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APPLIED RESEARCH

IoT- Enabled Firmness Grades of Tomato in Cold Supply Chain Using Fusion of Whale Optimization Algorithm and Extreme Learning Machine

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ABSTRACT The assessment of tomato firmness is pivotal in determining optimal harvest time, evaluating shelf life, and gauging ripeness. This attribute plays a crucial role in guiding the distribution and transportation processes. Post-harvest, tomatoes tend to lose firmness and can deteriorate into a rotten state during transportation within the supply chain, mainly due to environmental fluctuations. To mitigate such losses and uphold tomato quality, the cold supply chain, with its controlled environmental conditions, proves instrumental. Monitoring this cold supply chain is imperative to combat the adverse impact of ambient temperatures on tomatoes during logistics. This research introduces an innovative approach, employing an Internet of Things (IoT) framework and the Whale Optimization Algorithm for temperature prediction within the cold supply chain. Ambient and tomato temperatures, along with stable temperature calculations under variable conditions using the Whale Optimization Algorithm, were collected. The predictions were executed using the Extreme Learning Machine of Artificial Intelligence. The data is collected during tomato cold storage for experimentation. The proposed technique with mean average precision 84.957%, mean average recall 96.9% and accuracy 99.83%. Evaluation through precision, recall, and F-measure accuracy metrics demonstrates the superior performance of the proposed approach compared to conventional models such as Decision Tree, Linear Model, Naïve Bays, Random Forest, and Support Vector Machine.

INDEX TERMS Artificial intelligence, cold supply chain, deep learning, Internet of Things, Newton's law of cooling.

I. INTRODUCTION

According to the Food and Agriculture Organization of the United Nations (FAO), half of vegetables and fruits are wasted during different stages of the supply chain (SC) [1], which causes famine for millions of people in the world [2]. The reduction of vegetable and fruit loss is critical for reducing famine. Several studies of tomato fruit have addressed the fact that the firmness decrease during ripening depends on significant solubilization and the depolymerization of

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polysaccharide in the cell wall and the middle lamella [3]. The lack of flavor complaints by consumers of tomatoes has been focused on for decades. The tomato breeding focused on disease resistance, firmness, and yield, but the flavor was not focused on [4].

The postharvest handling of tomatoes causes the depreciation of flavor [5] and for postharvest handling, firmness and appearance are the main factors that signal the shelf life of tomatoes. The tomatoes are harvested at the premature stage for the SC purpose from field to market with high firmness [6]. The postharvest quality is measured by consumers or wholesale buyers by considering parameters such as total soluble solids content, firmness, color change, and weight loss [7], [8]. The management of SC for tomato fruit increases the life of the tomato. In food, the SC freezing technique is used at various levels [9]. The traditional freezing techniques reduce the temperature of food products to − 18°C or lower.

The freezing temperature impacts the freshness of the tomato during the supply [10] and requires effective management to maintain the tomato's quality. In cold SC, temperature variations impact the life of tomatoes during storage and transportation. The freshness of tomatoes degrades over time and requires certain pressure, humidity, composition, and temperature to maintain freshness during SC storage. At every stage of SC, constant temperature and humidity are required [11]. Due to temperature variations, the economic loss affects the farmer and other participants in the storage process and transportation [12]. Continuous temperature control is challenging due to the modern complexities of the supply chain for different geographical locations.

Due to advancements in sensor technologies, temperature monitoring systems have been developed for sensing, storing, and transferring environmental measurements [13] in cold SC [14]. The tracing and tracking of products in cold SC is done by monitoring applications [15], [16], [17]. Artificial intelligence enables these applications to complete or partially automate the gathered environmental measurements [18], [19], [20], [21], [22], [23], [24]. The acceptable temperature ranges based on laboratory experiments for the cold supply chain provide the basis for monitoring applications [25]. The monitoring applications in practice [26] notify of occurrences but do not predict deviations. In practice, cold SC faces several situations, including rapid changes in the temperature of cargo and the ambient temperature, which require preemptive identification. The mentioned situations are not limited to the cooling unit or sensor malfunctioning or physical handling.

The existing research on temperature prediction approaches for cold SC focuses on the cargo's temperature approximation with relatively stable or unstable environmental temperatures for a long time span and does not address the immediate predictions [27], [28], [29]. For decision-making, unstable environmental temperature conditions are required for predicting temperatures. The stakeholders in cold SC for short-, medium-, and long-term requires temperature prediction for managing the potential variation of temperature. The real-time temperature prediction integration with the intelligent system for decision support overcomes the loss of tomato during the cold SC. Intelligent decision support systems perform the task, including informing users of the variations, interpolating the measurements in case of missing data, finding the cause of the variations, developing countermeasures, measuring the impact of the variation with predicted information, improving the service by monitoring and predicting, and avoiding the variation with immediate countermeasures.

Currently, the research on cold SC for tomato fruit is limited, and the temperature prediction of refrigerated trucks for tomato fruit supply chains is not covered by the research. The shortcoming of existing research raised the question: how will the temperature of a refrigerated truck be predicted with higher accuracy and temperature deviation adjustments over time? The mathematical modelling of temperature for refrigerated trucks was difficult due to the impact of several factors on the temperature of the truck and the difficulties in temperature prediction [30]. The machine learning (ML) approaches of AI have revealed the prospects for addressing the above-mentioned issue. The understanding of physical relationships among the several variables is not required by the ML, which is able to predict temperatures using driving data as well as avoid the establishment of complex mathematical models [27].

In ML approaches, extreme learning machine (ELM)-based approaches have been widely used for prediction due to their robust generalization ability and fast learning rate [31], [32], [33]. Parameter optimization is the key issue in ELM, as parameters like hidden bias and input weight have a great impact on prediction outcomes [34]. The behaviour of humpback whales for searching for prey is mimicked by the Whale Optimization Algorithm (WOA) [35]. The WOA uses the bubble-net chasing approach for the selection of optimal prey from the best search agent. The cold supply chain for tomato fruit requires long-term prediction to maintain the environmental temperature and reduce food loss. Previous studies achieved limited accuracy in cold SC temperature prediction due to its exclusion of key influencing factors. In this study, the use of multiple parameters, including tomato box temperature, humidity, and the surrounding temperature and humidity within the refrigerated truck, for improved temperature prediction. To reduce tomato fruit loss, a real-time temperature prediction approach is proposed in research based on WOA-ELM. The proposed technique selects the optimal number of measurements to enhance the accuracy of the prediction for stabilizing the ambient temperature by decreasing the error in measurements. The presented method uses environmental temperature stability under the variation conditions and considers the errors in sensor measurement for robust predictions. The WOA and ELM use the environmental temperature for temperature prediction. Furthermore, the experimental outcome demonstrates the

TABLE 1. Related literature with reference, title, used sensors and purpose of study.

