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An IoT-Based Real-Time Intelligent Monitoring and Notification System of Cold Storage

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ABSTRACT The intake of the perishable fruits and vegetables (FVs) in the human diet can contribute to reduce the risk of some chronic diseases. But unfortunately, FVs loss rate is high among all the food produced annually and occurs at storage stage of post-harvest life cycle. One of the key factors contributing to this high loss rate is inability to gauge vital ambient environmental parameters in cold storage. The existing monitoring solutions about cold storage are limited to only gauge temperature, relative humidity and ignore other vital ambient environmental parameters such as luminosity and concentration of gases. This is a critical issue that needs to be addressed to overcome the loss rate of FVs. This paper presents a real-time intelligent monitoring and notification system (RT-IMNS) banked on an Internet of Things (IoT)-enabled approach for real-time monitoring of temperature, relative humidity, luminosity and concentration of gas in cold storage and notifies the personnel on exceeding of dangerous limits of these parameters. Moreover, decision support is implemented in the RT-IMNS using Artificial Neural Network (ANN) with forward propagation to classify the status of commodity into one of three classes i.e. good, unsatisfactory or alarming. The proposed prediction model outperforms Compress Sending (CS), Adaptive Naïve Bayes (ANB), Extreme Gradient Boosting (XGBoost) and Data Mining (DM) with respect to forecasting accuracy. We achieved 99% accuracy using forward propagation neural network model while existing models such as CS, ANB, XGBoost, DM achieved 95.60%, 87.50%, 93.59%, 90% accuracy respectively. Moreover, proposed approach achieved 100% precision, 100% recall, 100% F1-score for good class is achieved, for unsatisfactory class precision is 98%, recall is 99%, F1-score is 98% and for alarming class precision is 100%, recall is 98% and F1-score is 99%.

INDEX TERMS ANN, cold storage, IoT, FVs.

I. INTRODUCTION

According to FAO (Food and Agriculture Organization), 1.3 billions of tons per year food loss is reported which represents 33% of the total production [1]. The food demand is continuously increasing and could reach about 150-170% of the current demand by 2050 [2]. Moreover, according to an estimate of World Health Organization (WHO), approximately 1.7 million deaths per year around the globe are associated with low intake of FVs. The WHO recommends a minimum intake of 400g FVs per day [3] which helps to reduce risk of diseases such as diabetes, certain cancer, respiratory conditions and cardiovascular disease (CVD) [4]. While the loss rate of FVs(45%) is high among all other foods including meat(20%), oil seeds (20%), diary(20%),cereals(30%), fish and sea-food(35%) [5]. The loss of FVs which occur at storage stage is 10% that is higher than all other stages [6] includes harvesting, storage, processing and distribution of post-harvest life cycle [7]. These convincing evidences indicate that a critical measure should be immediately taken to reduce the loss of perishable products like FVs. To overcome the loss of perishable FVs, it is vital to monitor ambient environmental parameters that affect the quality of FVs. Traditionally, low temperature is considered as primary factor in cold storage to slow down the ripening process of FVs that does not stop even after picking and continues up to over-ripe or rot of FVs. It causes postharvest pathogens like bacteria, fungi etc. that ultimately reduce the quality of FVs and results into loss of FVs. Although, except temperature [8] and relative humidity[9], there are many substantial environmental parameters such as, concentration of gases (CO_2 [10, 11], O_2, C_2H_4 [12]), light intensity [13], [14], dust that affect

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TABLE 1. A comparative analysis of the existing cold supply chain monitoring solutions.

Work Year	Technology	Purpose	Limitations							
			Tem.	Hum.	LI	CO2	DS	AP	Expensive	Notify
[24]2010	RFID, decision Rule base	To reduce the transportation losses of perishable products	✓	✓	×	×	✓	×	✓	✓
[25]2011	Linear model	To manage food quality	✓	×	×	×	✓	×	✓	×
[26]2014	WSN and Clustering	To improve quality of perishable food through monitoring	✓	×	×	×	✓	×	✓	×
[27]2015	RFID, WSN	To monitor quality of refrigerated fruit storage	✓	×	×	×	×	×	✓	×
[28]2016	WSN,CS	To monitor aquatic product in cold chain logistics	✓	×	×	×	×	×	✓	×
[29]2016	RFID and sensors	To monitor dairy products logistics	✓	×	×	×	×	×	✓	×
[30]2017	IoT-based, Fuzzy Logic	To assure the quality of ESPs during cargo	✓	✓	×	×	✓	×	✓	×
[31]2017	IoT-based, Rule mining	To find food safety for a sustainable food supply chain	✓	×	×	×	✓	×	✓	✓
[32]2017	IoT-based, Clustering	To real-time monitor perishable food supply chain	✓	✓	×	×	✓	✓	×	✓
[33]2018	IoT-based, Adaptive Naïve Base	IoT-based monitoring to protect food from spoilage	✓	✓	×	×	✓	×	×	×
[34]2018	NN	To make temperature predictions of perishable food	✓	×	×	×	✓	×	✓	×
[35]2019	IoT-based, Fuzzy Logic	IoT-based food traceability	✓	✓	×	×	✓	×	×	✓
[36]2020	RFID, XGBoost	Traceability of perishable food	✓	✓	×	×	×	×	×	×
[37]2020	WSN, SVM and K-means	To maintain frozen shellfish quality in cold storage	✓	✓	×	✓	✓	×	×	×
Proposed Study	IoT-based, FPNN	To overcome the loss of FVs in cold storage	✓	✓	✓	✓	✓	✓	✓	✓

Remarks: WSN stands for wireless sensor network, RFID stands for radio frequency identification, CS stands for compress sending, SVM stands for support vector machine, Temp stands for temperature, Hum. stands for humidity, LI stands for light intensity, DS stands for decision support, AP stands android application, ESPs stands for environmentally sensitive products.

the quality of FVs in cold storage. All these environmental parameters excluding temperature and relative humidity are ignored in existing cold storage of developing countries that cause high loss rate of FVs. Traditional cold storage gauges only temperature, relative humidity and ignores all other environmental parameters that contribute to uplift the shelf-life of FVs ultimately reduce the high loss rate of FVs. Henceforth, it is vital to address this issue and a critical measure is needed to reduce the loss of perishable FVs in cold storage through real-time monitoring of vital environmental parameters such as temperature, relative humidity, CO2 [15] and light intensity [16]. The existing studies about cold supply chain that bank on an IoT-based approach and prediction model are illustrated in Table 1 and having following challenges.

-Previous cold supply chain monitoring solutions remain limited to gauge only two environmental parameters i.e. temperature and relative humidity. Furthermore, results are analyzed on the basis of only two parameters.

-Previous cold supply chain monitoring solutions ignore other important environmental parameters such as luminosity and concentration of gases that can contribute to reduce the loss rate of perishable FVs.

-Previous cold supply chain monitoring solutions based on expensive technology that is not feasible for small and medium-sized enterprises.

-Previous cold supply chain monitoring solutions do not have any mechanism to intimate personnel in case of dangerous limits of environmental parameters.

-Previous cold supply chain monitoring solutions do not provide support of Android App for remote monitoring.

-Previous cold supply chain monitoring solutions gauge temperature at only one place inside a cold storage using single sensor that is insufficient to predict status of the commodity.

To maintain the quality of perishable products from production to consumption, cold storage is used as an effective strategy [17], [18]. Here, our main concern is to perform real time monitoring of environmental parameters inside cold storage to reduce the loss of perishable product like FVs and also intimate personnel. This paper presents an IoT-enabled approach for real-time intelligent monitoring and notification of environmental parameters such as ambient temperature, relative humidity, light intensity and concentration of gas in cold. We applied ANN model with forward propagation for analysis and interpretation of commodity status on the basis of gauged environmental parameters. The proposed RT-IMNS exhibits features given as follows.

-Our proposed system used cost-effective hardware components which ultimately provide an affordable solution for small and medium-size enterprises.

-Our proposed system gauged four vital ambient environmental parameters and analyzed results on the basis of gauged parameters.

- Our proposed system provides support of Android App for remote monitoring and personnel can check the status of commodity at anytime from anywhere.

-Our proposed system also sends an automatic notification to personnel on dangerous limits of these parameters which contribute to take timely necessary action to mitigate the loss of FVs.

-Our proposed system used forward propagation neural network model with softmax activation function to efficiently perform multi-classification about commodity status.

-Our proposed solution gauged ambient environmental parameters at multiple places inside cold storage using multiple sensing modules to efficiently predict the status of commodity.

IoT is becoming a promising technology due to its cutting-edge fusion of sensor techniques, predictive analytics and efficient wireless-connectivity [19]. There are many IoT applications including environmental monitoring, augmented mapping and assisted driving are included in current applications of transportation, logistics domain [20] and manufacturing [21]. Therefore, it indicates that real-time monitoring of food supply chain is feasible in IoT platform [22], [23].

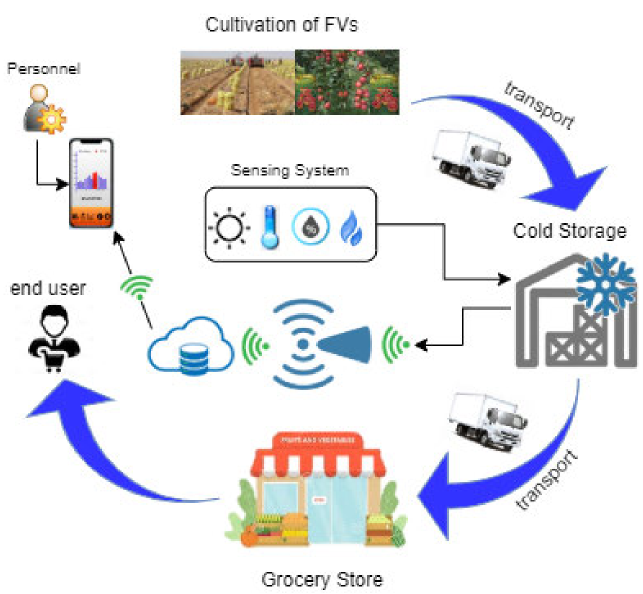

FIGURE 1. The supply chain of FVs and RT-IMNS.

