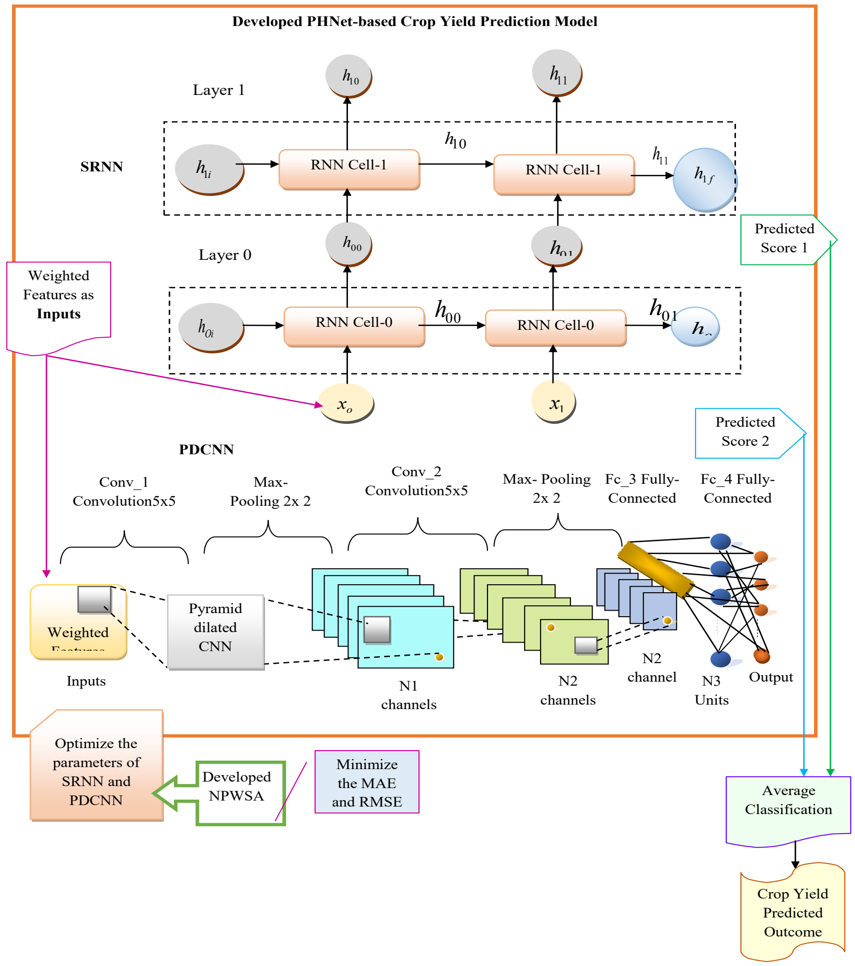


Fig. 6 Pictorial representation of recommended PHNet

5. Results and Discussion

5.1. Comparison Setup

In order to deliver extensive results, the proposed crop yield prediction framework was demonstrated by employing the PHNet technique. Recent techniques employed to carry out the crop yield prediction were GNN-LSTM [35], IQ-GRU [36], ConvLSTM-ViT [37], and Bi-GRU-LSTM [38].

5.1.1. Limitation

A limitation of the current study is its exclusive reliance on benchmark datasets for the validation of the proposed PHNet architecture. While this approach is essential for ensuring a fair and direct comparison with existing state-of-the-art methods, it does not assess the model's performance on unprocessed, real-world data. We also collected preliminary real-time data during this project (presented for context in Tables 3-9). A full validation using this data was not performed, as it would require significant preprocessing and feature extraction steps, the development of which constitutes a separate research challenge. Integrating this data would also introduce complexities to the network architecture that could obscure the core contribution of this paper. However, this dataset represents a valuable resource for future investigation. Subsequent research will focus on developing robust preprocessing pipelines and adapting the PHNet model to leverage such noisy, unstructured real-world data, which we believe is a critical next step for the practical deployment of this technology.

5.1.2. Training and Testing Process

Training and testing details of the developed crop yield prediction technique were offered as follows. Here, the dataset was randomly separated into two different classes, such as testing and training. Initially, the training process was carried out by considering 75% data from the dataset. The remaining data were employed to carry out the testing process.

In the training phase, essential data were sourced from benchmark resources, and they were classified based on their classes to identify the exact patterns and structures. Then, the prepared data were subjected to PHNet to execute the prediction process. In this phase, all the data were contrasted with others to make the prediction process highly efficient. Comparing the actual labels over the prepared data helps to verify the errors. Once the training process is finished, the training process takes place in the network by considering different performance metrics. Moreover, various optimization and prediction mechanisms were employed to observe the overall performance of the developed framework by considering various experimental conditions. Here, various analyses were carried out with the consideration of multiple performance measures like MAPE, RMSE, MPE, MAE, and so on. Finally, various experimental outcome plots were attained at the final stage. A detailed description of the experimental setup of the developed crop yield prediction technique is offered in Table 2.

Table 2. Description of experimental setup

Descriptions	Details
System	OS, CPU, RAM, and GPU
Environment Specification	Python and libraries
Data Preprocessing	Normalization, train and split, random seed
Model Architecture	Clear Layout of PHNet: PDCNN and SRNN
Parameter Tuning	NPWSA Optimizer
Training Steps	Python Code, Epochs, Loss Function, and Metrics
Evaluation Metrics	MAE, RMSE, MAPE, MEP, etc
Reproducibility	Random Seeds, Cross-validation, Result Format
Graph and Table Results	Generate an option for editable graphs and tables in Python

5.2. Evaluation Metrics

Mean Percentage Error (MPE): The formula for MPE is given in Equation (14).

$$MP_E = \left(\frac{100}{o}\right) * \left(\sum_1^o \frac{(y(u)-z(u))}{y(u)}\right) \quad (14)$$

From Equation (6), the variables y $z$are the actual and the forecast values. Further, the factor $o$represents the number of values. Mean Squared Error (MSE): The expression for MSE is given in Equation (15).

$$MS_E = \left(\frac{1}{o}\right) * (\sum_1^o((y(u) - z(u)^2))) \quad (15)$$

Mean Absolute Percentage Error (MAPE): The examination for MAPE is evaluated in Equation (16).

$$MAP_E = \left(\frac{100}{o}\right) * \left(\sum_1^o Absolutevalue \frac{(y(u)-z(u))}{y(u)}\right) \quad (16)$$

Root Mean Squared Error (RMSE): The estimation for RMSE is provided in Equation (17).

$$RMS_E = \sqrt{\left(\frac{1}{0}\right)} * \sum_1^o\left((y(u) - z(u)^2)\right) \quad (17)$$

Mean Absolute Error (MAE): Elaboration for MAE is expressed in Equation (18).

$$MA_E = \left(\frac{1}{o}\right) * (\sum_1^o Absolutevalue(y(u) - z(u)))) \quad (18)$$

5.3. Convergence Analysis for the NPWSA

Figure 7 shows the convergence function of the designed NPWSA-PHNet compared to the classical methods for the provided database. The convergence function is validated to verify the performance of the heuristic mode by considering the iteration factors. This function works by differentiating the total number of iterations for multiple run times. It is employed to fulfill different objectives related to the developed NPWSA-PHNet over different classes. Here, the optimal outcomes are accomplished in the search space that supports attaining more precise crop yield prediction outcomes. Attaining a minimal convergence rate in the search space is termed the best solution over the iteration that supports improving the prediction over different classes. In the validation, the developed NPWSA-PHNet accomplished optimal outcomes from the 5th iteration. The outcomes showed that the NPWSA-PHNet model achieved a better optimum calculation than the traditional approach. Thus, higher efficiency and functionality are obtained.

5.4. Comparative Evaluation for NPWSA-PHNet

The comparative evaluation of the developed NPWSA-PHNet-crop yield prediction model over the classical algorithms and approach is provided in Figures 8 and 9, respectively. In this phase, the validations are carried out over the activation functions such as linear, sigmoid, tanH, ReLU, softmax, and leaky ReLU. By assuming the linear activation function of the MEP measure from Figure 9 (c), the outputs acquired are 0.2% for LSTM, 29.2% for SRNN, 0.02 % for PDCNN, and 25.2% for PDCNN+SRNN, approximately.

