

An Intelligent Feature-optimized Lightweight Neural Network Model for Water Stress Detection Using Archimedes Optimization Algorithm

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Abstract

Crop water stress detection involves many features which are categorized as climatic, geographical and biological data of crops. Machine learning models with feature subset identification play a vital role in early detection of crop water stress. In the proposed work, utilizes 13 infield climate data such as soil moisture, temperature and relative humidity collected from cotton cropland using smart sensors along with metrological data obtained from the Indian Rice Research Institute (IRRI), Adudurai, Tamilnadu, India. This work deployed a light weight Artificial Neural Network (LANN) in conjunction with a feature subset identification using Archimedes' Optimization Algorithm (AOA). AOA is a nature-inspired optimization algorithm that utilizes the physical laws of flexibility and balance to find optimal features from the dataset. ANN detects the crop stress by employing this feature subset identified by AOA. The proposed model was evaluated using Accuracy, Precision, Recall and F1-score and compared with conventional machine learning algorithms (Logistic Regression, SVM, Decision Tree, Random Forest and Naïve Bayes) and meta-heuristic selection methods (Genetic Algorithm, Particle Swarm Optimization and Ant Colony Optimization). The proposed model achieves a classification accuracy of 94.5% when compared with meta-heuristic methods (ACO, PSO and GA) achieves 92.8%, 91.9% and 89.2% respectively. These findings indicate that AOA-based feature selection with a lightweight ANN provides a scalable solution for crop water stress detection.

Keywords: AOA Feature Identification, Crop Water Stress, LANN Classifier, Light Weight ANN, Water conservation.

Introduction

In India, agriculture is the foremost important sector to preserve a better economy. In conventional system, the farmers used the forefathers' experience for irrigation. In this modern era, a scheduled irrigation system is needed to optimize water use for crop production and its environment in addition to create sustainable farming practices (1). Water stress in crops damages the quality and yield. Conventionally tracking crop water stress involves two major processes: soil water monitoring and crop field weather monitoring. Hence, it is important to find a solution for the reduction of water consumption in addition to increase in crop productivity. Since crop water stress is highly associated with irrigation systems in the crop field it is necessary to monitor the availability of water for plants growth. Changes in soil water content below the required level can affect crop yield and quality (2). Soil moisture with metrological parameters such as evapotranspiration, rainfall,

ambient temperature and relative humidity were used as important attributes for water stress detection (3). The data models involved with variety of features that are directly or indirectly influence the system targets. These features are also influences in reduction of system resources like model complexity and computation time. Hence, prediction of relevant features from the original feature set will ease the reduction processes for various machine learning models. Effective feature selection is a critical pre-processing step for building precise machine learning models, as it eases complexity and avoids the performance degradation associated with unrelated data (4). Machine learning is a subset of Artificial Intelligence (AI) and is the scientific approach of statistical models and algorithms that are executed by computers for performing particular functions without having to explicitly write instructions, but use patterns and inference strategies instead. Among varieties of machine

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learning algorithms, the most popular classification models for monitoring crop stress, soil moisture and irrigation requirement are the Support Vector Machine (SVM), Decision Tree, XGBoost, Random Forest (RF) and k-Nearest Neighbor (k-NN). There are numerous feature selection strategies available for selecting the optimum set of input variables (5, 6). A machine learning classifier was developed with the traditional feature selection algorithm principal component analysis in an intrusion detection system. Several studies and experiments have proven that various meta-heuristic algorithms can be used in optimizing the feature selection process and are employed in many applications like telecom churn prediction, text classification, medical image classification and others. These machine learning and deep learning models are combined with several meta-heuristic algorithms such as genetic algorithm (GA), ant colony optimization (ACO), particle swarm optimization (PSO) and others (7, 8). These meta-heuristic algorithms proved their strength when used for feature subset selection as they improved overall model accuracy by predicting optimum feature subsets from complex data frameworks. Recent studies have also adapted some physics inspired algorithms such as gravitational search (GS), electromagnetic field optimization (EFO), Archimedes optimization (AO) and others for model optimization (9, 10). Integration of nature inspired algorithms with neural network models increases the performance of feature subset identification process. Several applications like medical image classification, telecom sector churn prediction and intrusion detection deployed AOA for feature selection and produced promising outcomes (11, 12). An intelligent facial recognition model was proposed using AOA based feature selection technique that was used to analyze human genders (men or women). Another facial analysis system with AOA based feature selection technique used a trigonometric operator (13). The authors have implemented a hybrid convolutional neural with network-auto encoder classification with a feature selection model to detect the essential attributes from the telecom complex datasets for churn prediction. (14, 15). The success of feature selection or optimization task is to minimize the number of selected features for