The working of RT-IMNS in supply chain of FVs is represented in Figure 1. The transportation of FVs is performed immediately after cultivation, FVs are placed in cold storage where commodities keep for short or long period and then transfer to grocery store from where consumer takes it. In the presented approach, sensing system of RT-IMNS is mounted in cold storage that gauges real-time environmental parameters. Using ESP-WROOM-32, these values are sent to cloud database where these values will be stored. A personnel can monitor these environmental parameters and also check the status of commodity predicted by prediction model at anytime from anywhere using RTIMNS android app. The physical presence of personnel is not required in cold storage as traditional approaches require. Henceforth, it become easy to take time necessarily action due to automatic real-time monitoring of environmental parameters in cold storage.

To address the deficiencies of existing monitoring solutions about cold storage, we have proposed the following research questions (RQ).

RQ1: What is the role of luminosity and concentration of gas on commodity status in cold storage?

RQ2: How to reduce the loss rate of perishable commodity in cold storage?

RQ3: How to facilitate personnel to take timely necessary action according to commodity status in cold storage?

We have formulated research objectives (RO) to address the research questions about the proposed study which are described herein.

RO1: To find the role of luminosity and concentration of gas on commodity status in cold storage.

RO2: To develop a real-time monitoring and notification system of cold storage which reduces the loss rate of perishable commodity in cold storage.

RO3: To develop an android application for personnel to take timely necessary action according to commodity status in cold storage.

The rest of the paper is structured in five main sections. The second section illustrates the literature review regarding IoT and cold storage. The third section of the article describes the architecture of proposed real-time automatic monitoring and notification system about cold storage. The fourth section contains the implementation details. The experimental results are described in fifth section. The last section of the article comprises of conclusion and future development perspectives respectively.

II. STATE OF THE ART

The quality of perishable products like FVs is decreasing from farm- to- fork ultimately, escalates the loss rate of FVs. It is of utmost importance to maintain the quality of FVs through proper monitoring that will extend the shelf-life of these products. Traditionally, temperature is an atomic factor that is monitored in cold storage and all other environmental factors such as humidity, concentration of gases, light and dust particles are totally ignored. Moreover, there is no mechanism to send an alert message to personnel in case of dangerous limits of environmental parameters. Therefore, It is required to pay attention in a cost-efficient manner regarding real-time monitoring and notification about environmental parameters in cold storage ultimately impact on morality rate, food hunger, food borne illness, loss of food quality and integrity. According to my best knowledge, a lot of work has been done regarding transportation, retail distribution and packing in food supply chain illustrated in this section. But there is a research gap regarding real-time monitoring of environmental parameters in cold storage and researcher's attention is required regarding this perspective to mitigate the loss of FVs in cold storage.

The contribution of the researchers regarding real-time monitoring of factors that affects the quality of FVs in cold storage is described herein. Moreover, a comparative analysis of the existing studies about monitoring of cold supply chain is illustrated in Table 1 that describes the used technology, purpose and limitations includes the gauge parameters(temperature, humidity, light intensity, CO2), decision support, Android App, expensiveness and notification.

A RFID-based approach was presented to reduce the transportation losses of perishable products. A rule-based decision support system was proposed to generate warning on exceed the safety limits of temperature and humidity levels [24]. An optimization model base approach was presented to manage the quality of food during production and distribution stage of supply chain by considering only temperature [25]. A temperature management based method was presented to improve the quality and quantity of perishable commodities in food supply chain. In the presented approach, three methods were employed named centroid, clustering and weigh-centroid to define the optimal target temperature. The authors performed an experiment using wireless sensor network for monitoring the optimal temperature of multiple commodities having minimal impact[26]. A combination of two wireless technologies RFID and WSN had combined to monitor the temperature of refrigerated fruits storage. The authors assessed the effect of sensor housing in wireless devices for monitoring of temperature and big data management, versatility and polyvalence. However, in many cases commercial potential of these technologies cannot be realized due to its cost [27]. A temperature monitoring system for frozen and chilled aquatic product in cold chain logistics was presented based on wireless sensor network (WSN) for data acquisition integrated with compress sending (CS) to improve the data transmission efficiency. The presented paper described the compress model comprised of sparse-sampling, data reconstruction and shelf-life prediction [28].

A traceability system based on RFID and sensors technology was presented to monitor dairy products logistics. The presented approach aimed to improve the logistics decisions using real-time monitoring of dairy products in food supply chains [29].

A cargo monitoring system was presented to monitor the environmental change of environmentally sensitive products (ESPs) in order to ensure their quality in cold chain environment. The authors employed WSN together with fuzzy logic and case-based reasoning practices to determine the storage conditions about ESPs. The presented approach basically focused on temperature and humidity monitoring of ESPs to assure the quality during cargo [30].

A pre-warning system based on data mining presented for food safety in supply chain. The presented system is based on rule mining and IoT technology to monitor food products and find food safety risk in advance [31].

A smart phone-based approach was presented for real-time monitoring of food supply chain. The presented approach was supported with an Android App used to monitor temperature, humidity, GPS and image data using smart phone sensors. The sensors data was stored in MongoDB and clustering technique was employed to find outlier data. The authors claimed to handle massive data efficiently on increase of sensors and clients [32]. An IoT-based system presented for food monitoring and adaptive naïve base model was used to make prediction about food by measuring temperature and humidity [33]. A neural network based approach was presented to predict the temperature of perishable food in the supply chain. The presented approach leveraged the theoretical foundation of a physical heat transfer model to develop a neural network model in order to predict the temperature distribution of perishable food inside a pallet [34]. A perishable food shelf-life management approach was presented based on IoT, fuzzy logic modeling which contributes to handle perishable food throughout the entire supply chain. In this approach, data acquisition was performed in cost-effective manner. The change in environment was considered during entire supply chain to manage the shelf-life of perishable food [35]. A perishable food traceability system based on RFID was proposed by utilizing IoT and machine learning models. The machine learning models were employed to find the direction of passive RFID tags during shipment. The presented system helped customer and managers by providing real-time product information and history of gauged parameters i.e. temperature and humidity [36]. An intelligent IoT- based quality monitoring system was presented for vacuum-packed food. The presented approach evaluated the quality of packed product on the basis of monitored values of temperature, humidity and gas. The presented approach did not comprise of decision support system and only works for vacuum-packed food for home users [38]. A multi-sensors block-chain based monitoring approach was presented to maintain the quality of frozen shellfish in cold storage. A SVM and K-means based algorithm used to evaluate the quality loss of shellfish in cold storage [37].

III. MATERIAL AND METHODS

In order to reduce the loss of perishable FVs, a cost- effective IoT-based solution is presented in this paper that automatically monitors real-time environmental parameters like ambient temperature, relative humidity, light intensity and concentration of CO2. These real-time values are stored on Firebase database. After retrieving data from Firebase, ANN classifier is applied to predict the status of perishable FVs into three classes i.e. good, unsatisfactory or alarming. An automatic notification will be sent to personnel on unsatisfactory or alarming status of commodity for timely necessary action. Moreover, an android app is also developed which is used to monitors real-time environmental parameters at anytime from anywhere but also has decision support to predict the status of a commodity on the basis of gauged real-time parameters. The simulation work is performed using python and scikit-learn package [39], [40].

The proposed system consists of sensing module, wireless communication technology, status prediction module and Android App module as shown in the block diagram of RT-IMNS in Figure 2.

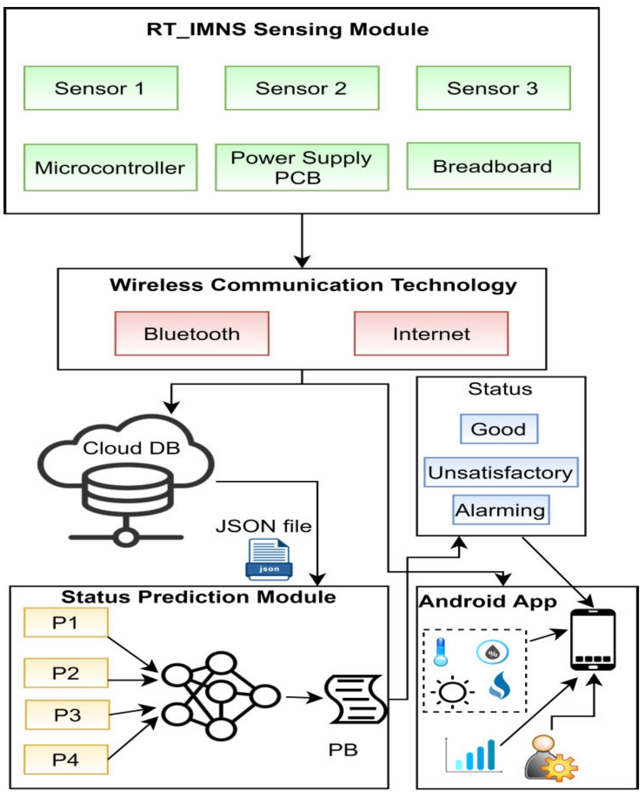

FIGURE 2. **Block diagram of RT-IMNS of cold storage.**

These modules interact with each other by using wireless communication technology to ensure seamless working of the proposed RT-IMNS of cold storage. The RT-IMNS sensing module comprises of sensors, microcontroller, power supply PCB and bread board to gauge the environmental parameters such as temperature, relative humidity, light intensity and concentration of CO2. The wireless communication technologies ensure connectivity and communication. It comprises of internet and Bluetooth. The RT-IMNS sensing module ensures the real-time environmental data transmission from hardware to cloud for storage using these communication technologies. The real-time gauge data is stored in Firebase database on cloud and this data is exported as JSON file for further processing done by status prediction module.