From the gained results, the SRNN got the highest value, whereas PDCNN acquired the lowest value. In the RMSE validation, the suggested NPWSA-PHNet gained fewer errors than the classical schemes like FDA-PHNet, EGSOA-PHNet, AOA-PHNet, and WSA-PHNet. Therefore, the analysis outcomes displayed that the error rate of the proposed NPWSA-PHNet is lower than that of the classical techniques under MEP validation. Minimizing the errors helps reduce the delay while training procedures are carried out in the network and also enhances accuracy in dynamic conditions. Thus, the experimental outcomes displayed that the developed NPWSA-PHNet achieves higher functionality in both the optimizers and prediction models. From the validated graph, it is clear that when compared to the other classical approaches, the obtained values attained higher efficiency.

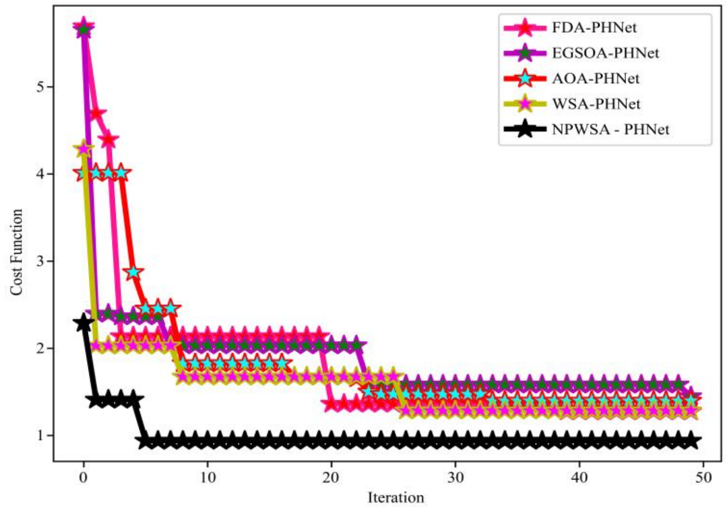
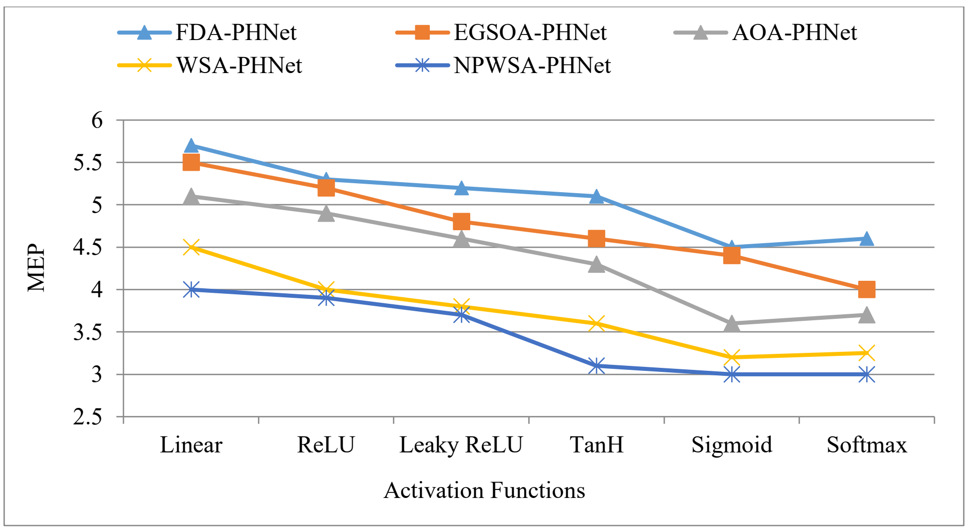
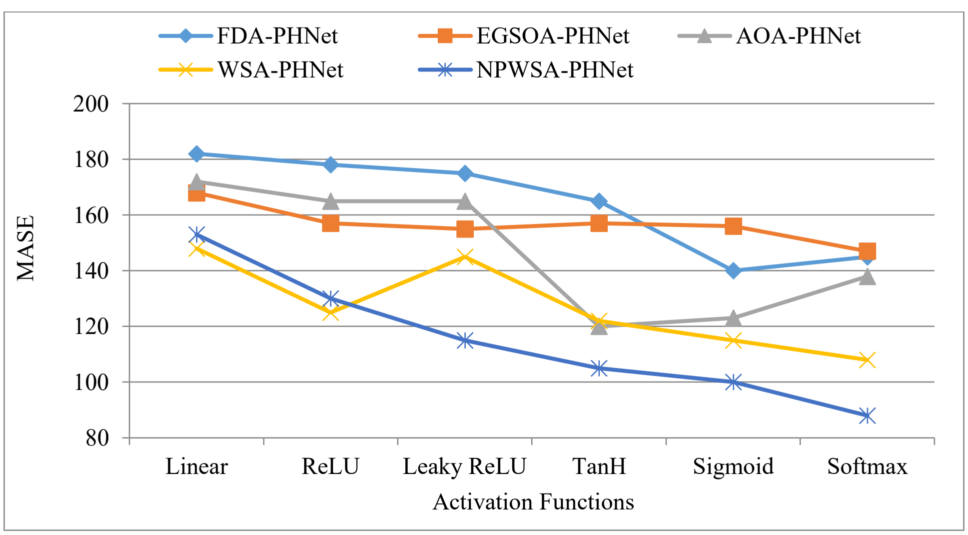


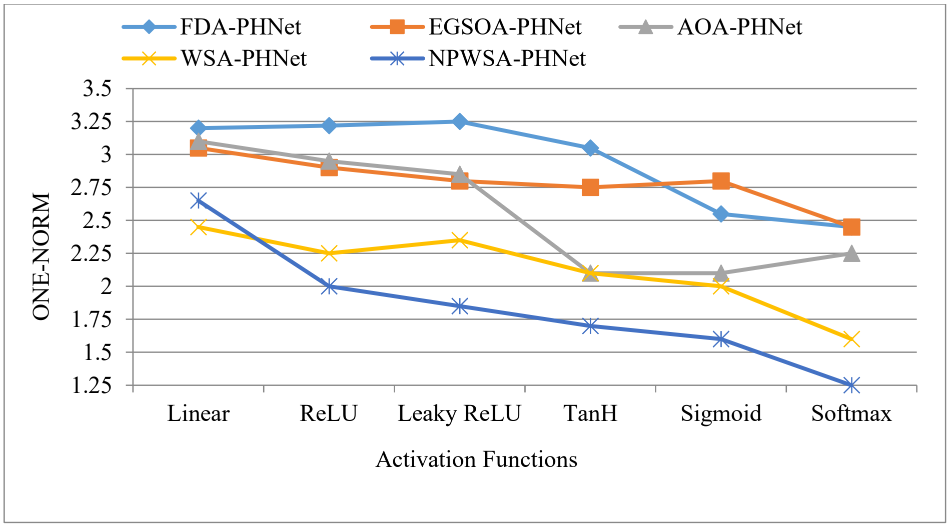
Fig. 7 The cost function for the proposed algorithm over the standard algorithms



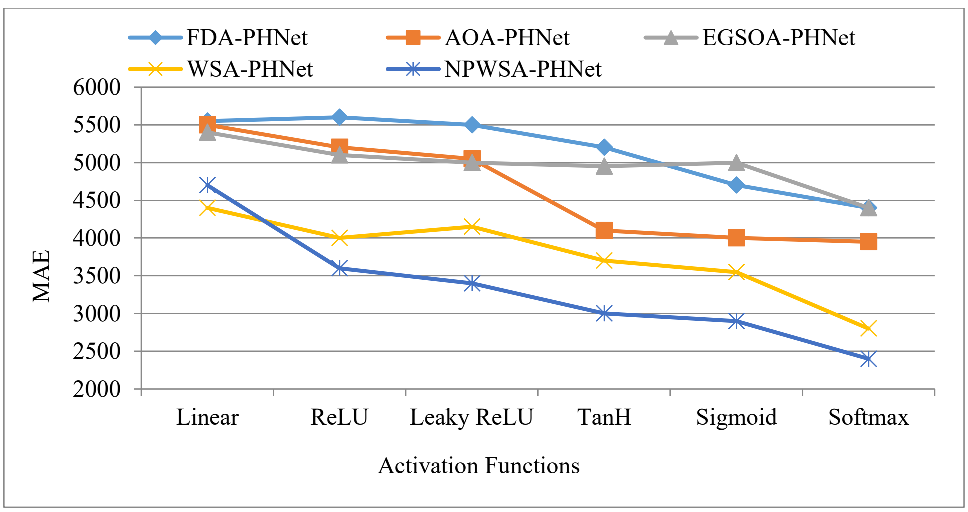
(a)