improving or maintaining the models' performance and computational efficiency. There are few effective methods to do feature selection for enhancing the performance of ANN models which are concentrated on feature subset selection as its primary task in order to increase the overall performance of the system (16, 17). The ANN with reduced architectural complexity (lightweight) is combined with feature selection, significantly reduce over-fitting and increase the generalization capacity of the model (18, 19). The uniqueness of this work lies in the integration of the Archimedes Optimization Algorithm (AOA) with a Lightweight Artificial Neural Network (LANN) for crop water stress detection. While existing works have considered feature selection using meta-heuristic algorithms or employed ANN-based classifiers independently, limited research has motivated on optimizing feature subset selection and neural network architecture to achieve both feature selection with low computational complexity (20, 21). With this context, this work implements a novel light weight ANN model with feature subset selection through Archimedes optimization algorithm for crop water stress identification from cotton field data. The major contributions of the proposed work are:

- a) selecting the feature subset by applying AOA from the collected dataset,
- b) creating a lightweight ANN classifier with the identified feature subset and
- c) evaluating the model with machine learning models and meta-heuristic algorithms to showcase the model generalization with the infield collected dataset and benchmark datasets and improved model performance.

The main objective of this work is to develop a lightweight Artificial Neural Network (LANN) model assimilated with the AOA algorithm for crop water stress detection. Specifically, this work aims to:

- a) To identify the optimal subset of input features using the Archimedes Optimization Algorithm (AOA).
- b) To develop a lightweight Artificial Neural Network (LANN) using the selected feature subset for crop water stress classification.
- c) To evaluate the proposed AOFs-LANN model against conventional machine learning classifiers and existing meta-heuristic feature selection approaches.

Methodology

The proposed work is intended to identify the crop water stress using a light weight method using

neural network classifiers. The overall flow of the system is shown in Figure 1.