The next module is status prediction that contains prediction model for decision making about commodity status using real-time environmental parameters exported as json file from firebase database. The Artificial Neural Network(ANN) prediction model with forward propagation is implemented in python using TensorFlow [41]. The status prediction module generates protobuf file that is imported in android app. It performs inference and predicts status of the commodity. A personnel can do real-time monitoring of environmental parameters in cold storage by using an android application. Android App also facilitates the personnel to check the status of commodity predicted by decision model and an automatic notification is also sent to personnel on dangerous limits of environmental parameters. Therefore, it becomes possible for personnel to take timely necessary action in order to mitigate the loss of perishable FVs in cold storage. Moreover, graph of gauged environmental parameters can also be monitored on Android App which is shown in result section.

A. USED ALGORITHMS

The storage process of commodity in cold storage is crucial because any negligence in monitoring of environmental parameters such as temperature, relative humidity, concentration of CO2 and light intensity result into huge loss of perishable commodity. Therefore, a real-time monitoring of perishable commodity in cold storage is required to overcome the loss. The proposed approach presents an intelligent real-time monitoring and notification system of cold storage that contributes to reduce the loss of perishable commodity. For working of proposed RT-IMNS, we have designed algorithms based on prediction model. Here, we describe all these three algorithms. The proposed approach works according to these three algorithms.

For the working of presented RT-IMNS, we have used three algorithms. First algorithm is used for data acquisition using sensing system of RT-IMNS. At first step of algorithm 1, it is necessary to set Wi-Fi connection and if it is established then call *Server_Firebase_Host*.

After reading data from sensors, gauged data is placed into JSON file and update *rtimns-FirebaseNode*. In the second algorithm, data processing is performed and after that a protobuf file of frozen and inference model is generated which will further employed in algorithm3 to accomplish the working of Android App Moreover, third algorithm is developed to describe the working of Android App which is developed in Android Studio. The proposed RT-IMNS system works on the basis of the proposed algorithms1, algorithm2 and algorithm3.

B. USED HARDWARE

The embedded sensing devices are employed in IoT based systems to efficiently and economically gauge real-time environmental parameters in supply chain [42]–[47]. A sensor is a device that can sense change in its surrounding environment [48], [49]. To implement the proposed RT-IMNS, we used different sensors and hardware components described in Table 2. The real-time environmental parameters of commodity in cold storage are gauged

Algorithm 1 Data Acquisition

```
Set WiFi_connection
if WiFi_status == connected then
    Call Server_Firebase_Host
    while WiFi == connected do
        Read Sensors_Data
        Set JSON(Sensors_Data)
        Update rtimns_FirebaseNode
    end while
else
    WiFi connection failed
end if
```

Algorithm 2 Data_Processing

```
Set WiFi_connection
if WiFi_status == connected then
    Call Firebase_database_connection
    if Connection_established == True then
        rtimns = Read rtimns_Firebase_database
        dataset = Call Normalize(rtimns)
        traindata,testdata = Call Train_Test_Split(dataset)
        protobuf_file = Apply ANN_Classifier(traindata)
    else
        Connection_failed
    end if
else
    WiFi connection failed
end if
return protobuf_file
```

Algorithm 3 Android App Working

```
Inference_model = CALL Data_Processing()
if Mobile_WiFi == connected then
    Call rtimns_database_connection
    if Connection_established == True then
        values = Read rtimns_FirebaseNode
        Status = Inference_model(values)
        Display Status on Mobile Screen
        if Status == 0 OR Status ==2 then
            Notification generated
        end if
    else
        Connection failed
    end if
else
    WiFi setup error
end if
```

using sensor based circuit that sends these values to firebase database and further prediction model is applied on gauge data to evaluate the status of the commodity. The devices described in Table 2 communicate with ESP-32 module which is intended to received data from these devices and further transmit to firebase using internet. The sensing system of RT-IMNS contains microprocessor based system ESP32-WROOM-32(ESP-WROOM-32) with the built-in support of Wi-Fi, Bluetooth and BLE communication protocol.

It is out-of-box proficient to communicate by means of Wi-Fi protocol [50].

ESP-WROOM-32 is suitable for application of an IoT device due to its dual-core implementation for wireless communication and also facilitates data processing [51], [52]. ESP-WROOM-32 module is embedded on power supply PCB board. ESP-WROOM-32 and power supply PCB specifications and descriptions are given in Table 2. The sensing system contains a temperature sensor DHT-22 to gauge temperature and humidity in cold storage. It is a cost- effective digital sensor that can measure surrounding air and further split out digital signal on data pin by using a capacitive humidity sensor and thermistor. The concentration of gas is also an important environmental parameter that needs to be measured and affects the shelf-life of FVs in cold storage. We have used MQ-135 sensor to measure the concentration of CO2 and its description is given in Table 2. It is cost-effective sensor and can also measure NH3, NOx, Benzene and smoke.

To gauge the light intensity, light sensing module is used in proposed RT-IMNS. Light Dependent Resistor (LDR) module is photosensitive resistor module generally use to detect the ambient bright and intensity of light. It has both analog and digital pin labeled as A0 and D0. The complete description of light sensing module is given in Table 2.

Moreover, we write a program in c language using Arduino IDE to connect all sensors to ESP32-WROOM-32 and connectivity of ESP32-WROOM to Firebase. The gauged values of environmental parameters such as temperature, relative humidity, light intensity and concentration of CO2 are stored as JSON node in firebase database that will be further used for data processing.

C. SIGNIFICANCE OF ENVIRONMENTAL PARAMETERS

The loss of perishable FVs occur at storage stage due to inability to gauge multiple vital environmental parameters such as temperature, relative humidity, light intensity and concentration of CO2. In presented approach, we have chosen multiple environmental parameters due to their vital effect on quality of perishable FVs i.e. illustrated herein.

1) TEMPERATURE

The respiratory process of perishable FVs does not stop even after being unplugged from ''mother- -earth'' and continues up to over-ripe and rot. Temperature is a primary and most important factor among all other environmental factors [53] to slow down the respiratory process of FVs in cold storage [8].

The fluctuating temperature in cold storage results in loss of perishable FVs. Henceforth, real-time monitoring of temperature is required to slow down the ripening process of perishable commodities like FVs and prevents decay of these commodities after harvest [54], [55].

TABLE 2. Specifications of the sensing system.

Component	Specifications	Descriptions
ESP-WROOM-32	Wi-Fi Certification	Wi-Fi Alliance
	Bluetooth certification	BQB
	Reliability	HTOL/HTSL/uHAST/TCT/ESD2.4 GHz ~
	Wi-Fi Frequency range	2.5 GHz
	Integrated SPI flash	4 MB
	Operating voltage	3.0 V ~ 3.6 V
	Operating current	Average: 80 mA
	Operating temperature	range –40 °C ~ +85 °C
	Security	IEEE 802.11 including WFA, WPA/WPA2 and WAPI
Power supply PCB board	Development Board	Yes
DHT-22	Type	Capacitive
	Stability	Long term
	Operating Voltage	3.3-5.5V
	Temperature Measuring range	-40-80 °C
	Humidity Measuring range	0; 99.9%RH
MQ-135	Operating Voltage	+5V
	Analog output voltage	0-5V
	Digital output voltage	0V or 5V(TTL Logic)
	Operating Voltage	3.3-5.5VDC
LDR	Output	A0&D0
	Operating current	15milli amps
	Sensitivity	Adjustable
	PCB size	3.2cm×1.4cm

2) RELATIVE HUMIDITY

Relative humidity is another substantial environmental parameter except temperature which affects the quality of perishable commodities in cold storage [9]. The water diffusion of perishable food closely related to relative humidity [56]. Therefore, to keep well perishable commodities, it is required to gauge temperature as well as relative humidity.

3) LIGHT INTENSITY

Light intensity is one of the vital environmental factors which is totally ignored in existing monitoring solutions of cold storage. We have selected to gauge light intensity [13], [14] which will also influence on respiratory process of commodities ultimately mitigate the chance of over-ripe or rot of commodities.

4) CO2

The concentration of carbon dioxide (CO2) is used to reflect the speed of metabolic activities [57]. Therefore, it is also vital to gauge concentration of CO2 in cold storage to predict the quality of perishable commodities according to the rate of metabolic activities. Moreover, carbon dioxide concentration strongly affects food shelf-life. [58].

D. USED ANN MODEL FOR IoT-BASED APPROACH

We used forward propagation neural network to predict commodity status on the basis of environmental parameters gauged through sensing system of proposed RT-IMNS. Although, different machine learning and deep learning algorithms such as Decision Tree (DT), Support Vector Machine (SVM), Random Forest (RF), Recurrent Neural Network (RNN), Convolutional Neural Network (CNN) respectively that can be used to solve classification problem. According to the problem scenario, researchers applied different classification techniques. In presented approach, we used forward propagation neural network that is most widely used ANN architecture due to the following reasons [59]–[61].