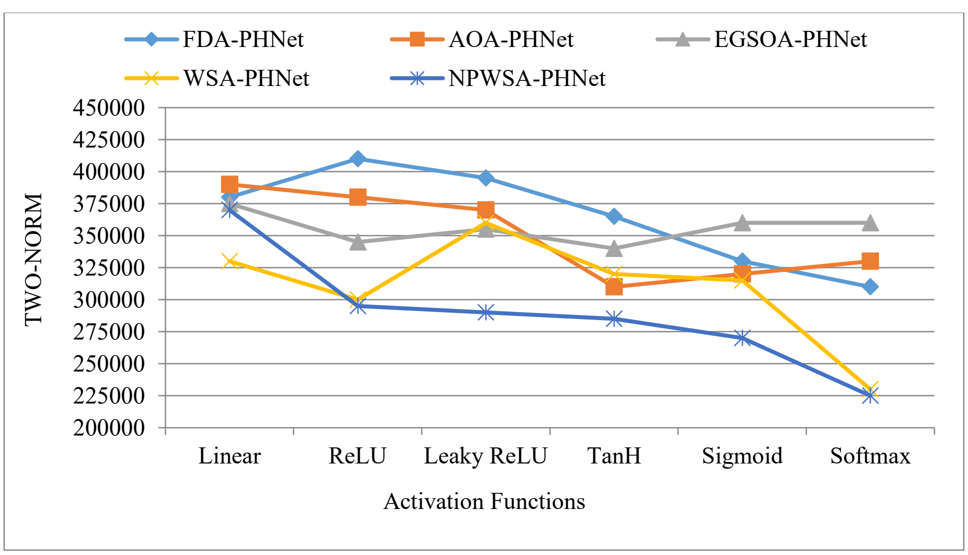
(b)


FDA-PHNet
EGSOA-PHNet
AOA-PHNet
WSA-PHNet
NPWSA-PHNet
3.5
3.25
3
2.75
2.5
2.25
2
1.75
1.5
1.25
ONE-NORM
Linear
ReLU
Leaky ReLU
TanH
Sigmoid
Softmax
Activation Functions

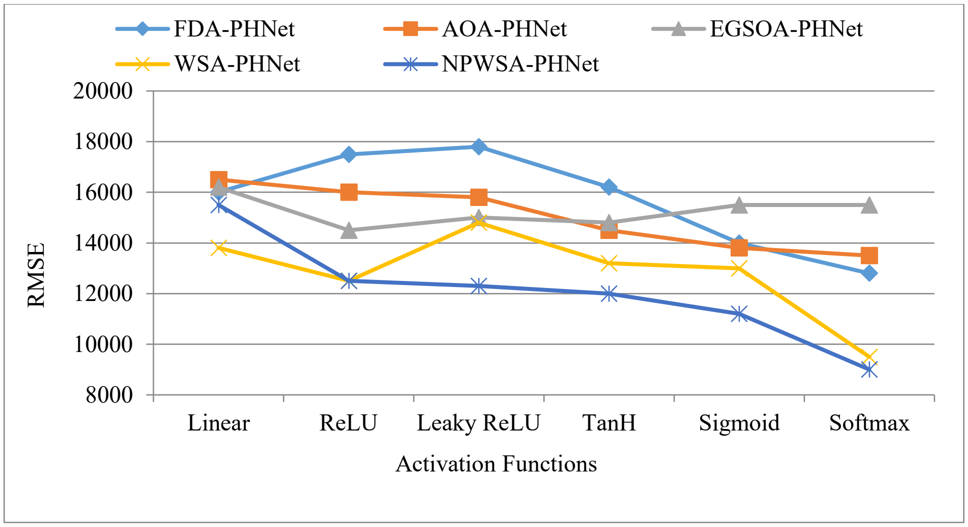
(c)


FDA-PHNet
AOA-PHNet
EGSOA-PHNet
WSA-PHNet
NPWSA-PHNet
6000
5500
5000
4500
4000
3500
3000
2500
2000
MAE
Linear
ReLU
Leaky ReLU
TanH
Sigmoid
Softmax
Activation Functions

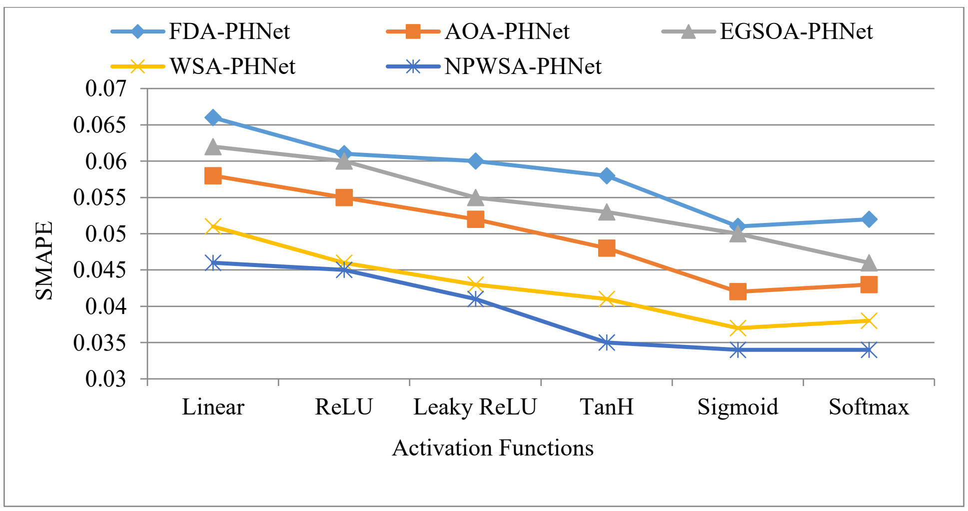
(d)


FDA-PHNet
AOA-PHNet
EGSOA-PHNet
WSA-PHNet
NPWSA-PHNet
450000
425000
400000
375000
350000
325000
300000
275000
250000
225000
200000
TWO-NORM
Linear
ReLU
Leaky ReLU
TanH
Sigmoid
Softmax
Activation Functions

(e)

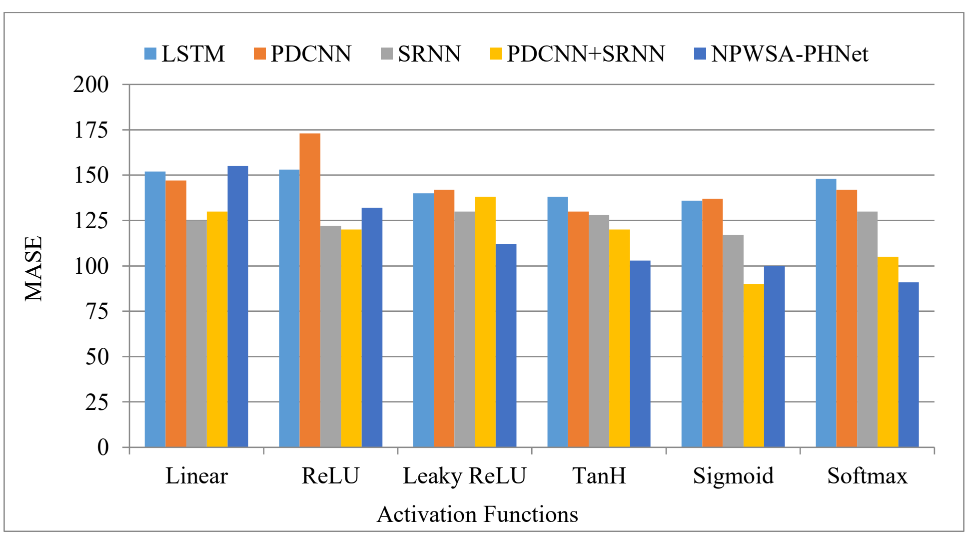


(f)