Reference	Title	Sensors	Purpose
[11]	"Real-Time Data Monitoring in Cold Supply Chain Through NB-IoT"	Temperature Sensor, Humidity Sensor, Shock Sensor, and GPS with Narrowband Communication	Low cost optimize chain to reduce the loss.
[36]	"Study on supply chain strategy based on cost income model and multi-access edge computing under the background of the Internet of Things"	Temperature Sensor	Influence of ambient temperature on product during the logistics.
[37]	"An Internet of Things (IoT)-based risk monitoring system for managing cold supply chain risks"	Temperature Sensor, Humidity Sensor, light Intensity Sensor.	Improve product quality and reduce worker health risk.
[38]	"An intelligent tracking system based on internet of things for the cold chain"	GPS, Temperature sensor and Humidity Sensor.	Real-time monitoring of ambient conditions for product.
[40]	"Integrating wireless sensor networks with statistical quality control to develop a cold chain system in food industries"	Temperature and GPS sensor.	Preserve product quality by time temperature based cold chain management.
[42]	"Real-time temperature prediction in a cold supply chain based on Newton's law of cooling"	Temperature Sensor	Prediction of temperature during the cold SC by mean of stabilizing temperature using Newton's law of cooling method for prediction.
[43]	"IoT based cold chain logistics monitoring"	GPS, Moisture Sensor, and Temperature Sensor.	Reduce the product spoilage due to failure of system failure during SC.
[44]	"An IoT-based cargo monitoring system for enhancing operational effectiveness under a cold chain environment"	Temperature, Humidity, Pressure and Light Sensors.	The humidity, ambient and object temperature, pressure, and light are the parameters for the functional quality management of cargo using IoT technology.
[45]	"Compact supervisory system for cold chain logistics"	Temperature Sensor	Temperature measurement during the cold SC.
[46]	"Experimental Investigation of A Real-time Monitoring System for Cold Chain Logistics"	Temperature and Humidity Sensors.	Real time temperature and humidity data collection during the SC.
[11]	"Real-Time Data Monitoring in Cold Supply Chain Through NB-IoT"	Temperature Sensor, Humidity Sensor, Shock Sensor, and GPS with Narrowband Communication	Low cost optimize chain to reduce the loss.
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[40]	"Integrating wireless sensor networks with statistical quality control to develop a cold chain system in food industries"	Temperature and GPS sensor.	Preserve product quality by time temperature based cold chain management.

outstanding performance of the presented system as compared to Decision Tree, Linear Model, Naïve Bays, Random Forest, Support Vector Machine, Mine Blast Optimization Algorithm based Extreme learning Machine models.

The rest of the study is organized into five sections. The related studies are discussed in Section II, and the proposed approach is elaborated in Section III. The experimental outcomes are represented in Section IV, discussions, and limitations in Sections V, VI, and at the end, the study is concluded in Section VII.

II. RELATED WORK

The amount of tomato loss after harvesting is due to poor postharvest management during the SC and storage. Effective cold SC management approaches reduce the postharvest loss of tomatoes. The ambient temperature in real-time is crucial for cold SC management to reduce the risk of loss. With the fourth industrial revolution, Internet of Things (IoT) based smart systems are being focused on by researchers. A significant amount of literature has been published on cold SC management. An IoT-based SC model is discussed in [36] from an agriculture product loss, cost, and income perspective with multi-access edge computing in IoT.

The aroma modelling and heat transfer-based approach for vegetable and fruit cold SC is presented in [28], and during the experimentation, the environmental conditions are measured at different positions. The temperature variation of the product and air depends on the distance from the air inlet and is controlled by means of fans. The aroma evaluation of tomatoes was done by considering the tomato varieties and ambient temperature, but the humidity effect was not considered during the experimentation. A risk monitoring system based on IoT was proposed in [37] to monitor the risk of cold SC. The presented system design operates on a fuzzy logic approach, cloud-based data services, and a wireless sensor network. The data collection was done by temperature, humidity, and light intensity sensors for ambient condition monitoring and managed by a cloud database service. The data coverage is not complete, and there is a lack of parameter optimization.

A narrow-band IoT-based system is proposed in [11] which reduces the cost of cold chain solutions by reducing power consumption. The narrow-band IoT device is embedded with a temperature sensor, humidity sensor, shock detector, and GPS module for environmental condition monitoring with simulation. The empirical validation of the data is missing in the study. For monitoring the environmental conditions in cold SC, an IoT-based intelligent tracking system is presented in [38]. The wireless sensor network of the tracking system is based on Zigbee for the collection and transmission of environmental conditions [39]. The cold SC system, based on the time temperature indication presented in [40], uses the critical control point criteria for temperature management throughout the food delivery process. The hybrid solution for food SC management using cloud computing and IoT technologies is presented in [41], which monitors the environmental variation during the logistics process for two sector case studies.

The Newton's law of cooling (NLC) based approach for temperature prediction in cold SC is presented in [42], with the implementation of NLC for ambient temperature variation under consideration of stable temperature conditions. The optimal stable measurements are selected, and ANN and autoregressive moving average models are compared for result evaluation, but the effect of other environmental parameters on temperature is ignored, such as location, humidity, and shock. A cold SC management system with IoT technology proposed in [43] reduces human intervention and the chance of product spoilage in the case of refrigeration failure. The system communicates the environmental details for better decision-making in SC management for vaccine logistics, but empirical verification is not covered in the study.

The IoT based cargo monitoring system presented in [44] monitors ambient changes for the improvement of functional quality. The sensor network is implemented for data gathering, and fuzzy logic is applied to the data for storage condition suggestions to reduce the environmental effect on the product and reduce the loss during the SC process. The ambient temperature, object temperature, humidity, pressure, and light are the parameters for functional quality management. The rules set for fuzzy logic need to be refined to improve reliability and feasibility for implementation.

The cold SC management system proposed in [45] tracks the temperature during the SC. The box type testbed is built for the simulation trailer of refrigerated vehicles with four modes and four supervisory modules to detect temperature variations and modes. The door state and temperature collected from the testbed are represented by a correlation matrix, and the data is arranged in seven classes for applying machine learning. The SVM, decision tree, and weighted k-NN algorithms were applied to the data for evaluation. The empirical implication is not explored in the study. An IoT-based automation system for cold chains is presented in [46] to collect real-time humidity and temperature data from storage boxes. The system provides temperature monitoring under the conditions of temperature-effective factors.

The WOA technique is used to evaluate the long range IoT network and then optimize LoRA network in [47]. The WOA for load frequency control is presented in [48] to assess the efficiency of 2DOFTIDF controller and to enhance the controller parameters. The WOA-ELM is developed for windspeed forecasting in [49]. The temperature and humidity forecasting system based on IoT is presented in [50]. The LSTM model is applied with WOA for humidity and temperature forecasting. The fused WOA and grey wolf optimization approach for inventory stock management presented in [51]. The WOA optimized extreme learning machine is proposed for ageing assessment of shielded gate bipolar transistor modules in [52] for stability insurance in operational mode. The key focus of the study was the optimization of biases in the hidden layer and input weights for the ELM.