1) ANN is suitable for non-linear problems because it has ability to learn and model non-linear and complex relationship.
2) We selected ANN due to its flexibility as new features can be added by increasing training data size and in case of any change no extra configuration is required.
3) One important reason to choose ANN is its ability to outperform over other techniques due to improvement in performance can be accomplished by increasing training data size.

Artificial neural network is a computational model inspired by biological neural networks of the brain due to its function and structure. A biological neuron contains three parts i.e. dendrites, axon and cell body. The biological neuron structure is shown in Figure 3 where information is received at dendrites as input signal, processed at cell body and provided to axon as output [60].

Similar to biological neuron, in ANN, there are number of nonlinear processing units called artificial neuron

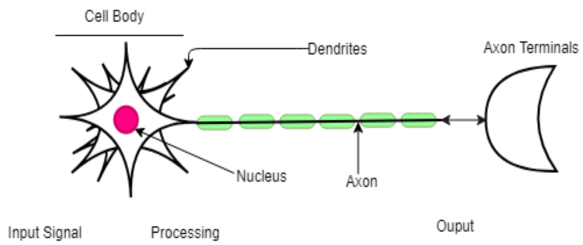

FIGURE 3. Basic structure of biological neuron.

where inputs are received. These neurons are interconnected through weights. By adjusting weights, ANN can learn a task. Each input ($I_1, I_2, I_3 \ldots I_n$) is multiplied by weight (W_1, W_2, $W_3 \ldots W_b$) and summation of all weighted inputs and bias is performed by a neuron j. After that an activation function processed the summary of previous weighted contributions and bias and delivered the output Y.

The mathematical description of the ANN can be understood using equation (1) [62]–[64] and it is also shown in Figure 4.

$$y = f\left(\sum_{j=1}^{n} I_j W_j + b\right) \tag{1}$$

There are many types of neural network activation functions such as *Sigmoid, linear, Gaussian, exponential, Tanh, Softmax* etc. that can be chosen according to problem scenario [65]. Generally, *Softmax* activation function is used in deep learning to return class probabilities for prediction purpose on the output layer [66]. We have used softmax activation for the last layer due to its ability to handle multi-classification problem efficiently [65], [67] as in our proposed solution have four input features and three outputs for target. The softmax activation function returns the exponential of one specific input i.e. x_i to the summation of exponential of all inputs as illustrated in Equation 2 [68], [69]. The x represents the input, denotes the exponential and j ranges from 0 to n as illustrates in equation (2).

$$f(x_i) = \frac{e^{x_i}}{\sum_j^n e^{x_j}} \tag{2}$$

In proposed approach, we have employed the forward propagation neural network to address the supervised learning problem. i.e. data set contains all possible values of environment parameters as input data along with their truth values. According to pattern of input data set, neural network learns and could provide desired output class of test dataset that contains only input data excluding truth values. There are two steps of ANN learning i.e. Forward Propagation(FP) and Back Propagation(BP) [70], [71]. In presented approach, forward propagation developed by Agatonovic-Kustrin and Beresford has been used. A forward propagation neural network is neural network with layered architecture comprises of layers named, input layer, hidden layer and output layer respectively [72]–[74] as shown in Figure 5. The information is only forward between these layers using forward propagation neural network architecture and there is no feedback information [75]. We have developed a small neural network with only a single layer having ten neurons because it gives accurate prediction possibly the evolution of the environmental parameters inside cold storage is relatively smooth and contains few local peaks. Moreover, there are fewer weights in a small neural network to estimate from training data ultimately proves its practical identifiability and also uplift better generalization ability of the neural network.

We used FP neural network to classify the status of commodity in cold storage. It is a multi-layer feedforward network with an input layer, one hidden layer and an output layer.

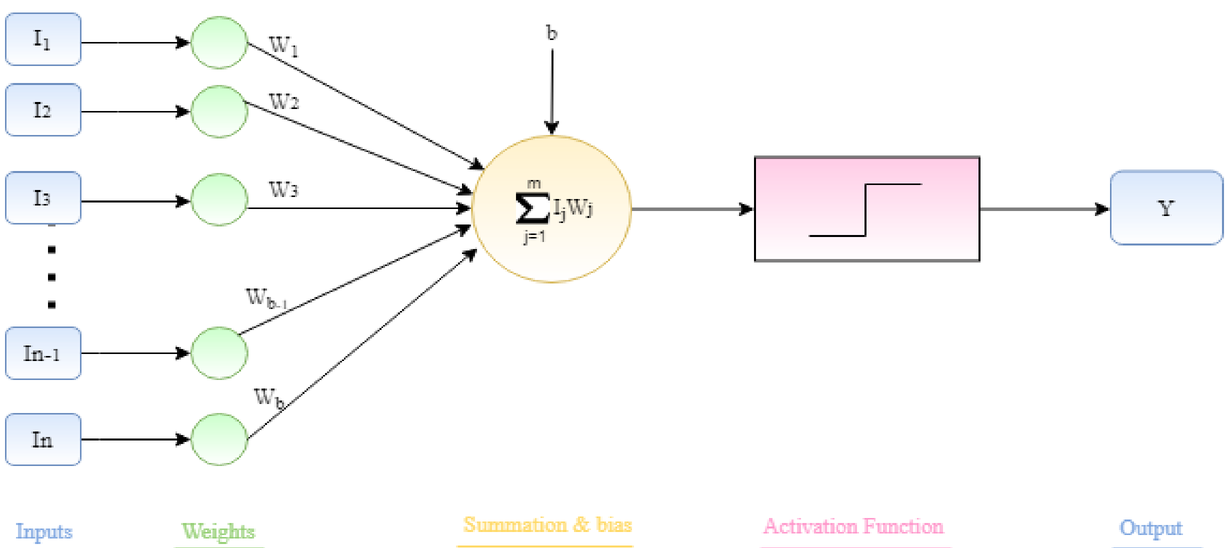

FIGURE 4. Schematic of artificial neuron.

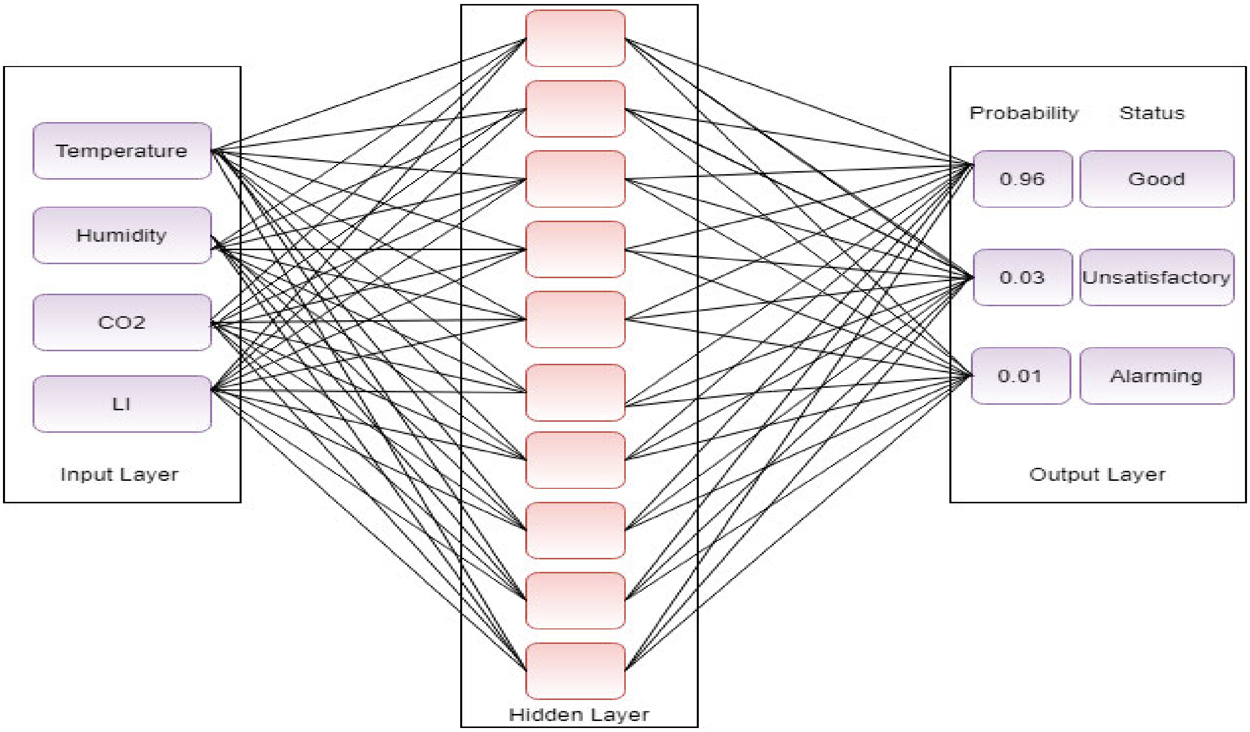

FIGURE 5. ANN architecture for RT-IMNS.

These layers are fully interconnected with each other. The input layer consists of four neurons represent features i.e. temperature, humidity, CO2, light intensity (LI).

Each neuron in the input layer is connected to all neurons in the hidden layer and each interconnection has an associated weight with a subscript to uniquely identify the interconnection. The hidden layer consists of ten neurons and output layer consists of three neurons equal to number of status classes. The dot product of every feature and weight is calculated and bias is also added inside the dot product and overall summation is performed. This result is transferred to activation function that will finally generate an output for first neuron and for first hidden layer. The whole process will be repeated until the last weight for last input generated. The whole process is shown in Figure 5 collectively.