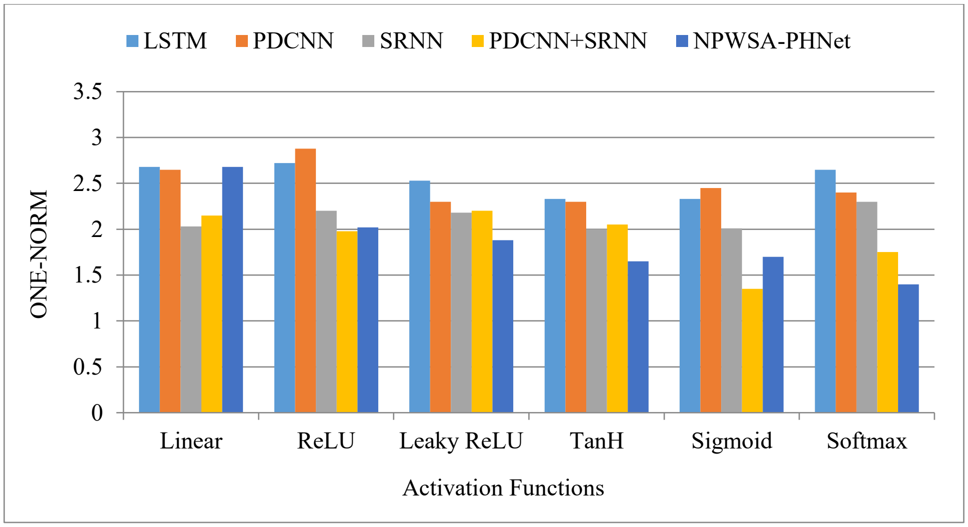


(g)

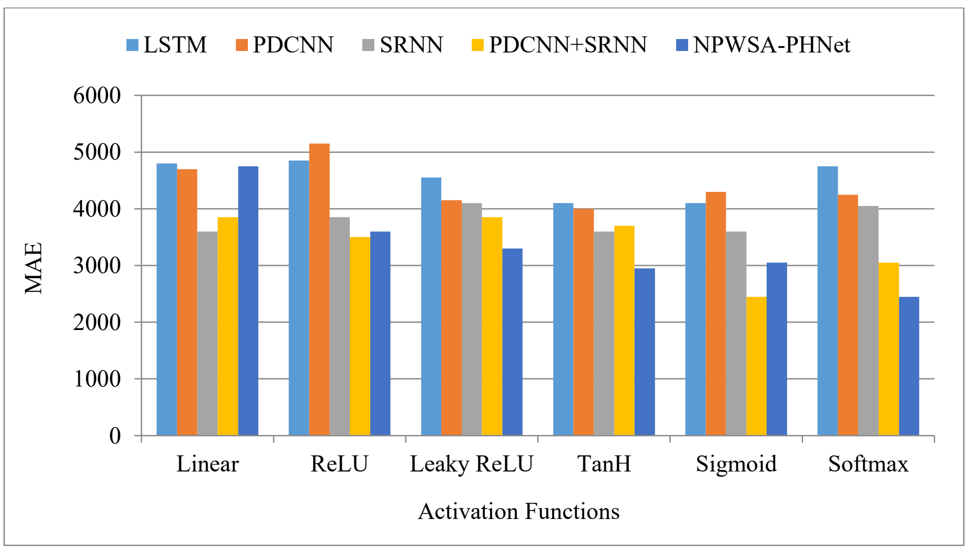
Fig. 8 Comparative analysis on prediction model over standard optimizers regarding: (a) MEP, (b) MASE, (c) One-Norm, (d) MAE, (e)Two-Norm, (f) RMSE, and (g) SMAPE.



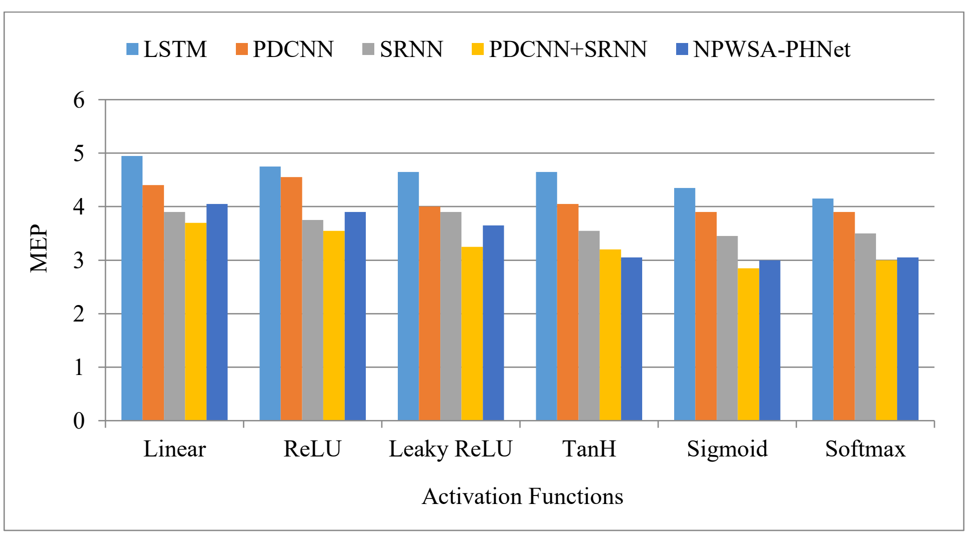
(a)


LSTM
PDCNN
SRNN
PDCNN+SRNN
NPWSA-PHNet
ONE-NORM
3.5
3
2.5
2
1.5
1
0.5
0
Linear
ReLU
Leaky ReLU
TanH
Sigmoid
Softmax
Activation Functions

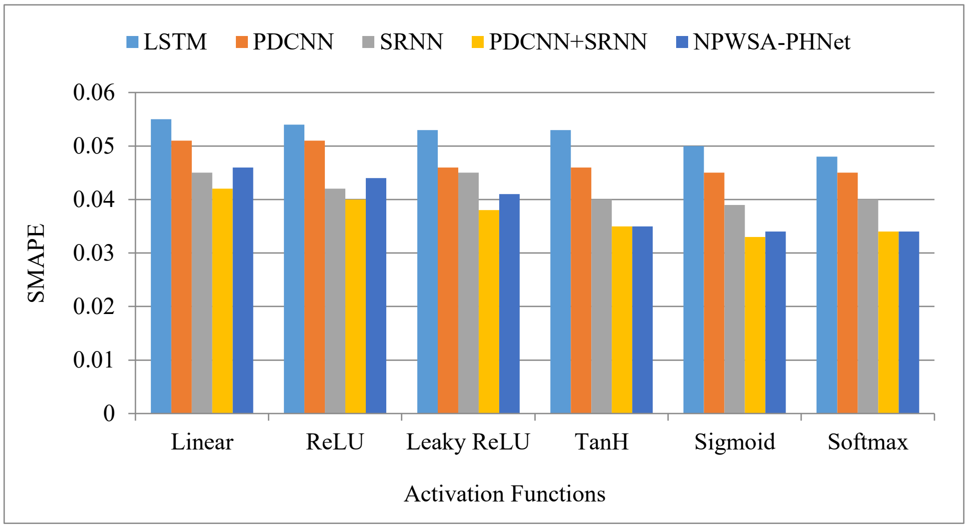
(b)


LSTM
PDCNN
SRNN
PDCNN+SRNN
NPWSA-PHNet
MAE
6000
5000
4000
3000
2000
1000
0
Linear
ReLU
Leaky ReLU
TanH
Sigmoid
Softmax
Activation Functions