A mayfly algorithm (MA) with an ELM fusion-based approach for the prediction of the temperature of a refrigerated truck is presented in [53]. The hidden layer biases and input weights of ELM are improved using the MA for the prediction of temperature by ELM. The model evaluation is done by comparing the results with those of PSO and

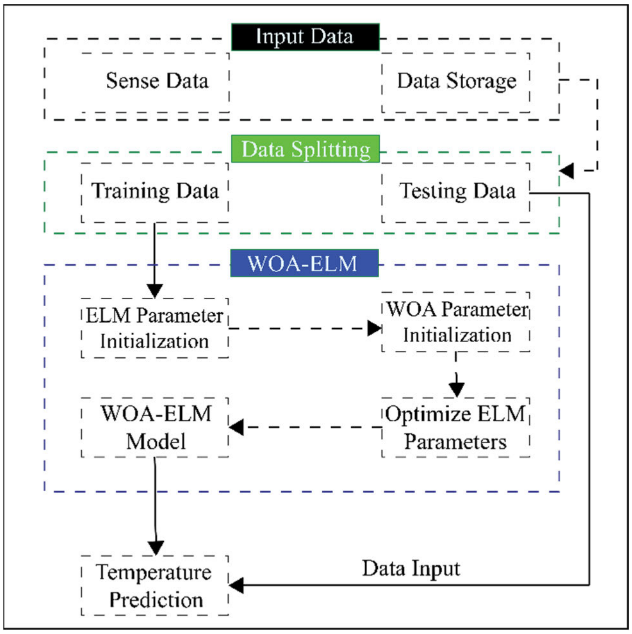

FIGURE 1. Flow graph for temperature prediction WOA-ELM.

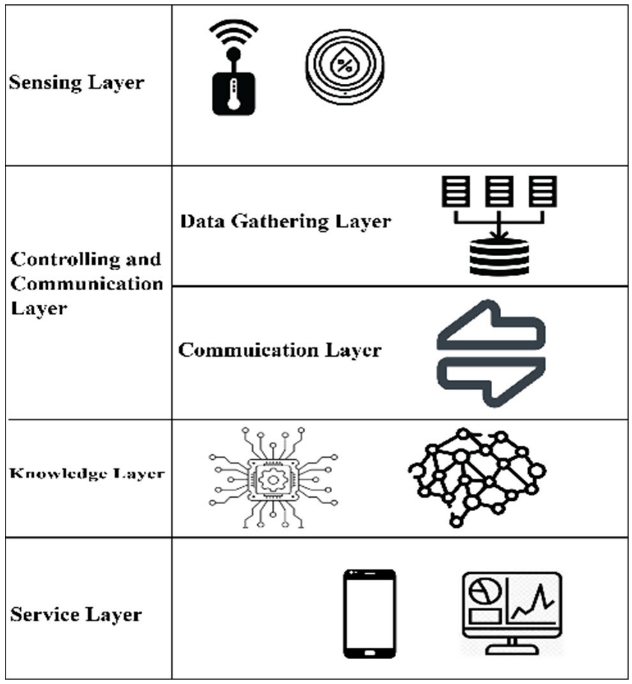

FIGURE 2. Layered architecture of proposed approach.

GA. The MA with impulsive conjunction, which affects the performance of MA-ELM, and the limited variants of ELM are used for prediction in the study. The ELM-based model for daily dew point prediction is proposed in [54], and the daily averaged measured data of weather is used by ELM for prediction. The performance evaluation of the model was done by comparison with SVM and artificial neural networks under nonlinear variations of daily temperature in different ranges.

The ELM based model is represented in [55] for the prediction of the daily water temperature of rivers, and the day of year, discharge, and air temperature are the predictors for the prediction task. The ELM and dragonfly algorithm (DA)-based hybrid approach for prediction tasks is presented in [56]. The huge number of hidden layer nodes in ELM increases testing and evaluation time as optimal weights and biases for the hidden layer are not available. The DA selects the optimal biases and weights for ELM and reduces the testing and evaluation time for the prediction tasks, but the generalized ability is limited.

The multi-layer perception (MLP) model with WOA for wind speed prediction for renewable energy is presented in [57]. The data is collected from stations in the north of Iran, and the dataset was generated using data from 2004 to 2014. The result comparison was done with genetic Algorithm based optimized MLP and simple MLP. The optimized weights obtained by WOA for the MLP layers improve the accuracy of prediction. The WOA optimized SVM for tool-wear prediction was proposed in [58] for the promotion of intelligent development in the manufacturing industry. The SVM parameters are optimized by WOA. The WOA-SVM was studied under fixed cutting conditions with limited domain sensitive features.

The WOA and multivariate adaptive regression splines (MARS) fusion based method is presented in [59] for the prediction of the critical temperature of a superconductor. The parameters for MARS are optimized by using the WOA and the prediction done by MARS. In our research, we collected the ambient and object's temperatures and measured the stabilized temperature under unstable conditions by developing a prototype model. Last but not least, the key focus of our study is cold SC temperature prediction for tomatoes to reduce the loss.

III. PROPOSED MODEL

To achieve the objectives, the proposed solution is based on ambient conditions such as temperature and humidity monitoring during the cold SC of tomatoes to maintain the environmental conditions for a reduction in tomato loss. The deep learning model is applied to sensed data for prediction to manage the temperature throughout the SC. The flow graph of the proposed solution is illustrated in Fig. 1. The presented solution is separated into four layers: the sensing layer, the controlling and communication layer, the knowledge layer, and the service layer, as shown in Fig. 2.

A. SENSING LAYER

The sensing layer includes the sensors for capturing environmental details. In cold SC, humidity and temperature sensors gather the temperature and humidity for monitoring during the transportation of tomatoes.

B. CONTROLLING AND COMMUNICATION LAYER

1) DATA GATHERING LAYER

The data collection task is managed by the data gathering layer, which is also responsible for filtering the collected data

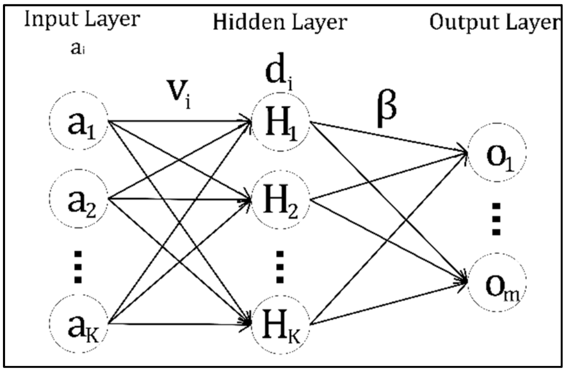

FIGURE 3. **Extreme learning machine input, hidden and output Layers.**

and preparing it for physical unit conversion. The components of this layer are the amplifiers, filters, and analog to digital converters.

2) COMMUNICATION LAYER

The data transfer from the monitoring area to the control room is managed by the communication layer. The data communication between the sensor and radio module is performed by the communication layer. The communication types are wireless, wired, and heterogeneous. In the monitoring area, nodes communicate by means of ZigBee, and the monitoring area controls the communication done by GSM, Ethernet, LoRa, or Wi-Fi.

C. KNOWLEDGE LAYER

The knowledge layer is responsible for storing and analyzing the collected data. For efficient monitoring of cold SC, the ambient conditions were sensed, stored, and analyzed. The cold SC based knowledge is maintained by this layer, which helps maintain the firmness grades of tomatoes by reducing environmental variations. The WOA-ELM based model applied for temperature prediction for tomato fruit during the cold SC.The variations in an object's temperature are proportional to the difference between the environmental temperature and the object's temperature, according to Newton's law of cooling [60], which can be represented by a differential equation as the temperature differences expressed as a function of time.

$$(\partial \mathrm{TEMP\_OBJECT})/\partial \mathrm{T} \propto \mathrm{TEMP\_OBJECT} - \mathrm{TEMP\_AMBIEN} \tag{1}$$

The solution to (1) shows the exponential deterioration of temperature differences over time. The flow of energy to and from an object is determined by the temperature difference between the ambient and the object [61]. The temperature prediction of the environment during the cold SC process reduces the risk of failure by alerting before temperature variations occur.