IV. IMPLEMENTATION

To continuously monitor the real- time environmental parameters, the proposed RT-IMNS has employed cost- effective sensors in its sensing module. The data acquisition is performed using sensing module of RT-IMNS that gauges temperature, relative humidity, CO2 and light intensity. This section covers the working of RT-IMNS by illustrating the experimental setup used to validate the working of proposed system.

A. DATA ACQUISITION USING EXPERIMENTAL SETUP

An experiment is performed in a cold storage consists of two rooms with approximate dimensions of 45f×70f×40f (W×L×H). Moreover, there are total hundred racks in both rooms and each rack consists of twenty sacks.

The total 110kg potatoes are stored in each sack. It is estimated that the annual cultivation of potato (*Solanum tuberosum*) around the world is 320 million tons approximately that covers 20 million hectares of land. This ranks the potato as world's fourth staple food crop after maize, wheat and rice. Henceforth, we have chosen the commodity potato also called tater, spud or tattie due to its long shelf-life in cold storage and demand in the world [76]–[78].

The data acquisition is performed using sensing system of RT-IMNS that gauges real-time values of environment parameters such as temperature, humidity, concentration of CO2 and light intensity. The optimal values for ambient temperature are between 38 to 40 degree Fahrenheit and for humidity its range from 90-95%[79]. ESP32-WROOM-32 sends these real-time gauged data to Firebase database using internet where these gauged values are stored in real-time database. We have exported this real-time database as json file and then used an online converter that converts json file into.xlsx. After that, uses this recorded data for training of prediction model. Our dataset contains 5361 instances that are gauged by sensing system of RT-IMNS at different time intervals. There are four input features and a target variable y contains 0, 1 and 2 values to denote the status of commodity as alarming, good and unsatisfactory respectively. An experimental setup is shown in Figure 6. We have installed four modules in a room of cold storage for data acquisition one of out of which is shown in Figure 6. We have installed

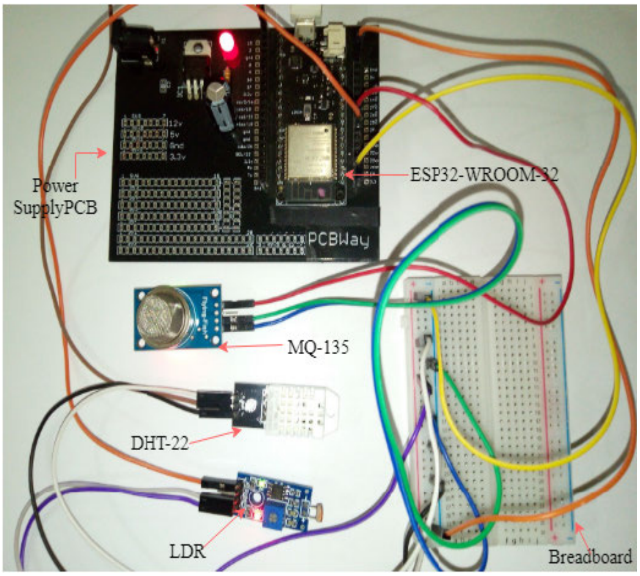

FIGURE 6. Experimental setup of proposed RT-IMNS.

data acquisition module at different places inside cold storage instead of installing all modules at one place unlike traditional measurement strategy adopted in cold supply chain. In data acquisition module, there are three sensors which are connected to ESP-32 (Wi-Fi+Bluetooth) module. The data acquisition module wirelessly communicates with Firebase database and simulation work is done in python. We have also applied spearmanr(),KENDALL TAU-B, PEARSONR() correlation method to find the correlation between features and target. After data acquisition, the other steps required to describe the working of the proposed RT-IMNS includes data normalization, data preparation, build ANN model with forward propagation and android app. In Figure 7, a detailed description of remaining steps about working of proposed system is illustrated.

We have performed data acquisition at different time intervals up to fifteen days. The sensing module is started at baud rate of 115200 and then connects to Wi-Fi. If the connection is available then sensing modules read real-time environmental parameters and send gauged data to Firebase where it is stored in real-time database named rtimns. This process will continue till the Wi-Fi connectivity will available. We have exported rtmins database as json file and then convert it into excel file (.xlsx) using online converter. Then import this file into Juypter notebook using pandas library method *read_excel*() The whole dataset is stored in panda's dataframe. Moreover, features from the gauged dataset are

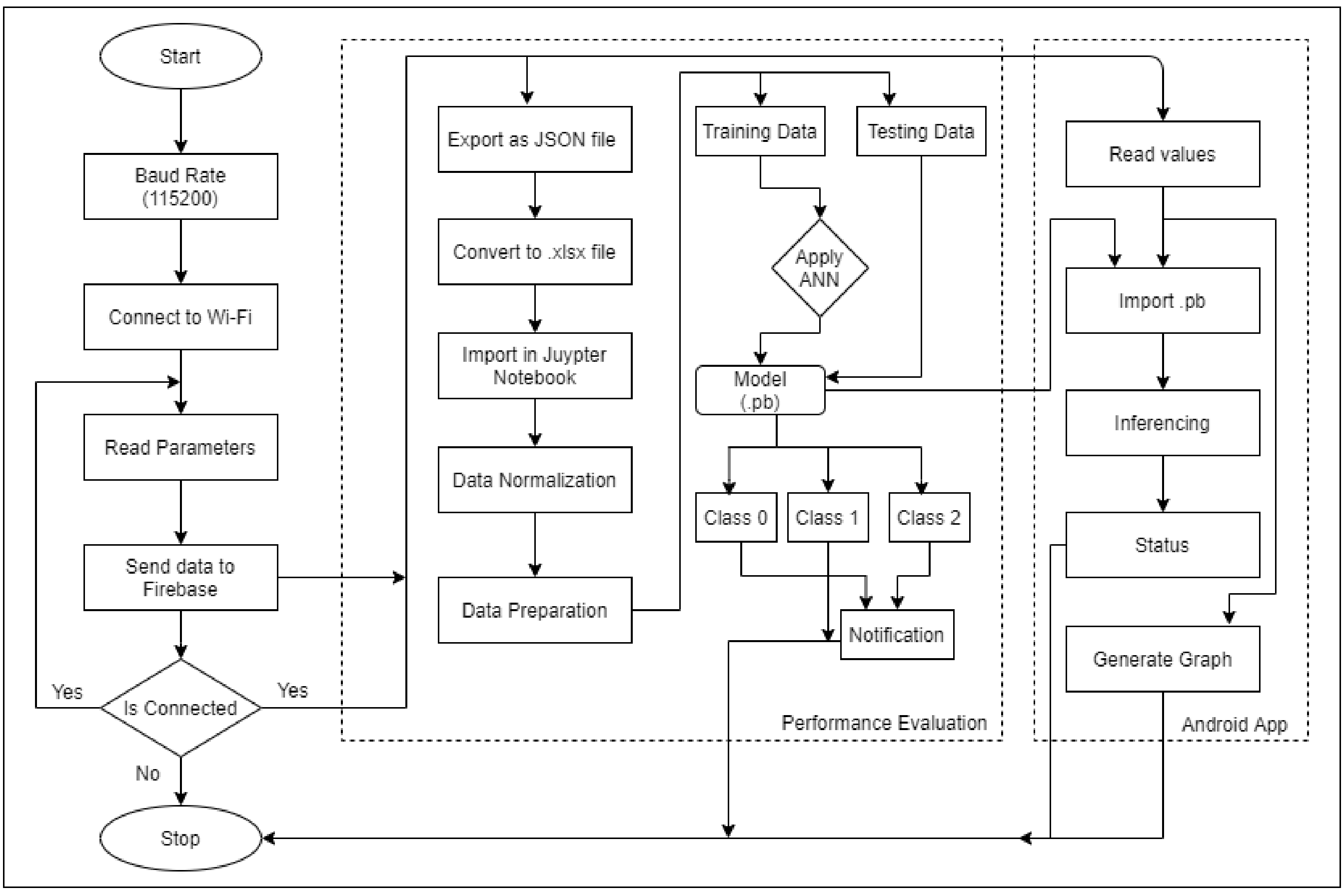

FIGURE 7. Schematic description of complete workflow of RT-IMNS.

TABLE 3. Specifications of the prediction model.

Hyper Parameters	Description	Best Value
Activation function (hidden layer)	softmax, softplus, softsign, relu, tanh, sigmoid, hard_sigmoid, linear	relu
Neurons(hidden layer)	1, 5, 10, 15, 20, 25, 30	10
Optimizer	SGD, RMSprop, Adagrad, Adadelta, Adam, Adamax, Nadam	Adam
Epochs	10,50,100	100
Batch_size	10, 20, 30, 40, 50, 60, 70, 80, 90, 100	30
Learn_rate	0.001, 0.01, 0.1, 0.2, 0.3	0.001
Momentum	0.0, 0.2, 0.4, 0.6, 0.8, 0.9	0.0
init_mode	uniform, lecun_uniform, normal, zero, glorot_normal, glorot_uniform, he_normal, he_uniform	Uniform
Cross-validation	2,3,4,5,6,7,8,9,10	3

stored into a variable X and status column is a target as y. The next step is data normalization that is described as follows.