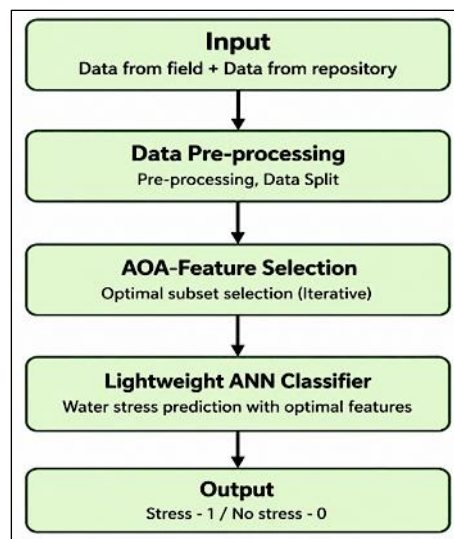


Figure 1: Proposed Model Workflow

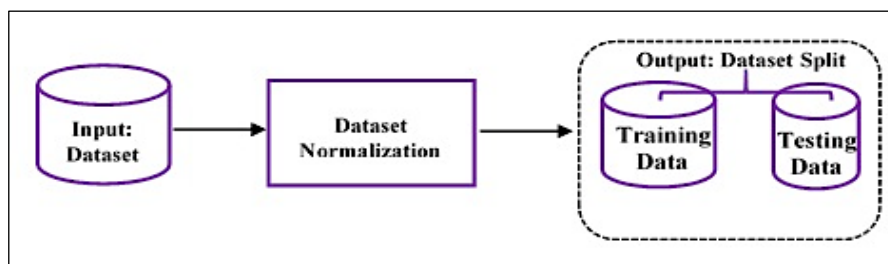


Figure 2: Steps of Data Pre-processing

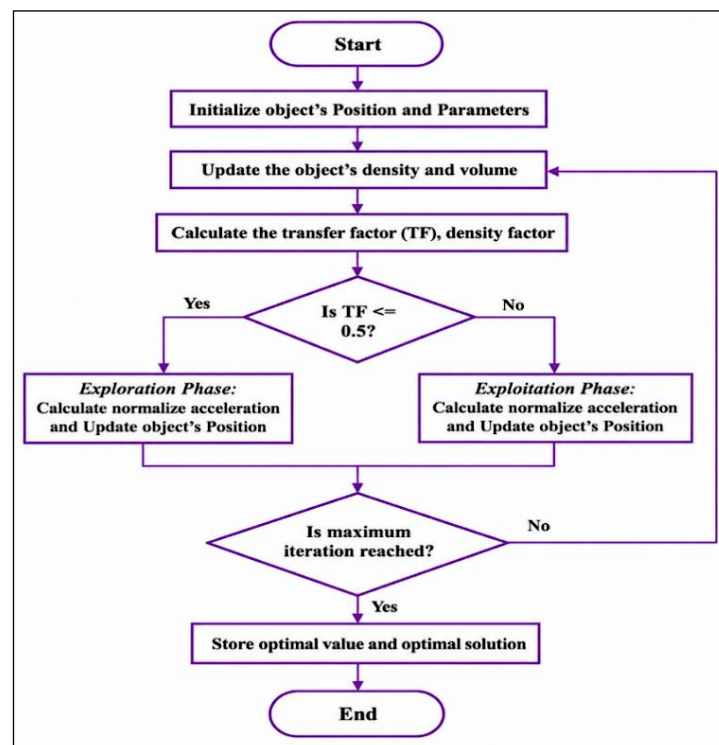


Figure 3: Feature Selection using AOA

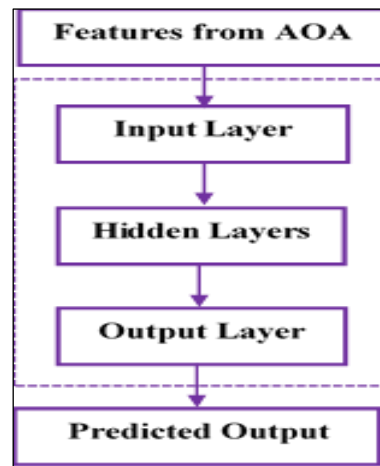


Figure 4: Output Prediction using ANN

Proposed Model: LANN

The proposed work contains three phases in which first phase involves the data set preparation with data pre-processing activities like data normalization followed by data set split produces the required data set for further process. Second phase involves the feature subset identification by selecting the vital parameters based on the Archimedes' optimization algorithm. Third phase involves the creation of proposed ANN model with

the selected features from the previous phase. The proposed work and its phases are clearly depicted in Figures 2, 3 and 4.

Dataset Pre-processing

The collected data is normalized using standard scaling technique, here X_i is the original input vector and X_{new} is computed scaled value by using the Equation [1] (22). The computed X_{new} value is the scaled value of X_i between -1 and 1.

$$X_{new} = \frac{X_i - X_{mean}}{X_{std}} \quad [1]$$

Then the computed scaled value is split into training and testing data is given as input for the feature subset selection phase with the ratio of 80% and 20% respectively.

Archimedes' Optimization Algorithm

Second phase is to identify the feature subset using Archimedes optimization algorithm (AOA) from the original data set. The objective of this phase to find the optimum set of features which will be used as input for the proposed LANN model. The AOA is

one among the nature inspired algorithms that is based on Archimedes principle in physics (23). This algorithm will adjust the convergence rate and amplifies the searching space to achieve the global optimum solution. Let F is the number of input features. Define $J(SF)$ be the objective function by finding minimum set of features $min(SF)$ that improves the model performance as given in Equation [2].

$$J(SF) = a \cdot |SF| / F + (1 - a) \cdot (1 - Acc(SF)) \quad [2]$$

Where,

F = total number of features

$SF \subseteq \{1, 2, \dots, F\}$ = Selected feature subset

$Acc(SF)$ = classification accuracy using features in SF

$a \in [0, 1]$ = balance coefficient

Consider t is current iteration, T_{max} is total number of iterations and λ is a shape control parameter. Define transfer factor TF as in Equation [3]:

$$TF(t) = 1 - \left(\frac{t}{T_{max}} \right)^{(1/\lambda)} \quad [3]$$

For each iteration i , position of object p is updated depends on TF from current position, p_i to new position in exploration phase, If $TF \leq 0.5$ then move object towards a random solution p_r in exploitation phase, If $TF > 0.5$ then move object towards the best object p_{best} as given in Equation [4]:

$$p_i^{t+1} = \begin{cases} p_i^t + r1.TF.(p_i^t - p_i^t), & \text{if } TF \leq 0.5 \\ p_i^t + r2.TF.(p_{best}^t - p_i^t), & \text{if } TF > 0.5 \end{cases} \quad [4]$$

During the exploration phase when collision between objects, the algorithm can search globally by moving candidate solutions randomly through the search space and avoiding local optima. On the other hand, the exploitation phase aims to strengthen the search around the best current solution and fine-tune it to converge to the best global solution. The transfer from the exploration phase to the exploitation phase in AOA is managed by a transfer factor (TF), which will allow AOA to gradually move from exploration ($TF < 0.5$) to exploitation ($TF \geq 0.5$) which means no collision between objects. This process is repeated until it

reaches to the maximum iterations T_{max} . In this work the maximum iteration value T_{max} was arbitrarily set to 100 iterations.