1) EXTREME LEARNING MACHINE (ELM)

The ELM is a Feed Forward Neural Network (FFNN) with faster convergence than the traditional methods. The ELM model is based on a tri-layer architecture with an input, hidden, and output layers, as illustrated by Fig. 3.

The K random samples (a_i, b_i) where a_i denotes the input and b_i represent the expected output and the predicted output value expression represented by o_j as given in (2) and v_i, d_i, $g(a)$, β_i and M represent the input weight, hidden bias, activation function, output weight and number of nodes of hidden layer respectively.

$$\sum_{I=1}^{K} B_I G(V_I.A_I + D_I) = O_J \tag{2}$$

The key goal of ELM is error reduction of the output to zero shown by (3).

$$\sum_{J=1}^{K} \|O_J - T_J\| = 0 \tag{3}$$

There exists v_i, d_i and β_i such that.

$$\sum_{I=1}^{K} B_I G(V_I.A_J + D_I)\, 0 = T_J, J = 1, 2, 3, \ldots K \tag{4}$$

The representation of equation 4 in matrix form is H β = T where H represents the hidden layers output as represented by (5).

$$H(V_1, \ldots, V_K, D_1, \ldots, D_K, A_1, \ldots, A_K) = \begin{bmatrix} G(V_1.A_1 + D_1) & \ldots & G(V_K.A_1 + D_K) \\ \vdots & \ldots & \vdots \\ G(V_1.A_N + D_1) & \ldots & G(V_K.A_N + D_K) \end{bmatrix}_{N\times K} \tag{5}$$

The output matrix is represented by H and weight matrix is represented by β as given in (6).

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_K^T \end{bmatrix}_{K\times M} \quad H = \begin{bmatrix} H_1^T \\ \vdots \\ H_K^T \end{bmatrix}_{K\times M} \tag{6}$$

During the training process of ELM, random generation of hidden bias and input weights and values is not changed, and output H is governed by (5).

2) WHALE OPTIMIZATION ALGORITHM (WOA)

The WOA is inspired by the Humpback Whale hunting approach. The hunting process of WOA is based on four stages: prey discovery, diving twelve meters deep in the sea, bubble-net feeding (creating the bubble-net around the prey in a spiral shape), and capturing the prey. The analysis of ELM for the performance evaluation shows input weights v and hidden biased d effect on the performance of ELM. The WOA is applied for the optimization of v and d in the presented study. The v and d optimization process consists of three stages, including encircling the prey, a bubble-net attack on the prey, and hunting the optimal prey.

Encircle the Prey: The prey's location is identified by the humpback whales, which encircle the prey. The prior optimal position is not available in the search space, and WOA reflects the present most excellent solution as the target prey. When the finest agent is appointed, other search agents update their locations with the most excellent search agent, and the behaviour is represented by (7) and (8).

$$\text{DIST} = |C \times \text{BESTP}(\text{T}) - \text{P}(\text{T})| \tag{7}$$

$$\text{P}(\text{T}+1) = \text{BESTP}(\text{T}) - \text{A.DIST} \tag{8}$$

where bestP is the position vector for the most excellent solution and P is the position vector. The coefficient vectors are represented by A and C, and the dot (.) shows the multiplication element by element of vectors. The iterations are represented by t. The (9) and (10) compute the values of coefficients A and C.

$$\text{A} = 2 \times \text{A.R} - \text{A} \tag{9}$$

$$\text{C} = 2.\text{R} \tag{10}$$

where the random vector with values from 0 to 1 denoted by r and the vector a decrease linearly from 2 to 0 based on iterations.

Bubble-net Attack: The bubble-net attack model is based on shrinking the encircle and updating the spiral position.

Shrinking the Encircle: The encircling is shrinking on the base of |A| as if |A| <1 then encircle shrinking done and the whales move toward the whale in current best position. The smaller value of |A| shows the smaller steps taken by whales and greater value of |A| shows the larger steps taken by whales.

Updating Spiral Position: The humpback whale from group of whales initially computes its gap from the optimal whale and goes along spiral path, the position update process represented by (11).

$$\text{P}(\text{T}+1) = \text{DIST}'.\text{E}^{\text{LB}}.\text{COS}(2\pi\text{L}) + \text{BESTP}(\text{T}) \tag{11}$$

where Dist′ is gap from separate whale to most excellent whale. The b is the constant and l is the arbitrary value from −1 to 1.

The location updated by the whale based on the spiral path and contraction path has a value of 0.5, as shown by equation 12.

$$\text{P}(\text{T}+1) = \begin{cases} \text{BESTP}(\text{T}) - \text{A.DIST} & \text{IF P} < 0.5 \\ \text{DIST}'.\text{E}^{\text{LB}}.\cos(2\pi\text{L}) + \text{BESTP}(\text{T}) & \text{IF P} \geq 0.5 \end{cases} \tag{12}$$

where p is a random value from 0 to 1. The humpback whales search for prey randomly using the bubble-net method.

Hunting the Optimal Prey: The humpback whales hunt for prey randomly conferring to location of each other. The global optimal solution achieved as the whales (search agents) are pushed away from each other according to value of |A| and current optimal search agent's position substituted by arbitrarily selected search agent and the behavior represented by (13) and (14).