B. DATA NORMALIZATION

After importing data, data scaling is required because it is advantageous to apply pre-processing transformations before data is presented to neural network models [80]. The most commonly used types of data scaling is normalization and standardization. We have applied normalization on features of our dataset that is stored into a variable X. Normalization is a technique of rescaling of the data from the original range to the range end up between 0 and 1. This is accomplished using the scikit-learn object MinMaxScaler by calling *fit()* and *transform()* function [81]. The min-max normalization is represented using equation (3).

$$W_i = \frac{X_i - \min(X)}{\max(X) - \min(X)} \tag{3}$$

where X_i is number of features that are required to normalize while W_i represents the normalized features. This process will transform all the features in one scope having same weights.

C. DATA PREPARATION

After data normalization, next step is data preparation to split dataset into training, testing dataset. The training dataset is 70% of the whole dataset while remaining (30%) is use for testing purpose. KFold cross-validation is used for both testing and training dataset where k is equal to 5. To accomplish this split, we used built-in function train_test_split The shape of our training and test dataset for features and target is (3752, 4), (3752,) (1609, 4), (1609,) respectively.

D. BUILD PREDICTION MODEL

After data normalization and data preparation, next step is to build prediction model by applying training dataset. There are three layers in our ANN model, input layers contains four nodes to represents four features, hidden layer contains ten nodes and output layer represents status of commodity having three nodes. The model summary of proposed ANN model is shown in Figure 8. We have used grid search cross validation approach to validate hyper parameters of the ANN model. A detailed description of prediction model is given in Table 3. We used 'ReLU' (Rectified Linear Unit) and 'softmax' activation function at hidden and output layer respectively [82]. The proposed prediction model is then compiled using Adam optimizer with learning rate of 1e-3 and categorical cross-entropy is used as loss function because our proposed approach contains three output classes (multi-class classification). We have used batch size equal to 30 and number of epoch equal to 100. After compilation fit the model and the protobuf file of ANN model is generated. Moreover, imports this file in Android App for further classification of real-time values. After build of ANN using training dataset next step is to make predictions using testing dataset that contains only features. Our proposed RT-IMNS also generates notification on unsatisfactory and alarming status of commodity and sends it to personnel for time necessary action in order to reduce the loss of perishable commodity.

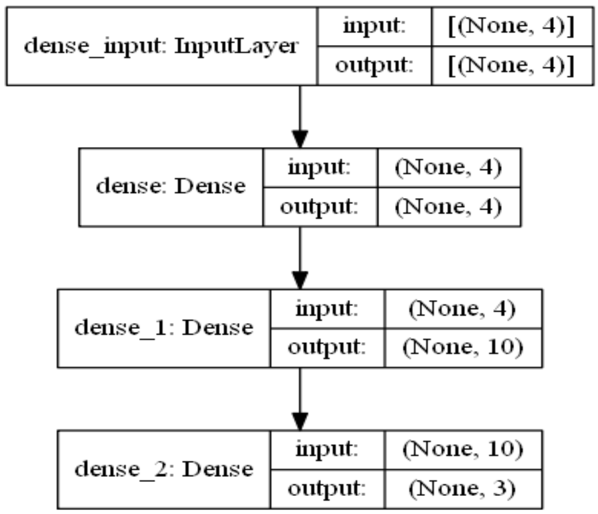

FIGURE 8. Summary of ANN model.

E. ANDROID APP

The last portion of schematic description of complete workflow of RT-IMNS illustrates the working of Android App as shown in Figure 7. The proposed android app is developed using Android Studio [83], [84]. With the help of RTIMNS app, the personnel can monitor the environmental parameters such as temperature, humidity, concentration of CO2 and light intensity in cold storage from anywhere at any time without physically presence in cold storage. RT-IMNS android app read real time values of environmental parameters from Firebase database named rtimns. The protobuf file of already trained ANN model is imported in Android App to make inference on real time values of environmental parameters and predicts the status of commodity as good, unsatisfactory or alarming. The RT-IMNS android app also generates graph of real-time gauged environmental parameters that are shown in result section.

These graph will showed the gauged values of real-time environmental parameters including temperature, relative humidity, concentration of CO2 and light intensity that are recorded at different time intervals.

V. RESULTS

There are enormous range of applications where ANN have been deployed including health care [85], pattern recognition [80], speech recognition [86], medical diagnosis [87], industry [88], food sciences [89] and data mining [90]. In presented approach, the experiments are accomplished on Core-I5 system having 12GB Ram and 1.8GHz processor. During data preparation, dataset is divided into training (70%) and testing (30%) dataset. We have used KFold cross validation for training and testing dataset.

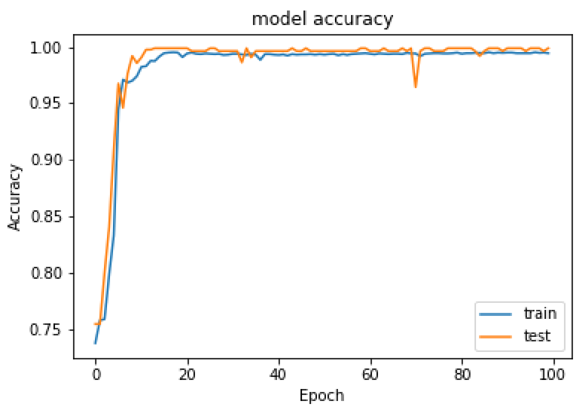

FIGURE 9. Training and testing accuracy of ANN model.

We have considered mean accuracy after KFold cross validation. We have plotted learning curves to show performance of ANN model overtime and calculated at the end of each training epoch. The accuracy learning curve of train and test dataset is shown in Figure 9. The blue line represents the training accuracy that start from 73% at first epoch and after 100 epochs it reaches up to 99.3% as shown in Figure 9. Similarly, the test accuracy is represented by orange line

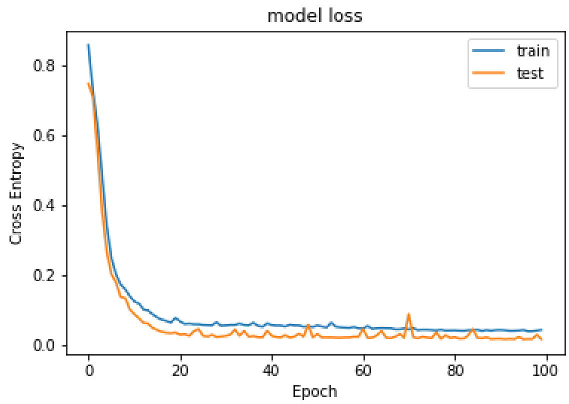

FIGURE 10. Training and testing loss of ANN model.

that starts from 76% and reaches up to 99.7% after 100 epochs. The training and testing loss curve for ANN model is represented in Figure 10.

The blue line represents the train loss that comes down to 0.035 after 100 epochs as we can see in Figure 10. Similarly, orange line represents the test loss that comes down to 0.016 after 100 epochs as shown in Figure 10.

We have also compared the proposed neural network model with forward propagation to other models such as Support Vector Machine (SVM), Naïve Bayes (NB), Random Forest (RF) and Decision Tree (DT). The results of comparison show that proposed ANN model outperform than others in the terms of accuracy as shown in Figure 11. The accuracy of ANN is 99.01%, SVM is 97.14%, NB is 93.52%, RF is 96.82 and DT is 97.21%.

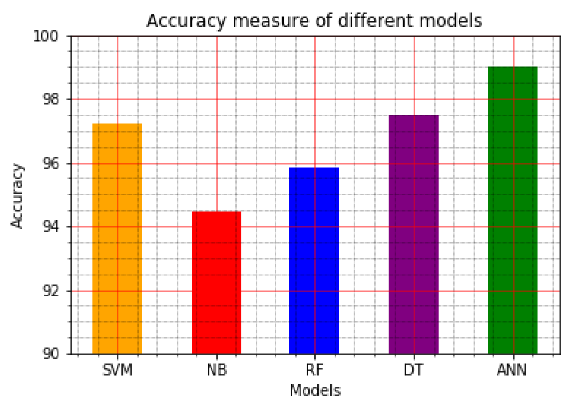

FIGURE 11. Comparison of different models in term of accuracy.

To evaluate the output of trained ANN classifier, we computed accuracy and error rate by using the formula given in equation (4) and equation (5) and results are illustrated in Table 4. The accuracy for good, unsatisfactory and alarming class is 99.83%, 99.21%, 99.21% respectively. While error rate for predicted classes (good, unsatisfactory,

TABLE 4. Accuracy and error rate.

Classes	Accuracy Rate for Predicted Class	Error Rate for Predicted Class
Good	1226/1228×100=99.83%	2/1228×100=0.163%
Unsatisfactory	252/254×100=99.21%	2/254×100=0.787%
Alarming	126/127×100=99.21%	1/127×100=0.787%

alarming) is 0.163%, 0.787%, 0.787% respectively.

$$Accuracy = \frac{Predicted\ Correctly}{Total\ Predicted} \times 100 \tag{4}$$

$$Error\ Rate = \frac{Predicted\ Wrongly}{Total\ Predicted} \times 100 \tag{5}$$

A. IMPLEMENTATION OF RESULTS

To check the performance of proposed RT-IMNS for prediction of commodity status, we did an experiment and gauged data of environmental parameters using sensing system of RT-IMNS at different time intervals in cold storage. Our gauged data set contains 1200 instances that are employed to evaluate the performance of proposed RT_IMNS. The collected data might contain missing values, noise and inconsistent values. Henceforth, it is necessary to apply data pre-processing techniques on gauged data before it will further be used for decision making.