Artificial Neural Network Model

Artificial Neural Networks (ANNs), a type of a machine learning (ML) algorithm designed to mimic the human brain's structure and functions that recognizes pattern from data. In recent years the use of ANN has revolutionized various applications, like natural language processing, image recognition, computer vision, recommender systems and speech recognition etc. (24).

Consider the hidden layer

$h^{(l)}$ = hidden layer activations for layer l

$W^{(l)}, b^{(l)}$ = weight values and bias values for layer l

f = activation function for layer l

$\hat{y}$ = observed output value at layer l

A single forward pass at layer l ,

$$h^{(l)} = f(W^{(l)}.h^{(l-1)} + b^{(l)}) \quad [5]$$

$$\hat{y} = \sigma(w^T.h^{(l)} + b) \quad [6]$$

Equation [5] represents the forward propagation in a neural network, where the output of layer l is obtained by applying the layer-specific weight matrix and bias to the output of the preceding layer. Equation [6] represents the neural network output, where the activation function σ is applied to the weighted input $w^T h^{(l)}$ combined with the bias

b . The arbitrary selection of model parameters of ANN architectures and their values is depicted in Table 1. Initial variables such as number of features (input parameters), hidden layers and its neurons, epochs, batch size, activation functions in hidden layer and output layer and loss function were listed along with its initial values.

Table 1: Structure of ANN with arbitrary variables

Variables	Values
Number of Features	13
Number of Hidden Layers	8,4,2,1
Neurons in Hidden Layer1	128, 64,32,16
Neurons in Hidden Layer2	64,32,16,8
Number of Epochs	100, 50
Number of Batches	32,16
Activation Function in Hidden Layers	ReLU
Activation Function in Output Layer	Sigmoid

Loss Function	Binary Cross Entropy
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Results and Discussion

The entire workflow of this model is trained and tested with the environment jupyter notebook an open-source web application tool.

Data Collection and Preparation

The proposed approach was deployed and experimented for the cotton field, located in Adudurai (approximate GPS coordinates 11.0140° N", 79.4751° E"), Tamil Nadu, India. The metrological data such as Temperature (Tmin,

Tmax), Humidity (RH), Wind speed (WS), Evaporation (Evap), Sunshine (SS), Radiation (RD) and Rainfall (RF), for five years calendar period between Jan 2018 to Jan 2023. The infield sensor data collected such as Temperature (Ta) Humidity (Ha) and soil moisture (SM) from canopy for the same crop cycle period for 5 seasons. The descriptions of the collected in-filed and metrological data is given in Table 2. Input features are continuous values and target variable is a categorical value.

Table 2: Description of the dataset

Feature ID	Description
Days	Crop data measurement days
Tmax	Average of daily maximum temperature (°C)
Tmin	Average of daily minimum temperature (°C)
RH	Daily average of relative humidity (%)
Evap	Average of daily evaporation (mm)
WS	Daily average of wind speed (km/h)
RF	Average rainfall for the day (mm)
SS	Average of daily sunshine (hours)
RD	Occurrence of radiation in the crop day
Ta	Air temperature measured in canopy
Ha	Relative humidity measured in canopy
SM	Soil moisture measured in canopy
Irrigation	Irrigation requirement (target)

The proposed ANN architecture is constructed after evaluating various structural parameters arbitrarily. The comprehensive evaluations were done on ANN architecture with respect to various design aspects such as based on feature selection methods, machine learning models, nature inspired meta-heuristic algorithms, model parameters like hidden layer neurons, epochs and batch sizes, optimizers. The main objective of the proposed architecture is to give an optimum solution for resource constrained application with reduced architectural complexity. Initially the model was trained and tested with entire set of features without using feature selection process that is implemented with all features. Then the resultant lightweight model was created after reducing the architectural complexities of ANN

with the set of features identified by AOA.

Comparison of Feature Selection

Methods

The proposed feature selection method is compared with basic feature selection methods such as filter based (mutual information), wrapper based (recursive elimination) and embedded (L1 regularization) which were evaluated to demonstrate the importance of proposed feature selection model as shown in Figure 5. From the figure, the proposed method can be used as an alternative for feature selection using meta-heuristic algorithm with the model accuracy of 99.5% when compared with accuracy of 98% mutual information and recursive elimination methods and 95.5% L1 regularization method.