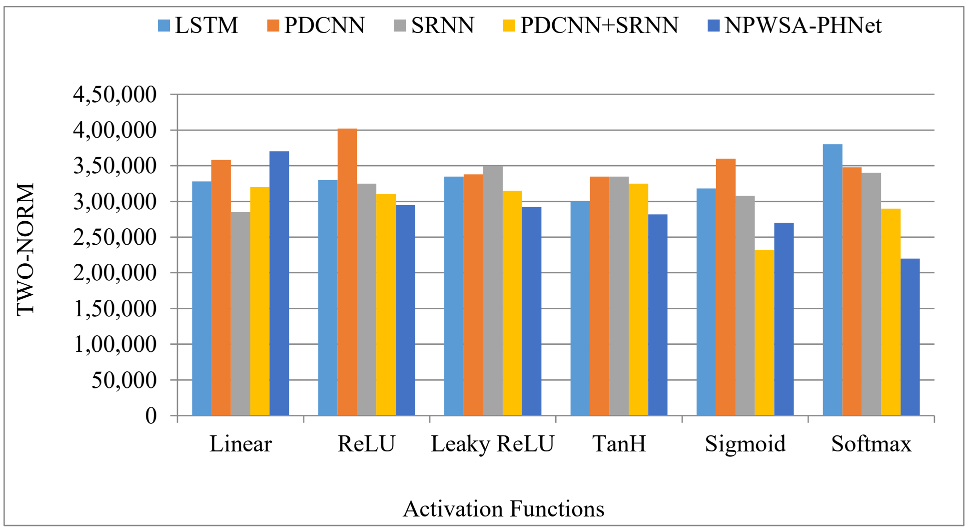
(c)


LSTM
PDCNN
SRNN
PDCNN+SRNN
NPWSA-PHNet
MEP
6
5
4
3
2
1
0
Linear
ReLU
Leaky ReLU
TanH
Sigmoid
Softmax
Activation Functions

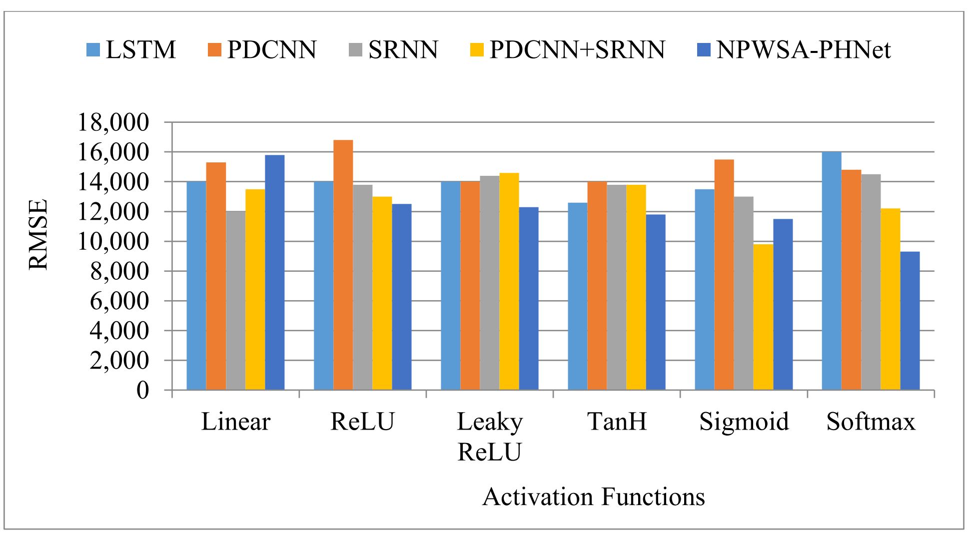
(d)



(e)



(f)



(g)

Fig. 9 Validation on developed prediction model over existing classifiers concerning (a) MASE, (b) One-Norm, (c) MAE, (d) MEP, (e) SMAPE, (f)Two-Norm, and (g) RMSE.

5.5. Overall Performance Evaluation of NPWSA-PHNet

Different performance analyses carried out in the developed NPWSA-PHNet-aided crop yield prediction model over classical heuristic models and prediction schemes are represented in Tables 3 and 4. Here, the efficiency of the developed NPWSA-PHNet is validated over various error measures. Tables 3 and 4 detail the performance analysis for exploring the efficacy of the proposed algorithm, offering the tuned parameters with the optimized values for the data source. While analyzing the RMSE values from Table 3, the developed framework NPWSA-PHNet accomplished better outcomes as 86.7% for EGSOA-PHNet, 87.3% for FDA-PHNet, 88.5% for AOA-PHNet, and 87.8 % for WSA-PHNet.

Attaining a better RMSE value helps to reduce the errors and also supports improving the interpretability. While analyzing the SMAPE validation, the developed NPWSA-PHNet achieved a minimal SMAPE value, indicating that the relative error in the network has been eliminated, and also that understanding efficiency has improved. The developed NPWSA-PHNet achieved optimal outcomes while carrying out the validations with standard techniques.

Table 3. Performance evaluation of NPWSA-PHNet-aided crop yield prediction framework with conventional algorithms

Performance Measures	FDA-PHNet [27]	EGSOA-PHNet [28]	AOA-PHNet [29]	WSA-PHNet [33]	NPWSA-PHNet
MEP	4.537475	4.22606	3.64776	3.20292	3.02497
SMAPE	0.05185	0.04829	0.041688	0.03660	0.034571
MASE	138.898	157.2017	123.4954	114.6220	99.39395
MAE	4484.048	4793.96	3755.969	3526.5302	3029.565
RMSE	14095.58	15156.25	13482.120	13119.901	11405.82
ONE-NORM	2520035	2694209	2110855	1981910	1702616
TWO-NORM	334155.733	359302.32	319614.41	311027.45	270392.65

Table 4. Performance evaluation of NPWSA-PHNet-based crop yield prediction technique with conventional prediction schemes

Performance Measures	LSTM [30]	PDCNN [31]	SRNN [32]	PDCNN+SRNN [31, 32]	NPWSA-PHNet
MEP	4.359560	3.914691	3.425346	2.891559	3.024973
SMAPE	0.049823	0.04473	0.039146	0.033046	0.034571
MASE	133.2492	133.649	118.8254	86.6197	99.39395
MAE	4095.975	4294.05	3593.985	2401.702	3029.5658
RMSE	13404.74	15237.85	13012.396	9796.718	11405.825
ONE-NORM	2301938	2413260	2019820	1349757	1702616
TWO-NORM	317780.08	361236.77	308478.89	232246.29	270392.65

5.6. Analysis of Features in Developed NPWSA-PHNet

Various analyses carried out by varying the features in the developed NPWSA-PHNet-based crop yield prediction model, compared to classical heuristic models, are represented in Table 5. Here, the normal features are indicated as WSA-PHNet, and also the weight-optimised features are termed as NPWSA-PHNet. Using optimally weighted features in crop yield prediction helps achieve optimal outcomes across different classes. Optimally selected weighted features help eliminate noise and provide more focus on the most relevant features, thereby enhancing accuracy.

In the ONE-NORM validation, NPWSA-PHNet-optimally selected weighted features achieved better efficiency, with improvements of 4.16% for AOA-PHNet, 20.42% for WSA-PHNet, 17.42% for EGSOA-PHNet, and 29.35% for FDA-PHNet, respectively. Moreover, the adaptability of NPWSA-PHNet is improved across various classes, and it also reduces validation complexity and training time. Hence, the analysis outcomes displayed that the developed NPWSA-PHNet gained comparatively higher crop yield prediction outcomes than others and also accomplished optimal outcomes.

Table 5. Performance evaluation on features in developed NPWSA-PHNet-based crop yield prediction model

Performance Measures	FDA-PHNet [27]	EGSOA-PHNet [28]	AOA-PHNet [29]	WSA-PHNet [33]	NPWSA-PHNet
MEP	4.71540	4.4040	3.825713	3.202945	3.11394
SMAPE	0.05389	0.05033	0.043722	0.036605	0.03558
MASE	155.379	138.818	118.1274	98.98479	109.7606
MAE	4824.603	4127.514	3556.2064	2830.035	3408.15
RMSE	14792.23	13588.67	12295.124	9793.274	12737.66
ONE-NORM	2711427	2319663	1998588	1590480	1915384
TWO-NORM	350672.72	322140.523	291474.858	232164.64	301966.01

5.7. Statistical Analysis on Developed NPWSA-PHNet

Table 6 presents the overall statistical estimation for NPWSA-PHNet based on the heuristic mechanism. Here, the analysis is carried out by considering various statistical measures, including mean, median, standard deviation, worst, and best.