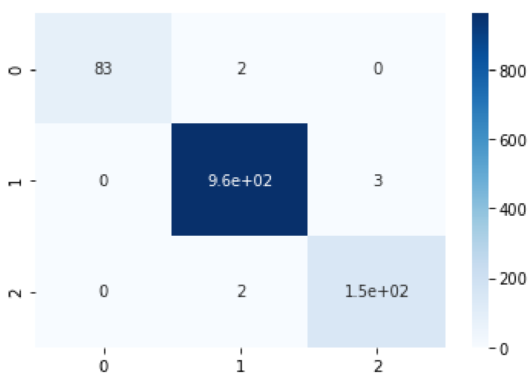

FIGURE 12. Confusion matrix of prediction model.

We have applied data normalization using MinMaxScaler that transforms each attribute value into a specified range end up between 0 and 1 as illustrated in data acquisition using experimental setup section in detail. After data normalization, we have provided dataset to already train ANN model of proposed RT-IMNS. Moreover, we employed the statistical measures of precision, recall and F1-score to evaluate the performance of ANN model. We have calculated statistical measures with the help of confusion matrix which is shown in Figure 12 and equation (6), equation (7) and equation (8).

$$Precision = \frac{TP}{TP + FP} \times 100 \tag{6}$$

$$Recall = \frac{TP}{TP + FN} \times 100 \tag{7}$$

$$F1 - score = 2.\frac{Precision\ .Recall}{Precision\ +\ Recall} \times 100 \tag{8}$$

where *TP* represents the true positive predicted instances and *FP* represents the false positive predicted instances and *FN* represents the false negative predicted instances by prediction model.

Moreover, the overall precision, recall and F1-score of ANN classifier reaches up to 99% as shown in Table 5.

TABLE 5. Ann predictions.

Class	Precision	Recall	F1-score
0	100%	98%	99%
1	100%	100%	100%
2	98%	99%	98%
Average/ Total	99%	99%	99%

The calculated results of statistical measures are given in Table 5. In Table 5, it is shown that precision of ANN classifier for class 0, class1 and class 2 is 100%, 100% and 98% respectively. The recall for class 0, class1 and class 2 is 98%, 100% and 99% respectively. While F1-score is 99%, 100% and 98% for class 0, class1 and class2 respectively.

The performance evaluation of the prediction model for each class i.e. alarming, good and unsatisfactory is shown in Figure 13.

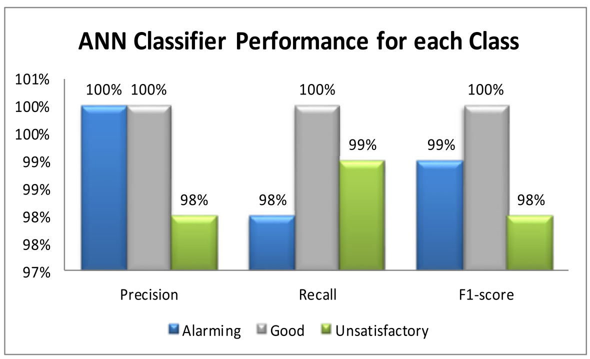

FIGURE 13. Performance evaluation of ANN classifier.

We have also computed the over-all accuracy of ANN model by taking the fraction of total number of true positive predicted instances diagonally to the total instances of dataset. The overall accuracy is also 99% that indicates the efficient performance of the proposed approach. We have

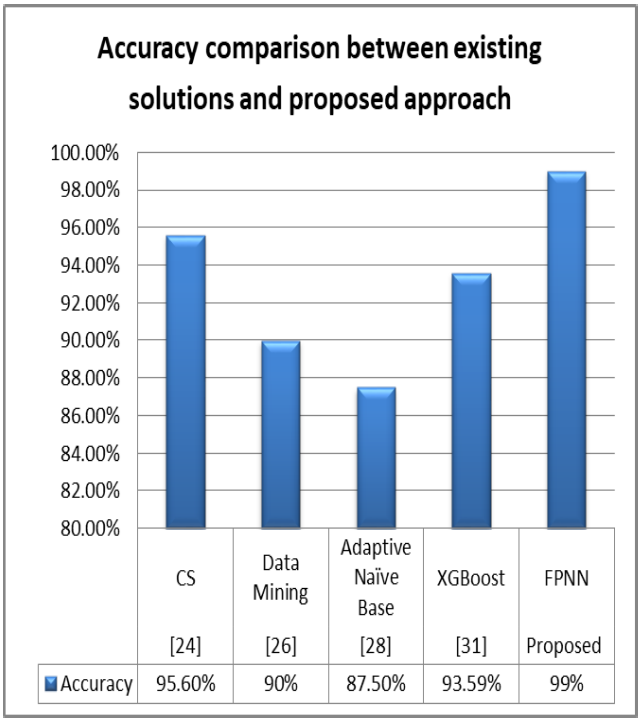

FIGURE 14. Outcome of proposed and existing approaches.

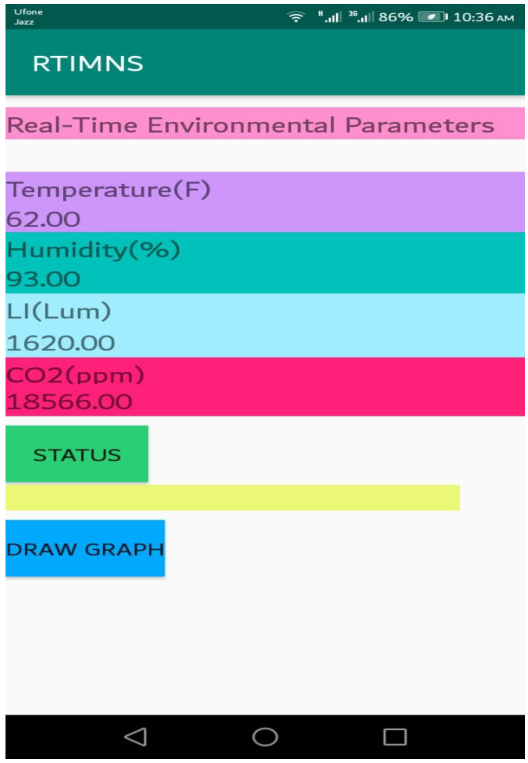

FIGURE 15. GUI of RTIMNS app.

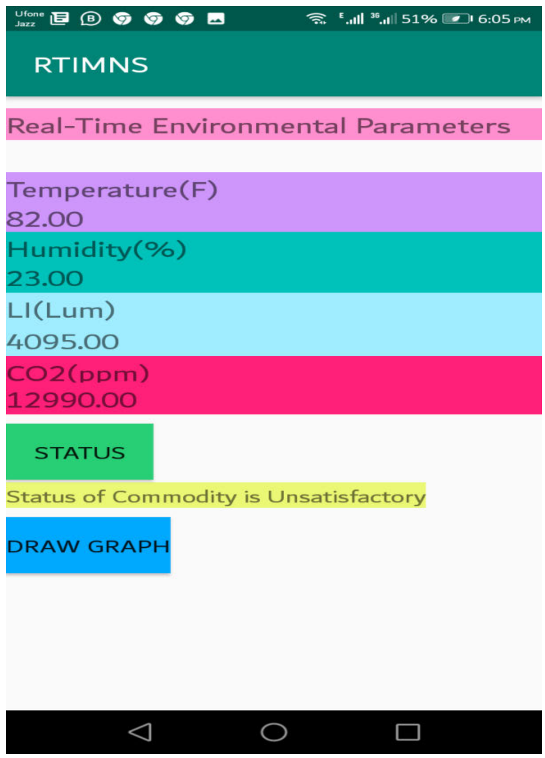

FIGURE 16. RTIMNS app shows commodity status.

also compared outcome of existing cold supply monitoring solutions and proposed RT-IMNS approach. Our proposed approach outperforms than existing approaches such as CS, ANB, XGBoost and DM with respect to forecasting accuracy as shown in Figure 14. Henceforth, according to performance evaluation, it is predicted that proposed approach contribute to overcome the loss of perishable FVs by real-time monitoring of environmental parameters in cold storage. Our presented approach also support real-time monitoring through android application from anywhere at any time. Moreover, the proposed RT-IMNS also generates a notification on dangerous limits of environmental parameters and sends it to personnel for timely necessary action. While existing monitoring solutions can only measure temperature and also does not have support of real-time monitoring through android app. Moreover, in existing approaches there is no mechanism to intimate personnel for time necessary action.

The presented approach also provides support of android app for real-time monitoring of environmental parameters.

When the user start RT_IMNS app, the first graphical user interface appears that reads real-time environmental parameters from rtimns firebase database as shown in Figure 15. When user clicks on status button, the prediction model predicts the status of commodity is good, unsatisfactory or alarming on the basis of read values.

The real-time environmental parameters have values i.e. temperature is 82F, humidity is 23.00%, LI is 4095 Lum and CO2 is 12990ppm which was gauged at other time interval. According to these values status of commodity is unsatisfactory as shown in Figure 16. On unsatisfactory and alarming status, an automatic notification is sent to personnel for timely necessary action.