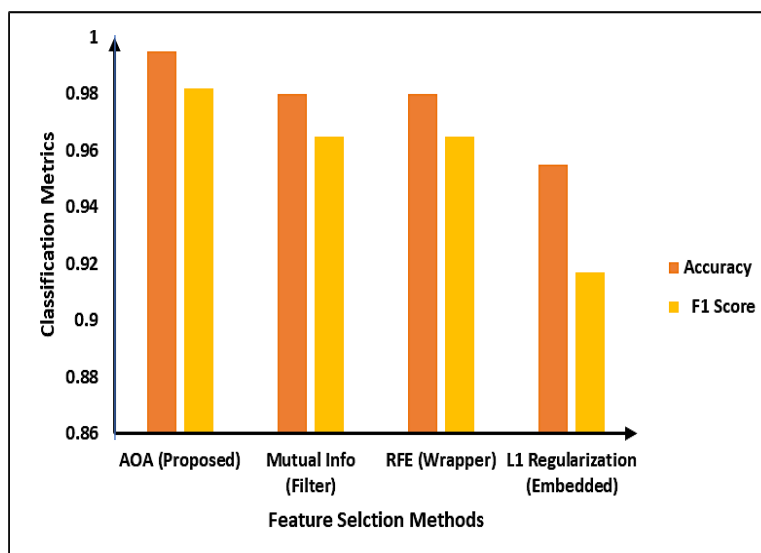


Figure 5: Comparison of Different Categories of Feature Selection Methods

Comparison of Machine Learning Models

The created ANN models are evaluated against metrics of classification models such as Accuracy of the Model, Precision, Recall and F1 Score. The ratio of correct predictions and total predictions is defined as classification Accuracy. The ratio of

correct positive predictions and total positive predictions is defined as Precision. Recall explains the proportion of all actual positives are predicted correctly as positives in the result. F1 score explains the harmonic means of the precision and recall values. Figure 6 explains the metrics of comparisons of various machine learning models with the proposed ANN model.

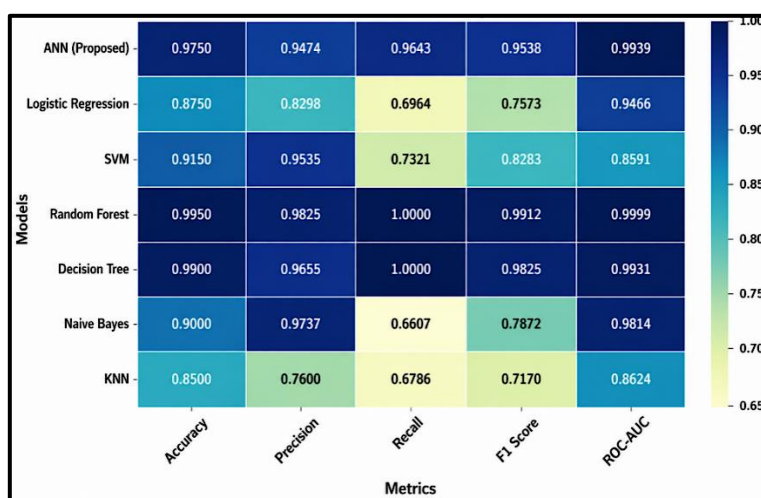


Figure 6: Machine Learning Models vs Proposed ANN Model (Classification Metric Comparison)

Comparison of Nature Inspired Algorithms

The proposed model is compared with well-known nature inspired meta-heuristic feature selection algorithms such as genetic algorithm (GA), particle swarm algorithm (PSO) and ant colony optimization (ACO). These algorithms were used

along with ANN model for feature selection with the classification metrics obtained for each model such as precision, recall and f1 score are shown in Figure 7. The proposed model achieves a classification accuracy of 94.5% while the meta-heuristic methods such as ACO, PSO and GA achieves 92.8%, 91.9% and 89.2% respectively.