$$\text{P}(\text{T}+1) = \text{P}_{\text{RAND}} - \text{A.DIST} \tag{13}$$

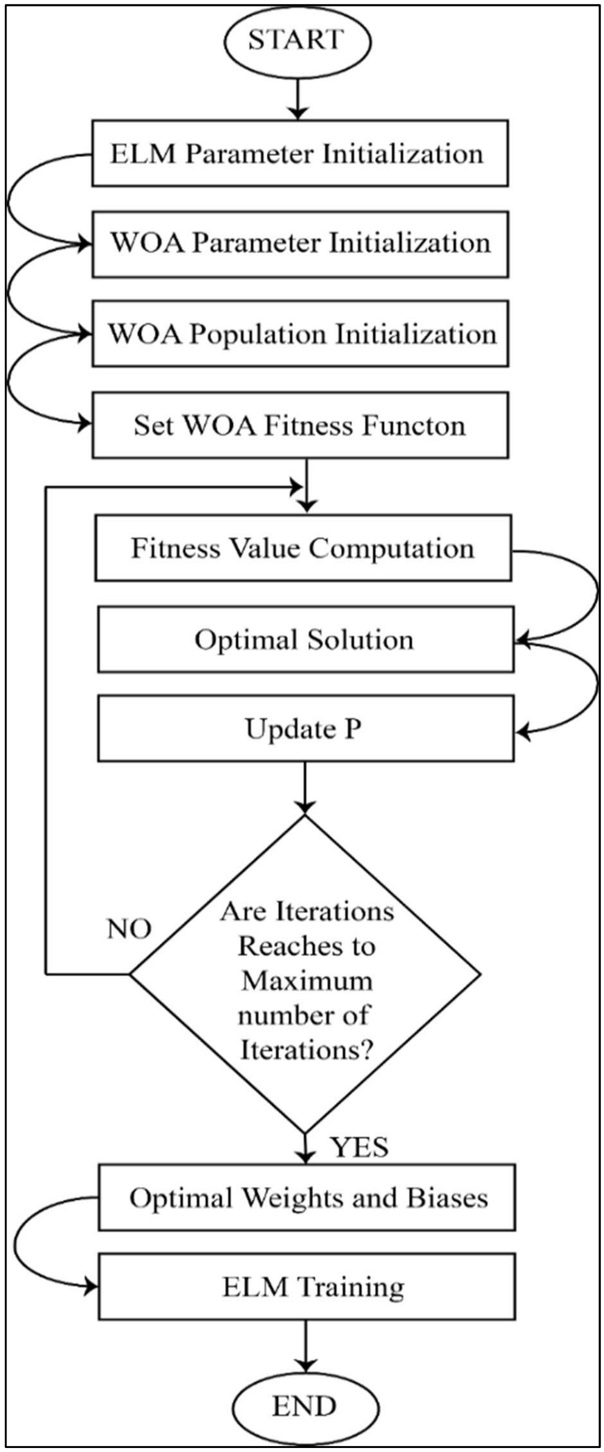

FIGURE 4. WOA base optimized ELM.

$$\text{DIST} = |\text{C.P}_{\text{RAND}} - \text{P}(\text{T})| \tag{14}$$

where P_{rand} represents the arbitrarily selected search agent.

3) WOA-ELM

The input weights and biases are randomly given to ELM, and due to randomization, the performance of ELM is

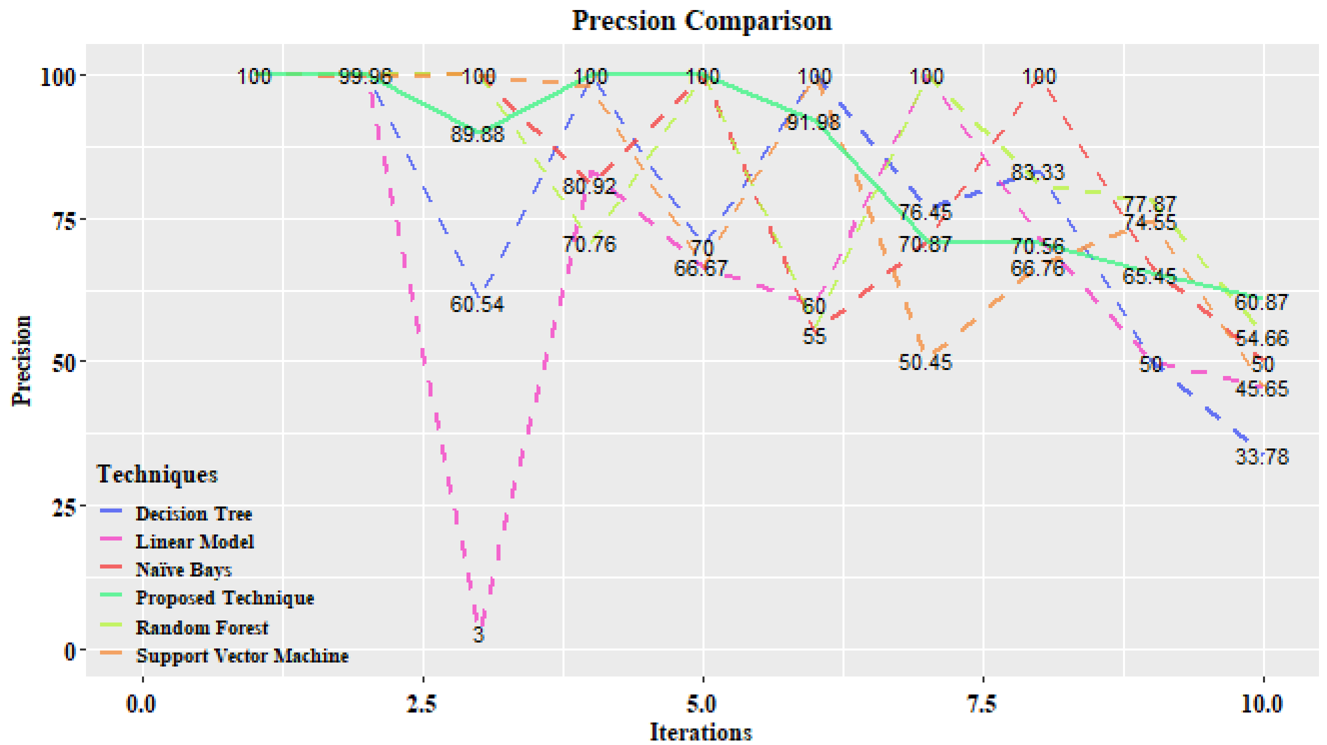

FIGURE 5. Precision comparison of proposed and other approaches.

compromised due to the lengthy training time and weak generalization ability.

The optimal selection of input weights and biases is done by means of WOA for ELM to increase the performance of ELM for temperature prediction. The algorithm of WOA-ELM is represented in Table 2. The flowchart of WOA-ELM visualized in Fig. 4.

D. SERVICE LAYER

This layer deals with the end users. The ambient conditions during the cold SC of tomato fruit are presented to the user through this layer.

IV. EXPERIMENTATION

Tomatoes are harvested from the field at an earlier stage of maturity and transported for storage. The tomatoes, which are a light red colour, are collected from the field for packing and transportation. The collected tomatoes are then packed for storage in boxes, and the boxes are shifted to the transportation vehicle for cold storage. The transportation vehicle is equipped with refrigeration devices and temperature-collecting devices, including sensors and microcontrollers. The vehicle used for the logistics of tomatoes reduced the vibration impact on the tomatoes during the cold SC process. The presented model is implemented in the logistic vehicle to reduce the failure of temperature control and improve the management of tomato logistics in the cold storage house. The tomatoes are supplied to the market from the cold storage house and require temperature management along with a longer route to market to improve the life of the tomatoes and reduce the loss to the stakeholders. The logistic process of transporting tomatoes from the field to the market is illustrated in Fig. 5.

The sensors set up at the logistics and cold storage houses provide the collected temperature and humidity data for the prediction. The WOA was applied to the collected data set to optimize the biases and input weights for improving the prediction of ELM. ELM is implemented with activation function sigmoid and 100 neurons in hidden layer. The whale population 110 is applied. The 28433 samples were collected from the logistic vehicle over the course of ten hours. The 22746 random samples are selected for the training set, and the test set consists of 5687 samples. The outcome of the presented model is evaluated using precision, recall, F1 measure, and accuracy metrics.