This validation is carried out over various run times in terms of iterations. Here, the highest value among all the iterations is known as the best, the lowest value in the entire iteration is termed the worst, the sum of the values is specified as the mean, and the middle value of the numbers is indicated as the median. In the best validation, the developed NPWSA-PHNet achieved 26.3%, 35.1%, 32.8%, and 26.8% better results than the classical techniques, such as FDA-PHNet, EGSOA-PHNet, AOA-PHNet, and WSA-PHNet, respectively. Increasing the best value supports accomplishing more precise crop yield prediction outcomes than others. In addition, statistical validation supports more accurate decision-making in complex classes and aids in achieving optimal outcomes in these complex situations.

Table 6. Statistical findings of the designed crop yield prediction over heuristic models

Performance Measures	FDA-PHNet [27]	EGSOA-PHNet [28]	AOA-PHNet [29]	WSA-PHNet [33]	NPWSA-PHNet
Standard Deviation	0.8813	0.60892	0.7191	0.4688	0.2236
Worst	5.69439	5.65281	4.0109	4.2844	2.2894
Median	1.36188	1.58292	1.4730	1.6735	0.9393
Best	1.27516	1.4476	1.3979	1.2840	0.9393
Mean	1.81975	1.90037	1.8253	1.5888	1.0039

5.8. Performance Validation on NPWSA-PHNet over Existing Literature

Table 7 elucidates the overall comparative estimation of the NPWSA-PHNet-based crop yield prediction technique over traditional literature. Considering the values of the SMAPE metric from the given table, the outcomes obtained are efficient as 14.9% for ELM, 19.4% for EL, 29.16% for HA-DecNet, and 4.61% for SVM. In total, validation, the developed NPWSA-PHNet supports enhancing the accuracy in the complex classes and also enhances the reliability under different conditions.

Moreover, the developed NPWSA-PHNet supports executing precise decision-making by reducing errors. In addition, uncertainty issues arise in the network support to maintain the reliability and also enhance the quality of the outcome. Reducing the errors in the validation helps to improve the accuracy while predicting the crop yield, and also eliminates the misclassifications.

5.9. Ablation Validation on Suggested Framework

Ablation validations carried out in the developed crop yield prediction technique over the classical schemes are represented in Table 8. Generally, the ablation validations are carried out to verify the overall efficiency of the network in various classes.

In the validation, the developed NPWSA-PHNet-based crop yield prediction scheme gained a minimal error compared to the classical schemes. Accomplishing reduced error in the validation displayed that the suggested approach effectively reduces the delay and errors for offering better outcomes. In the RMSE validation, the developed NPWSA-PHNet accomplished better outcomes, as 14.92%, 32.4%, 5.09% and 31.07% better than the classical schemes like CNN, RNN, PDCNN, and SRNN, respectively. Finally, the ablation study outcomes displayed that the developed NPWSA-PHNet-based crop yield prediction model is highly efficient in attaining better outcomes than other schemes.

Table 7. Performance analysis on suggested NPWSA-PHNet-based crop yield prediction framework over classical prediction models

Performance Measures	HA-DecNet [1]	EL [2]	ELM [3]	SVM [5]	NPWSA-PHNet
MEP	4.2705861	3.781257	3.5588121	2.891535	3.0250104
SMAPE	0.048806	0.0432145	0.0406722	0.0330462	0.03457171
MASE	149.66341	116.19526	123.4339	120.72474	106.16648
MAE	4955.09074	3509	3606.9003	3269.8718	2994.36654
RMSE	16151.3366	12200.121	13181.916	13920.793	12654.885
ONE-NORM	2784761	1972058	2027078	1837668	1682834
TWO-NORM	382892.295	289222.65	312497.61	330013.84	300003.539

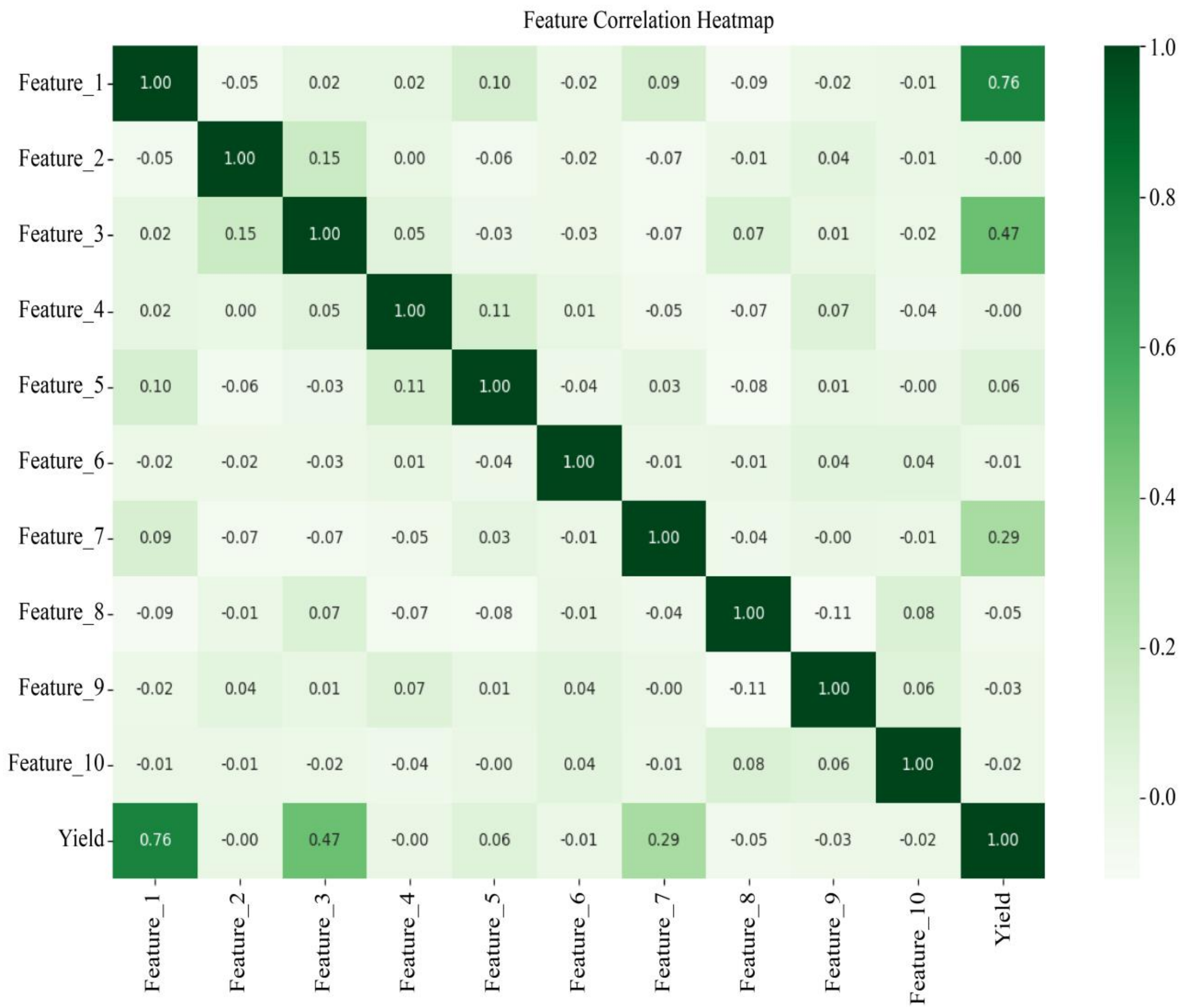
Table 8. Ablation computation on suggested crop yield prediction framework

Performance Measures	CNN [39]	RNN [34]	PDCNN [31]	SRNN [32]	NPWSA-PHNet
MEP	3.603298	4.003675	3.247416	4.137092	3.024973
SMAPE	0.041181	0.045756	0.037113	0.047281	0.034571
MASE	125.0753	152.0904	109.3124	137.1549	99.39396
MAE	3560.863	4487.632	3192.205	4395.228	3029.566
RMSE	13089.08	15579.73	12934.68	14632.75	11405.83
ONE-NORM	2001205	2522049	1794019	2470118	1702616
TWO-NORM	310296.9	369341.4	306636.4	346892	270392.7

5.10. Feature Correlation Analysis on Developed Framework

Feature correlation analysis carried out through heatmaps is offered in Figure 10. In this phase, the feature correlation validation is carried out over multiple features presented in the dataset. This computation supports verifying the overall strength as well as the relationship among multiple features.