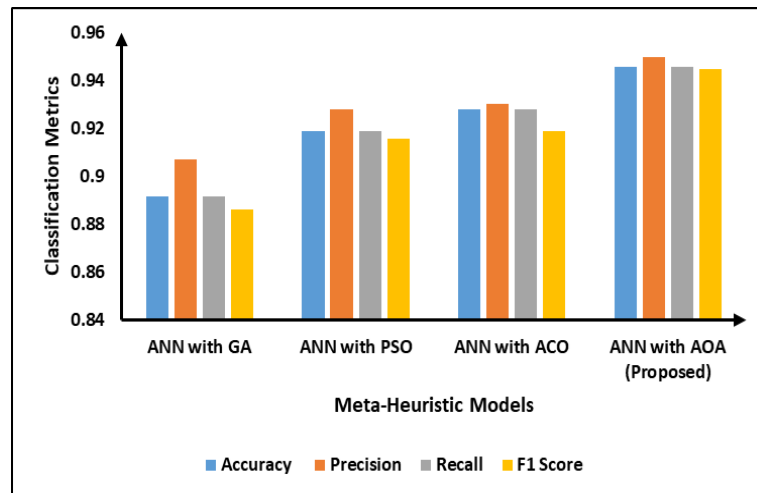


Figure 7: Comparison of different meta-heuristic algorithms with ANN

Each of these algorithms follow different conditions for selecting the features. Feature subsets generated from genetic algorithm are Tmax, RH, RF, SS, RD, Ta and Ha. Features generated from particle swarm optimization algorithm are Tmax, Tmin, RH, Evap, RF, SS and Ta. Similarly features generated from the proposed

ANN with AOA are RH, RF, SS, Ta, Ha and SM. The Figure 8, clearly claims that the features selected through ANN with AOA is systematically converges towards important features at every iteration. This model predicts features such as Soil Moisture and Temperature are highly correlated with the target (irrigation) as in Pearson correlation.

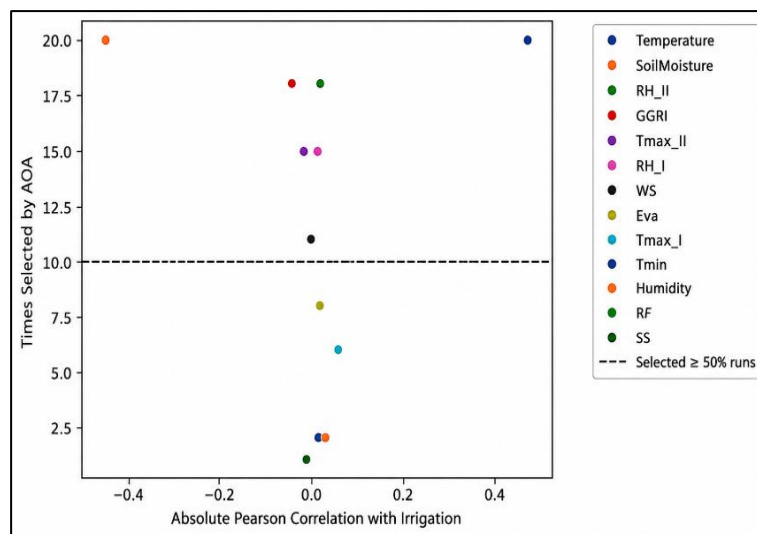


Figure 8: Correlation vs AOA Selection Frequency

Comparison of ANN Layer Variables

The architecture of the proposed model with number of features obtained from AOA feature selection process is compared against ANN with all features as shown in Table 3. The proposed AOA-LANN model consistently achieves superior classification performance while reducing the

number of trainable parameters from 369 to 257 with the minimum number of hidden layers units. Following Table 4 has shown the comparison of model accuracy based on number of epochs and batch sizes for the ANN model with selected features. Different ANN with hidden layer neurons were experimented by modifying the batch sizes 32 and 16 and its accuracies were evaluated.

Table 3: Number of Hidden Layer Neurons and Number of Trainable Parameters

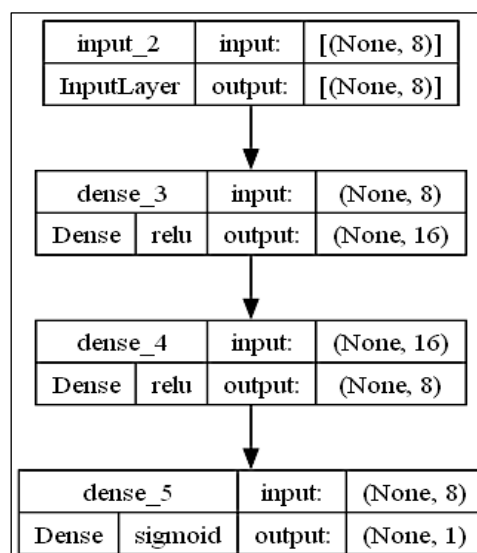
ANN Model	Number of Neurons in Hidden Layer 1	Number of Neurons in Hidden Layer 2	Number of Trainable Parameters
With All Features	128	64	10113
	64	32	3009
	32	16	993
	16	8	369
With Selected Features	128	64	9729
	64	32	2817
	32	16	897
	16	8	257