During the cold SC, ambient temperature collection is done by the temperature sensor. The DS18B20 and DHT11 temperature sensors are used for temperature monitoring during the cold SC of tomato fruit. DS18B20 digital sensor with one wire interface and operates with 3 to 5.5 volts with a temperature range of -55°C$\sim$ + 125°C (-67°F$\sim$ + 257°F) deviation ±2°C and -10°C$\sim$ + 85°C deviation ±0.5°C. The programable resolution of this sensor is 9 to 12 bits. DHT11 is used for sensing temperature and humidity. The operational voltage of DHT11 is 3.5 to 5.5 volts, the temperature range is 0°C to 50°C, and the humidity range is 20% to 90%. The

TABLE 2. WOA-ELM algorithm for temperature prediction.

```
Algorithm 1: Temperature prediction WOA-ELM
Input: Collected cold supply chain data
Output: ELM for prediction
BEGIN
Application of Newton's Law of cooling on sensed data
Training and Testing Data Preparation
ELM parameter setting
Set fitness function ROOT MEAN SQUARE ERROR between
actual and predictive value.
Initialize WOA population
Fitness computation for every search agent
bestP=selected best search agent initially
while(t<MaxT)
        for each search agent
                update constants: a, A, C, l, and p
                if(p<0.5)
                    if(A<1)
                        update position of agent by equation 7.
                    elseif(A≥1)
                        update position of agent by equation 12.
                    endif
                elseif(p≥0.5)
                    update position by equation 11.
                endif
        endfor
        compute fitness for every agent
        update bestP if other better one available
        t=t+1
endwhile
obtain the best biases for hidden layer and best input weights of
ELM by bestP
ELM train then test
END
```

programable resolution is 16 bits, the accuracy for temperature is $\pm1°C$, and the accuracy for humidity is $\pm1\%$.

The Arduino Uno is an ATmega328P microchip based open-source microcontroller developed by Arduino.cc. The board has six analogue input/output pins and fourteen digital input/output pins. The operational voltage is five volts, and the input voltage is 7 to 20 volts. Arduino IDE is used for programming and is connected to a USB type B cable. The RF433MHz is used as a gateway module for communication. The measuring range of the module is 105 dB, and the accuracy is $\pm$ 0.2 - $\pm$0.5.

V. RESULTS

The experimental results of the presented technique are described in this section. The prediction results evaluation was done by means of Precision (P), Recall (R), and F1-Measure (FM) accuracy.

A. ACCURACY ASSESSMENT

The accuracy assessment of the proposed approach is discussed in this section. The performance evaluation of the presented approach is performed with P, R, and FM. The P and R for the presented approach, Decision Tree (DT), Linear Model (LM), Naïve Bays (NB), Support Vector Machine (SVM), and Random Forest (RF), are computed and given

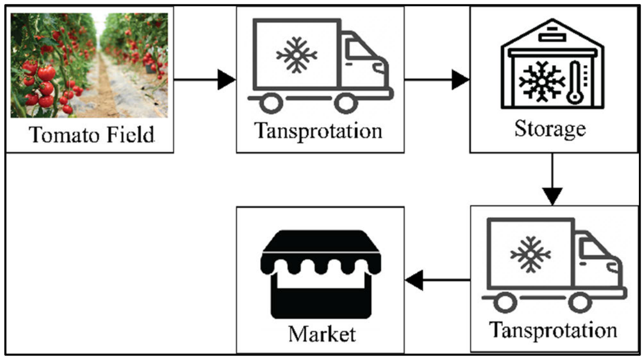

FIGURE 6. Operational visualization of cold supply chain.

by Tables 2 and 3. The precision criteria define how many temperature predictions are correct, and the recall criteria the how many temperature predictions are actually correct. The P, R, and FM are elaborated by (15), (16) and (17).

$$P = \text{True Positives}(\text{True Positives} + \text{False Positives}) \tag{15}$$

$$R = \text{True Positives}/(\text{True Positives} + \text{False Negatives}) \tag{16}$$

$$FM = 2\times P\times R/(P + R) \tag{17}$$

The P&R comparison of the presented model with NB, LM, DT, RM, and SVM is shown in figs 6 and 7. The proposed method shows higher precision than other approaches, which shows the higher performance of the presented model as depicted in Fig. 5. For ten iterations, the presented model got a mean average precision (MAP) of 84.957%, which is greater than other models as given in Table 3. The 67.972% MAP of LM shows deficient performance for predicting ambient temperature during the SC process. The RF has the second highest MAP of 83.977%, and the NB has the third highest MAP. The SVM got a higher MAP of 80.135%, and the fifth is DT with a 77.406% MAP for temperature prediction.

The recall rate comparison of the proposed model with Decision Tree, Linear Model, Naïve Bays, Random Forest, and Support Vector Machine verifies the outstanding performance of the presented approach. The Mean Average Recall (MAR) of the presented approach is 96%, which is better than the other approaches for ambient temperature predictions. The lowest MAR of the liner model shows deficient performance for prediction. After the presented method, the Random Forest has a MAR of 92%, which is higher than other methods except the proposed. The F1 measure comparison of the presented model and other state of the art approaches is illustrated by Fig. 8. The proposed approach has outstanding outcomes compared to the other algorithms. The results of the F1 measure for the proposed technique (NB, LM, DT, RF, and SVM) are shown in Table 5.

For ten iterations, the presented model showed higher results than the other models, which showed higher performance for ambient temperature prediction during the cold

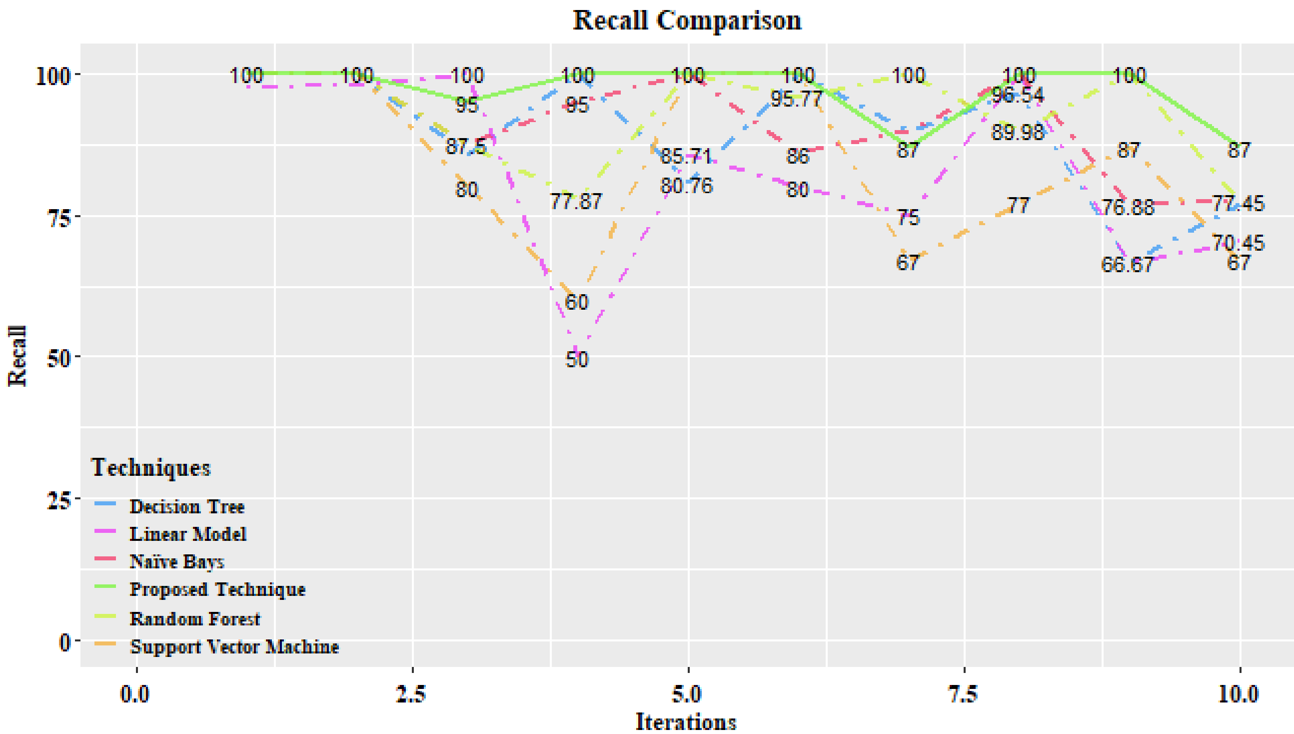

FIGURE 7. Recall comparison of proposed and other techniques.