Here, the analysis is carried out among 10 different features, and it helps to verify the crop yield. This validation supports identifying the most significant features and also redundant features, which affect the overall network efficiency. Using the higher quality features in the computation supports to reduce the errors and delay in the training phase.



	Feature_1	Feature_2	Feature_3	Feature_4	Feature_5	Feature_6	Feature_7	Feature_8	Feature_9	Feature_10	Yield
Feature_1	1.00	-0.05	0.02	0.02	0.10	-0.02	0.09	-0.09	-0.02	-0.01	0.76
Feature_2	-0.05	1.00	0.15	0.00	-0.06	-0.02	-0.07	-0.01	0.04	-0.01	-0.00
Feature_3	0.02	0.15	1.00	0.05	-0.03	-0.03	-0.07	0.07	0.01	-0.02	0.47
Feature_4	0.02	0.00	0.05	1.00	0.11	0.01	-0.05	-0.07	0.07	-0.04	-0.00
Feature_5	0.10	-0.06	-0.03	0.11	1.00	-0.04	0.03	-0.08	0.01	-0.00	0.06
Feature_6	-0.02	-0.02	-0.03	0.01	-0.04	1.00	-0.01	-0.01	0.04	0.04	-0.01
Feature_7	0.09	-0.07	-0.07	-0.05	0.03	-0.01	1.00	-0.04	-0.00	-0.01	0.29
Feature_8	-0.09	-0.01	0.07	-0.07	-0.08	-0.01	-0.04	1.00	-0.11	0.08	-0.05
Feature_9	-0.02	0.04	0.01	0.07	0.01	0.04	-0.00	-0.11	1.00	0.06	-0.03
Feature_10	-0.01	-0.01	-0.02	-0.04	-0.00	0.04	-0.01	0.08	0.06	1.00	-0.02
Yield	0.76	-0.00	0.47	-0.00	0.06	-0.01	0.29	-0.05	-0.03	-0.02	1.00

Fig. 10 Representation of feature correlation analysis on the developed framework

5.11. SHAP Summary Plot Analysis

Figure 11 represents the SHAP summary plot of the designed crop yield prediction framework over ensemble features. This computation helps to verify the importance of the features and also quickly identify which feature is useful to obtain better outcomes. Attaining a higher SHAP value represents that the feature is more efficient with significant features than others. Here, higher SHAP values are represented as red, and lower SHAP values are indicated in blue. In this phase, 10 features are used for the validation. In the graph below, the horizontal positions represent the magnitude as well as the direction of SHAP values.

5.12. Validation of Yield Prediction over Time

Figure 12 illustrates the yield prediction validation over time in the developed scheme. Here, the validations are carried out over the date and yield.

This graphical representation showcased the yield outcomes for the consequence date. In this phase, the historical data are used to execute the prediction over various points. This validation supports performing accurate crop yield forecasting in a limited time. Moreover, this analysis is widely helpful to use in farm management, market forecasting, and better decision-making.

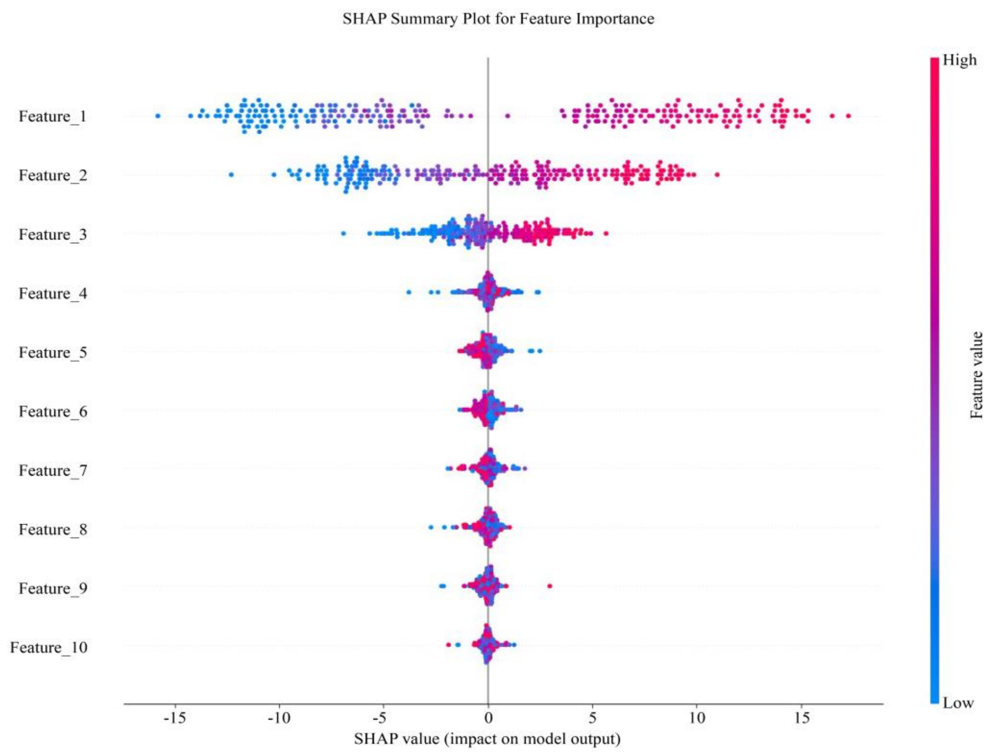


Fig. 11 SHAP validation on developed model

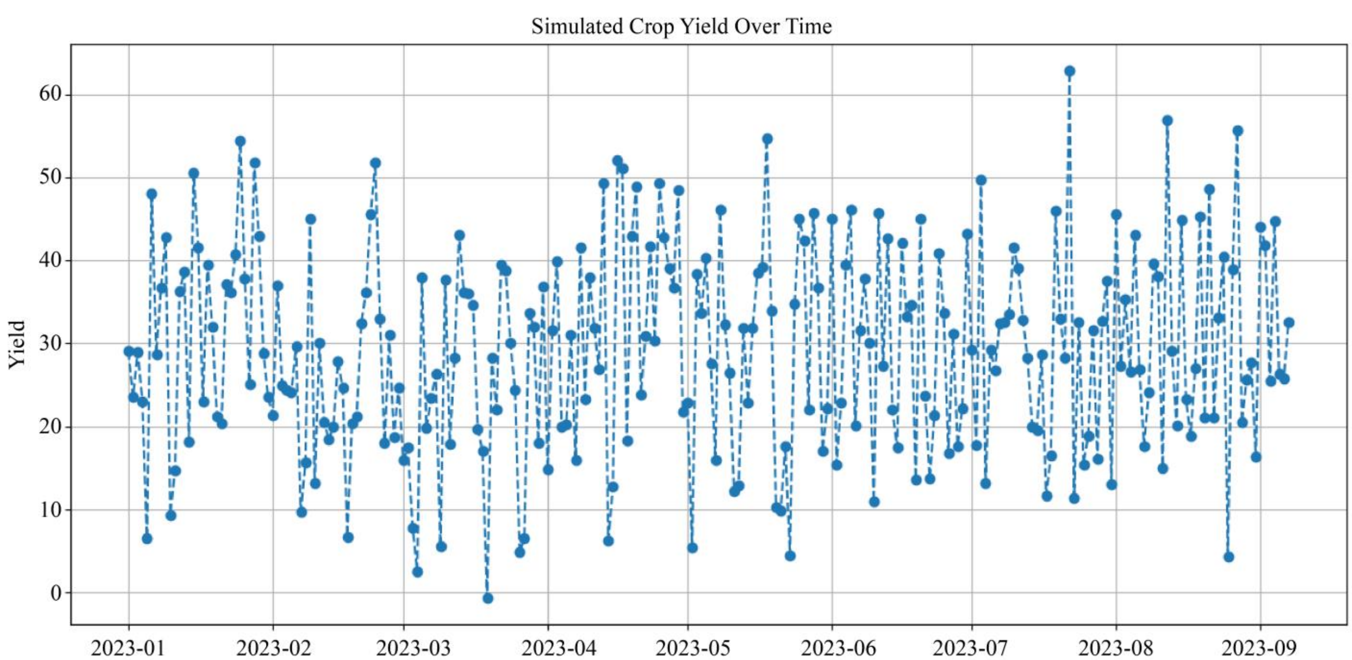


Fig. 12 Illustration of yield prediction over time

5.13. Ablation Study over Model Components

In the developed crop yield prediction technique, an ablation study is carried out over the model components, as shown in Figure 13. In this validation, various components presented in the developed NPWSA-PHNet, such as RNN, RNN+PDCNN, and RNN+PDCNN+NPWSA, are validated to identify their performances in predicting the crop yield. While analyzing the graph, using the RNN in the validation accomplished attained reduced performance than other schemes like RNN+PDCNN and RNN+PDCNN+NPWSA.