Table 4: Number of Batches and Number of Epochs

Number of Neurons in Hidden Layer1, Layer2	Accuracy for Batch Size 16		Accuracy Batch Size 32	
	100 Epochs	50 epochs	100 Epochs	50 epochs
128, 64	0.935	0.930	0.935	0.935
64, 32	0.945	0.945	0.930	0.935
32, 16	0.925	0.940	0.910	0.935
16, 8	0.950	0.940	0.940	0.940

Initially the model is trained and tested with entire set of features (all 13 features) without using feature selection process. Then the proposed LANN model is created after reducing the architectural complexity with set of features identified by AOA. The architecture of the proposed LANN model with reduction in number of neurons and number of features obtained from AOA feature selection process is shown in Figure 9. The proposed model compared against lightweight ANN without feature selection is shown in Figures

10 and 11. These figures clearly suggest the need of generalized lightweight ANN model by considering reduced amount of execution time i.e ANN with feature selection 12.55 seconds and ANN without feature selection 13.68 seconds, parameters and computing resources. This model can be used as generalized model for applications in which resource constraints like design complexity and computational time need to be solved.

**Figure 9:** Architecture of LANN Model with Selected Features

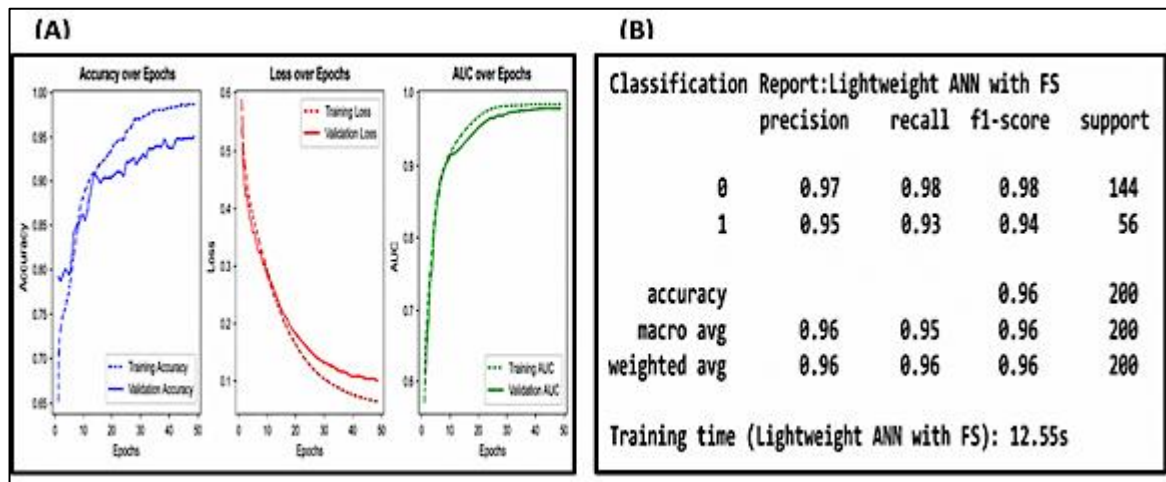


Figure 10: ANN Model with Feature Selection. (A) Epoch Wise Training and Testing Accuracies, (B) Classification Summary and Training time