TABLE 3. Precision comparison of proposed technique (PT) with NAÏVE BAYS (NB), Linear model (LM), decision tree (DT), random forest (RF) and support vector machine (SVM).

Sr.#	PT	NB	LM	DT	RF	SVM
1	100	100	99.98	100	99.98	100
2	99.96	99.96	99.57	99.96	99.96	99.42
3	89.88	100	3.09	60.54	100	100
4	100	80.92	83.33	100	70.76	98
5	100	100	66.67	70	100	66.67
6	91.98	55	60	100	55.89	100
7	70.87	70.87	100	76.45	100	50.45
8	70.56	100	71.43	83.33	80.65	66.76
9	65.45	66.67	50	50	77.87	74.55
10	60.87	50	45.65	33.78	54.66	45.5
Mean	84.957	82.342	67.972	77.406	83.977	80.135

TABLE 4. Recall comparison of proposed technique (PT) with NAÏVE BAYS (NB), Linear model (LM), decision tree (DT), random forest (RF) and support vector machine (SVM).

Sr.#	PT	NB	LM	DT	RF	SVM
1	100	100	97.35	100	100	100
2	100	100	98.02	100	100	100
3	95	87.5	100	85.71	87.5	80
4	100	95	50	100	77.87	60
5	100	100	85.71	80.76	100	100
6	100	86	80	100	95.77	100
7	87	90	75	90	100	67
8	100	100	100	96.54	89.98	77
9	100	76.88	66.67	66.67	100	87
10	87	77.45	70.45	77	77.43	67
Mean	96.9	91.283	82.32	89.668	92.855	83.8

SC. The accuracy and classification error of the proposed model are depicted in Fig. 9 and given in Table 4. The 99.83% accuracy verifies the outstanding performance of the proposed model for temperature prediction, rather than the NB 96.73%, LM 97.43%, DT 94.65%, RF 98.71%, and SVM 98.89%. The presented model had higher accuracy and the lowest classification error as compared to the NB, LM, DT, RF, and SVM models, as given in Table 6 and visualized in Fig. 9. The LM got the lowest accuracy and the highest classification error during the prediction of ambient temperature. The overall results elaborate on the outstanding performance of the proposed model for temperature prediction.

The accuracy and classification error of WOA-ELM and Mineblast- ELM is shown in Table 7 and 8.The twelve WOA-ELM models with remarkable results are selected and presented in Table 7. The presented approach shows outstanding results with 100 hidden units for ELM and 110 population size of WOA. The second remarkable results are obtained from model with 40 hidden units and 50 population size. The Mine Blast (MB) based ELM results are presented in Table 8. The results of WOA-ELM are better than MB-ELM which shows the poor selection of optimal parameters of ELM for temperature prediction. The MB-ELM model with 100 hidden units and 120 population size showed remarkable results

TABLE 5. F1 measure comparison of proposed technique (PT) with NAÏVE BAYS (NB), Linear model (LM), decision tree (DT), random forest (RF) and support vector machine (SVM).

Sr.#	PT	NB	LM	DT	RF	SVM
1	100.00	100.00	98.65	100.00	99.99	100.00
2	99.98	99.98	98.79	99.98	99.98	99.71
3	92.37	93.33	5.99	70.96	93.33	88.89
4	100.00	87.40	62.50	100.00	74.14	74.43
5	100.00	100.00	75.00	75.00	100.00	80.00
6	95.82	67.09	68.57	100.00	70.59	100.00
7	78.11	79.30	85.71	82.67	100.00	57.56
8	82.74	100.00	83.33	89.45	85.06	71.52
9	79.12	71.41	57.14	57.14	87.56	80.30
10	71.63	60.77	55.40	46.96	64.08	54.20

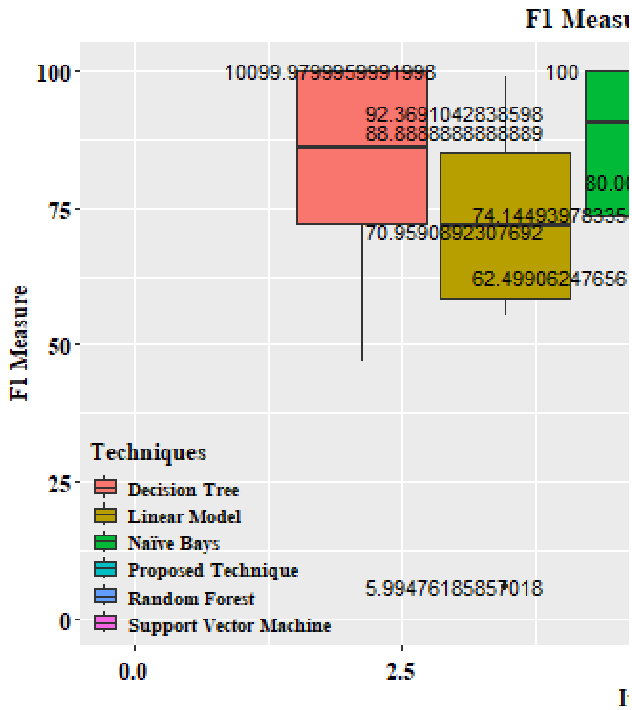

FIGURE 8. F1 measure comparison of proposed and other techniques.

TABLE 6. Accuracy and classification error comparison.

Algorithms	Accuracy	Classification Error
Proposed Technique	99.83	0.17
Naïve Bays	98.89	1.11
Linear Model	92.45	7.55
Decision Tree	94.65	5.35
Random Forest	98.71	1.29
Support Vector Machine	97.87	2.13
Proposed Technique	99.83	0.17
Naïve Bays	98.89	1.11
Linear Model	92.45	7.55
Decision Tree	94.65	5.35

TABLE 7. Proposed WOA-ELM results for 12 models.

Sr.#	Hidden Units	Population Size	Accuracy	Classification Error
1	10	140	32.11	67.89
2	30	60	33.02	66.98
3	30	80	59.01	40.99
4	30	90	49.05	50.95
5	40	50	**98.34**	1.66
6	40	60	60.66	39.34
7	40	140	49.09	50.91
8	90	20	35.08	64.92
9	90	30	37.11	62.89
10	100	110	**99.83**	0.17
11	100	120	33.38	66.62
12	100	150	67.50	32.5

TABLE 8. Proposed Mb-ELM results for 12 models.