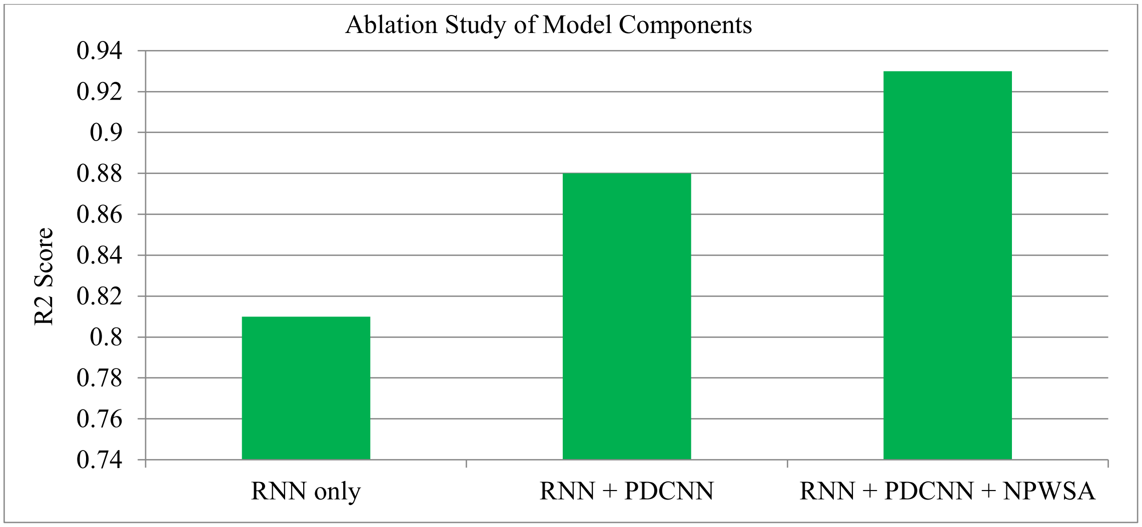


Fig. 13 Illustration of ablation study on model components

Then, three different techniques like RNN, PDCNN, and NPWSA are fused to verify their performance, and they gained a comparatively higher efficiency of 0.93% than others. This displayed that the developed model designed by fusing RNN+PDCNN+NPWSA gained optimal outcomes in predicting the crop yield in various classes. Hence, this experiment confirmed that the recommended crop yield prediction model is more efficient in attaining the optimal solutions and is widely suggested for use in agricultural firms.

5.14. Performance Analysis on Recent Techniques

Different performance analyses carried out in the developed NPWSA-PHNet-based crop yield prediction model over the recent techniques are represented in Table 9. This validation supports verifying the efficiency of NPWSA-PHNet with the recent techniques under different classes.

In the SMAPE validation, it was suggested that NPWSA-PHNet accomplished better performance with 16.05%, 24.4%, 6.8% and 26.8% better than the recent techniques like GNN-LSTM, IQ-GRU, ConvLSTM-ViT, and Bi-GRU-LSTM, respectively. The developed approach accomplished superior outcomes in the validation, as it includes a novel optimization scheme that supports offering better decision-making in various classes. Hence, the validation outcomes displayed that the suggested NPWSA-PHNet is widely suitable to use in the crop yield prediction models in the agriculture sector, as it offers better outcomes in complex classes.

Table 9. Analysis of suggested NPWSA-PHNet-based crop yield prediction framework over recent techniques

Performance Measures	GNN-LSTM [35]	IQ-GRU [36]	ConvLSTM-ViT [37]	Bi-GRU-LSTM [38]	NPWSA-PHNet
MEP	3.603298	4.003675	3.247416	4.137092	3.024973
SMAPE	0.041181	0.045756	0.037113	0.047281	0.034571
MASE	125.0753	152.0904	109.3124	137.1549	99.39396
MAE	3560.863	4487.632	3192.205	4395.228	3029.566
RMSE	13089.08	15579.73	12934.68	14632.75	11405.83
ONE-NORM	2001205	2522049	1794019	2470118	1702616
TWO-NORM	310296.9	369341.4	306636.4	346892	270392.7

5.15. Discussion on Results over State-of-the-Art Techniques

A deep discussion about the results in the developed crop yield prediction framework over state-of-the-art models is detailed as follows. In the results section, various experimental validations were carried out over classical heuristic techniques and prediction models. In the convergence validation, the developed NPWSA-PHNet model accomplished optimal solutions from the 5^{th} iteration, which displayed that the suggested NPWSA-PHNet is more efficient in predicting the crop yield without any errors. In the convergence validation, EGSOA-PHNet gained a poor convergence rate as it easily gets trapped in local optima issues, and the parameter tuning process is complicated. In addition, EGSOA needs to tackle the scalability issues in the higher-dimensional region. In the convergence validation, the developed NPWSA-PHNet accomplished superior outcomes by improving the random variable in a specific range through a novel fitness-based concept. Next, various experimental comparisons are carried out in the developed NPWSA-PHNet by varying the activation function. In this comparison, different error measures are used for the validation. Here, the developed NPWSA-PHNet gained a minimal error compared to the classical schemes, which displayed that NPWSA-PHNet effectively reduced the errors and also the delay while predicting the crop yield over different classes. Using the activation function in the validation supports to learn the complicated patterns and also maintains the overall relationship among the data.

In addition, this validation aids in offering faster training in various classes. Among all the activation functions, using ReLU offers better crop yield prediction outcomes than others by eliminating the vanishing gradient issues. In the classical techniques like LSTM, PDCNN, SRNN, and PDCNN+SRNN, maintaining robustness is a complicated task that affects the overall crop yield prediction efficiency. Reducing the training time in the NPWSA-PHNet network supports precise decision-making in predicting the crop yield. Next, a novel validation is carried out by considering the various features in the crop yield prediction framework. In the features-based validation, optimally weighted features are indicated as NPWSA-PHNet, where the random parameters of classical WSA are improved using a fitness-based concept.

In the feature-based analysis, normal features are indicated as WSA-PHNet, which attained a minimal outcome compared to the optimal features. Using the optimally weighted features in the validation helps to achieve precise outcomes and also effectively eliminates errors to attain better decision-making. In the statistical validation, the developed NPWSA-PHNet achieved the most accurate best value as an outcome. Accomplishing the best validation in the NPWSA-PHNet-based crop yield prediction network supports improving the decision-making and also quickly understanding different issues that take place while finding the best solutions.

In the worst case, more errors take place that generate potential risks in the network and also affect the decision-making process. Thus, it is concluded that the developed NPWSA-PHNet gained comparatively higher crop yield prediction efficiency than the classical state-of-the-art techniques.

6. Conclusion

This work conveyed a smart and automatic system for crop yield prediction by utilizing an adaptive classifier network, with the combination of IoT sensors. Initially, the essential set of data was obtained from the benchmark data source. Furthermore, the weighted features were also chosen, in which the weight was selected by deploying the NPWSA appropriately. Next, the weighted features were offered to PHNet to execute the crop yield prediction process. The PHNet was built with PDCNN and SRNN effectively. The developed PHNet offered the final crop yield predicted outcomes by fusing the dual predicted scores. Thus, the work of the implemented model was processed and confirmed by including several evaluation measures accurately. When compared to various traditional mechanisms, the implemented network performed well and provided accurate and efficient results for crop yield prediction. The model also exhibited high productivity in crops. Still, the feature selection process found difficulties while dealing with the high-dimensional data that may cause complexity and lead to misclassification. Therefore, various powerful methods will be incorporated in the future to deliver accurate and precise results. In upcoming research work, real-time data will be considered to carry out the entire validation procedure, and it will ensure the network design works well in real-world applications.

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