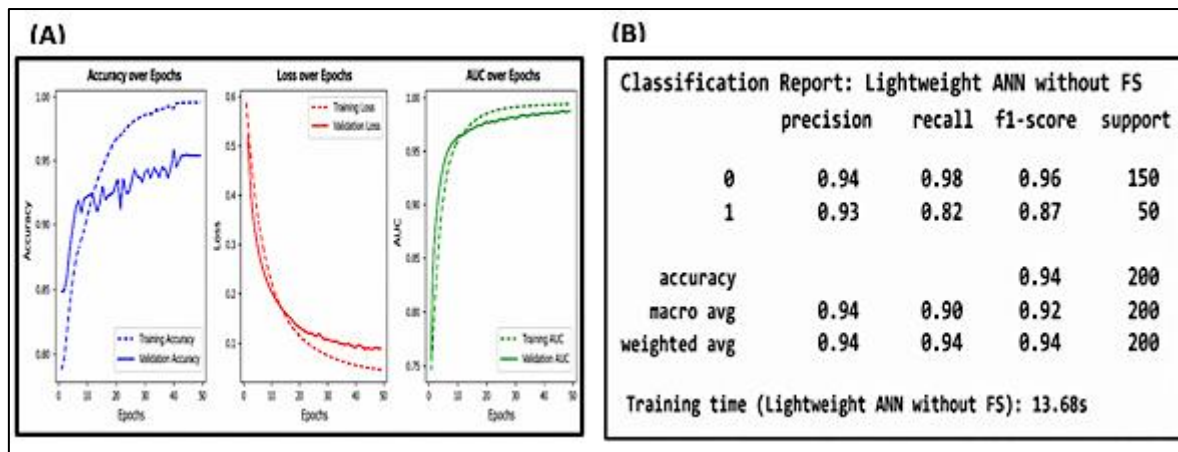


Figure 11: ANN Model without Feature Selection. (A) Epoch Wise Training and Testing Accuracies, (B) Classification Summary and Training time

The proposed model is also evaluated with a public dataset available for crop recommendation (Dataset1) contains sample records of 300 with 7 features and multiclass target label. Another public dataset for plant health prediction (Dataset2) contains sample records of 120 with 11 features

and multiclass target label (25, 26). The comparison of proposed model with public datasets shows their suitability in lightweight ANN application and the results as are shown in the Figures 12 and 13.

ANN Model without FS Accuracy: 85.32%		
Model: "sequential"		
Layer (type)	Output Shape	Param #
dense (Dense)	(None, 16)	128
dense_1 (Dense)	(None, 8)	136
dense_2 (Dense)	(None, 1)	9
Total params: 273		
Trainable params: 273		
Non-trainable params: 0		
ANN Model with AOA Feature Selection Accuracy: 87.67%		
Model: "sequential_6"		
Layer (type)	Output Shape	Param #
dense_3 (Dense)	(None, 16)	112
dense_4 (Dense)	(None, 8)	136
dense_5 (Dense)	(None, 1)	9
Total params: 257		
Trainable params: 257		
Non-trainable params: 0		

Figure 12: Model Accuracies on Dataset1

ANN Model without FS Accuracy: 76.64%		
Model: "sequential"		
Layer (type)	Output Shape	Param #
dense (Dense)	(None, 16)	192
dense_1 (Dense)	(None, 8)	136
dense_2 (Dense)	(None, 1)	9
Total params: 337		
Trainable params: 337		
Non-trainable params: 0		
ANN Model with AOA Feature Selection Accuracy: 77.83%		
Model: "sequential_3"		
Layer (type)	Output Shape	Param #
dense_9 (Dense)	(None, 16)	128
dense_10 (Dense)	(None, 8)	136
dense_11 (Dense)	(None, 1)	9
Total params: 273		
Trainable params: 273		
Non-trainable params: 0		

Figure 13: Model Accuracies on Dataset2

Conclusion

It is very difficult for farmers to identify water stress for the crops based only on the historical experience. An automatic classification of crop stress will be a solution for these problems. The proposed LANN model is intended to improve the overall classification accuracy by using reduced architecture with the optimum number of features from AOA. The model is evaluated with several architectural constraints for the collected dataset. From the result, it was observed that the AOA based LANN model shown significant

performances with these datasets. This model was also compared against the nature inspired algorithms such as GA, PSO and ACO. The results shown that the proposed model outperformed the other feature selection models, concluded that the AOA based LANN classifier can be used as a generalized tool for predicting the crop stress identification. The proposed model enables efficient crop water stress detection with reduced computational complexity, making it suitable for smart irrigation systems, edge devices and precision agriculture applications. Future work will focus on validating the model on larger and

diverse datasets, integrating IoT and remote sensing data and exploring advanced lightweight and explainable AI models for real-time crop monitoring.

Abbreviations

ACO: Ant Colony Optimization, ANN: Artificial Neural Network, AOA: Archimedes Optimization Algorithm, GA: Genetic Algorithm, PSO: Particle Swarm Optimization, LANN: Lightweight Artificial Neural Network

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Author Contributions

Jeyapandian Munisamy: Conceptualization, Manuscript Writing, Durga Karthik: Editing, Venkatesan R: Literature Survey.

Conflict of Interest

The authors have no conflict of interest regarding the publication of this work.

Data Availability

Data used in this work were sourced from public websites.

<https://kaggle.com/code/sulaniishara/plant-health-prediction-with-ml>,

doi:10.6084/m9.figshare.26308696.v2

Declaration of Artificial Intelligence (AI) Assistance

The authors declare that they did not use AI assisted tools during the writing process. The authors take full responsibility for the content's originality, interpretation and accuracy.

Ethics Approval

Not Applicable.

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