Sr.#	Hidden Units	Population Size	Accuracy	Classification Error
1	10	140	28.13	71.87
2	30	60	8.13	91.87
3	30	80	28.14	71.86
4	30	90	10.11	89.89
5	40	50	37.34	62.66
6	40	60	33.07	66.93
7	40	140	49.68	50.32
8	90	20	49.19	50.81
9	90	30	**71.86**	28.14
10	100	110	28.13	71.87
11	100	120	**79.29**	20.71
12	100	150	51.68	48.32

as compared to other MB-ELM models but the WOA-ELM showed higher accuracy.

VI. DISCUSSION

The temperature is the main factor with a higher impact on the quality of fresh food, as reported in [45]. Extensive previous research discussed temperature monitoring during cold chain logistics, but the risk of temperature variation during logistics and cold storage is not addressed.

To address the research gap, this study introduces a WOA-ELM-based model for enhancing temperature prediction in the cold SC process while improving temperature control. The performance of the proposed model is higher than that of the NB, LM, DT, RF, and SVM, as shown in Tables 3, 4, and 6. The WOA-ELM shown higher accuracy as compared to MB-ELM. The initial theoretical contribution of this research study lies in utilizing parameters like tomato box temperature, humidity, and the temperature and humidity of the refrigerated truck for predicting temperature.

The previous research [42] did not consider all the main factors for temperature prediction during the cold SC process and obtained limited accuracy. The second theoretical contribution of this study is the implementation of WOA for temperature prediction during the cold SC. In preceding research works, WOA [35] has been applied for various purposes such as predicting wind speed [57], evaluating aging degree [52], tool wear prediction [58] and predicting superconductor temperature [59]. According to the best of

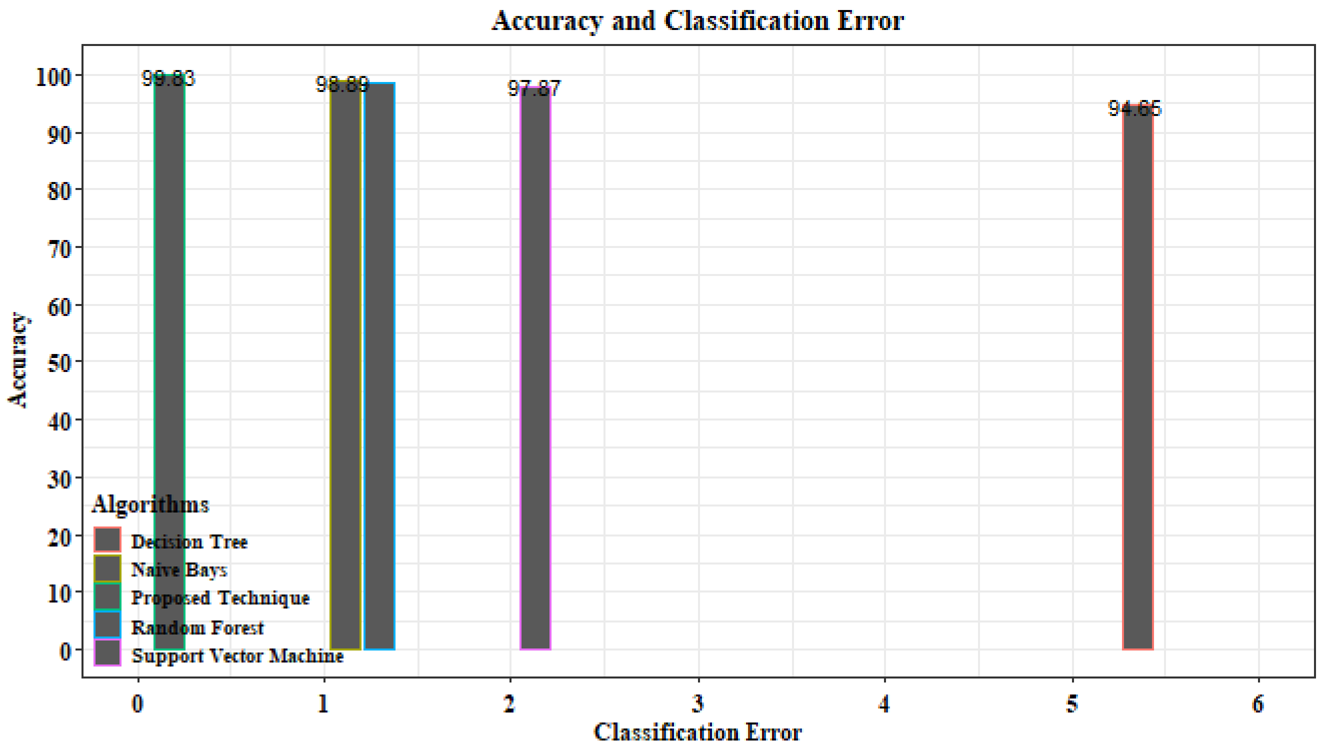

FIGURE 9. Accuracy and classification error.

our knowledge, the presented research study is first for the prediction of temperature during cold SC of tomatoes.

The third theoretical contribution is the layered model for an IoT based system for temperature prediction. The empirical contribution of this study is the analysis of the presented model and other state-of-the art approaches for evaluation. The presented model obtained outstanding performance for temperature prediction during the SC. The presented research is the first study for the prediction of the state of refrigeration during the cold SC. With the increase in hidden nodes and population size the computation time of proposed approach increases.

VII. LIMITATIONS

The limitations of the presented study are the limited state of the art models used. The parameters, including sunlight, oxygen, and vibrations, are not considered in the study. The firmness quality parameter of tomatoes is considered in this study.

VIII. CONCLUSION

In this research, an IoT based model is proposed for temperature prediction during the cold SC process for tomato fruit to maintain firmness during logistics. The Newton's law of colling used for accessing the temperature variation during the SC and whale optimization algorithm is fused with an extreme learning machine for optimized parameter selection for the temperature prediction with improved accuracy. The temperature sensors are used to collect data for analysis. The performance evaluation is done by using precision, recall, and F1 measures. The experimental results portray the best performance of the proposed techniques as compared to Decision Tree, Linear Model, Naïve Bays, Random Forest, Support Vector Machine and MB-ELM models.

The higher mean average precision of 84.957% and mean average recall of 96.9% show the outstanding performance of the proposed model for ambient temperature prediction for cold SC management to reduce tomato loss. The 99.83% accuracy of the presented model verifies the higher performance of the proposed model as compared to other models, and the error rate for temperature prediction is the lowest. The results verify the optimal selection of ELM parameters by WOA. In future studies, the presented system will be deployed in cold SC for other products with consideration of other respective parameters. The new biologically inspired algorithms, such as the artificial rabbit's optimization algorithm, the chaotic coot-inspired optimization algorithm, and the seagull optimization algorithm, can be used in future research and compared with this study for analysis.

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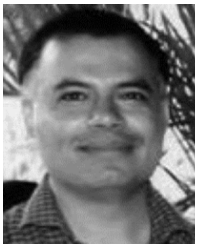

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