The user can also see the graph of gauged environmental parameters such as temperature, humidity, concentration of

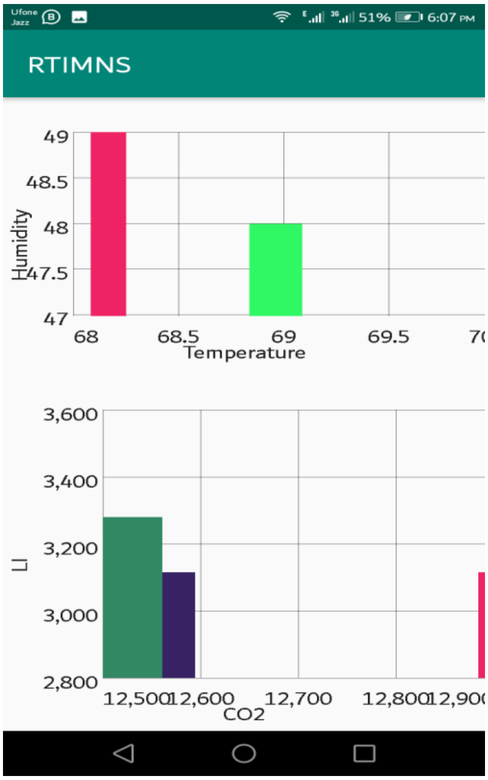

FIGURE 17. Graph of environmental parameters.

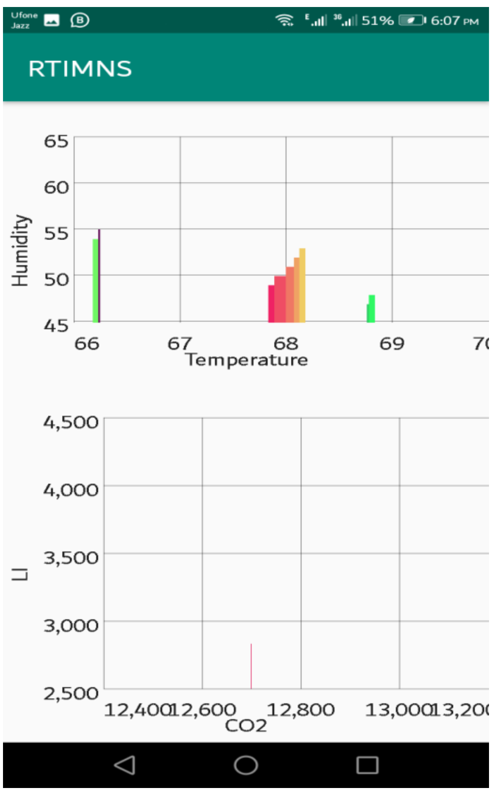

FIGURE 18. Graph of environmental parameters.

CO2 and light intensity on RTIMNS app. The graph of these environmental parameters gauged at different time intervals is shown in Figure17 and Figure18.

First graph showed gauge values of the temperature and humidity environment parameters that starts from 68F to 70F temperature along x-axis and 47% to 49% humidity along y-axis as shown in Figure 16. While second graph is drawn between CO2 and light intensity values that started from 12,500(ppm) and 2800(Lum) respectively as shown in Figure 17. Similarly, at another time interval, graph of gauged values of environmental parameters such as temperature, humidity, CO2 and LI are shown in Figure 18.

TABLE 6. Limitations of RT-IMNS.

Concern	Limitation
Commodity	Proposed RT-IMNS designed for only single commodity cold storage. It does not consider for multi-commodity cold storage.
Gas Concentration	Proposed RT-IMNS consider only CO2 concentration in cold storage while there are some other gases such as O2, CH4 etc. that can also be gauged and affect the status of commodity.
Technique	Proposed RT-IMNS used ANN for decision making while other techniques may also be applied and may it will provide better accuracy.
Dataset size	The dataset used in the proposed approach is not very large and accuracy rate may vary for a large dataset.

B. LIMITATIONS

The proposed real-time monitoring and notification system has aimed to classify the status of commodity into one of three classes i.e. good, satisfactory or alarming. The limitations of proposed approach are illustrated in Table 6. Currently, RT-IMNS used ANN with forward propagation but there are many other deep learning techniques that can be used for decision making such as RNN, CNN. Although, we have compared ANN with some machine learning techniques and ANN outperforms than others in the terms of accuracy as shown in Figure 11. We choose single commodity cold storage at this time but in future we will consider a multi-commodity cold storage. Moreover, we have considered concentration of CO2 only but there are many other environmental gases such as O2, CH4 etc. that will be used in future work.

C. MANAGERIAL IMPLICATIONS

To meet the challenges of food safety and integrity, the organizations can take advantage from IoT and Artificial Intelligence (AI) to improve the visibility of perishable commodity in cold storage with respect to environmental parameters monitoring and expected status of commodities. The proposed RT-IMNS ensures real-time monitoring and notification about multiple environmental parameters in cold storage. The proposed RT-IMNS facilitates personnel to get real-time status of commodity from anywhere at any time and take timely necessary action in case of dangerous limits of environmental parameters. Henceforth, loss of perishable commodity can be effectively reduced by employing RT-IMNS in cold storage. The proposed RT-IMNS is suitable for small and medium-sized organization due to following features.

1) Easily adaptable.
2) Cost-effective.
3) User-friendly due to android app.
4) Based on cutting edge technologies such as IoT and machine learning.
5) Elevate operational efficiency of personnel.

VI. CONCLUSION AND FUTURE WORK

Recent studies have shown that FVs are vital sources of phytochemicals, micronutrients and fiber. Moreover, according to WHO recommendation, minimum 400g FVs per day should be taken in the human diet to reduce the chances of chronic diseases. But unfortunately as per estimation of FAO, one third of all the food produced is lost around the globe approximately. Moreover, FVs loss rate is high among all the food produced annually and occurs at storage stage of post-harvest life cycle. Henceforth, loss of FVs at storage stage is a crucial issue that needs to be addressed around the globe. The major cause of this loss is inability to monitors real-time environmental parameters which contribute to slow respiration rates, ripening and senescence process of perishable commodity like FVs in cold storage.

Traditionally, existing approaches do not facilitate real-time monitoring of multiple environmental parameters excluding temperature and relative humidity. Moreover, there is no mechanism to intimates the personnel about real-time status of commodity in cold storage time by time. Henceforth, we have presented an intelligent real-time monitoring and notification system of cold storage that is based on an IoT-enabled approach and contributes to overcome the loss of perishable commodity in cold storage by automatic monitoring and notification regarding dangerous limits of environmental parameters such as temperature, relative humidity, concentration of CO2 and light intensity. Moreover, presented approach also provides support of android App named RTIMNS which facilitates real-time monitoring of environmental parameters at any time form anywhere. The android app facilitates the personnel to check the status of commodity on the basis of prediction model which is employed in it. RTIMNS app also visualizes the graph of real-time environmental parameters gauge in cold storage. On alarming or unsatisfactory status, a notification is also sent to personnel for timely necessary action. In our presented approach, we choose single commodity cold storage but in future we will choose a multi-commodity cold storage and will consider concentration of more gases which will contribute to reduce the loss rate of FVs. We will also address imbalance dataset issue as in our case by using resampling technique in future.

Moreover, the proposed RT-IMNS provides a theoretical implication for timely necessary action by status prediction through using proposed prediction model which could contributes to reduce the loss of perishable FVs in cold storage.

REFERENCES

[1] J. Gustavsson, C. Cederberg, U. Sonesson, R. Van Otterdijk, and A. Meybeck, "Global food losses and food waste," FAO, Rome, Italy, Tech. Rep., 2011. [Online]. Available: http://www.fao.org/3/mb060e/mb060e.pdf

[2] Food and Agriculture Organization (FAO). (2009). *How to Feed the World in 2050*. [Online]. Available: http://www.fao.org/fileadmin/templates/wsfs/docs/expertpaper/HowtoFeedtheWorldin2050.pdf

[3] WHO. *Promoting Fruit and Vegetable Consumption Around the World*. [Online]. Available: https://www.who.int/dietphysicalactivity/fruit/en/index2.html

[4] A. Robertson, C. Tirado, T. Lobstein, C. Knai, J. Jensen, A. Ferro-Luzzi, and W. James, "Food and health in Europe: A new basis for action (European series No 96)," WHO Regional Office Europe, Tech. Rep., 2004.

[5] *Save Food Global Initiative on Food Loss and Waste Reduction*, Food Agricult. Org. United Nations, Rome, Italy, 2015, vol. 25, p. 2018. [Online]. Available: http://www.fao.org/3/ai4068e.pdf

[6] L. Kitinoja and A. A. Kader, "Measuring postharvest losses of fresh fruits and vegetables in developing countries," PEF, Latham, NY, USA, White Paper, 2015, pp. 2–15.

[7] G. Liu, "Food losses and food waste in China: A first estimate," OECD Food, Agricult. Fisheries, Paris, France, Tech. Rep. 66, 2014.

[8] M. Eden, V. Raab, J. Kreyenschmidt, T. Hafliðason, G. Olafsdóttir, and S. Bogason, "Continuous temperature monitoring along the chilled food supply chain," in *Food Chain Integrity*. Amsterdam, The Netherlands: Elsevier, 2011, pp. 115–129.

[9] A. Ali, M. T. M. Muhammad, K. Sijam, and Y. Siddiqui, "Effect of chitosan coatings on the physicochemical characteristics of Eksotika II papaya (*Carica papaya* L.) fruit during cold storage," *Food Chem.*, vol. 124, no. 2, pp. 620–626, Jan. 2011.

[10] D. El-Rayes, "Effect of carbon dioxide-enriched atmosphere during cold storage on limiting antioxidant losses and maintaining quality of 'Barhy'date fruits," *J. Meteorol., Environ. Arid Land Agricult. Sci.*, vol. 20, no. 1, p. 208, 2009.

[11] M. Cantwell and T. Suslow, "Potato: Recommendations for maintaining postharvest quality," Postharvest Center, Davis, CA, USA, Tech. Rep. 9-10-2020, 2002.

[12] M. M. Blanke and R. Shekarriz, "Gold nanoparticles and sensor technology for sensitive ethylene detection," in *Proc. XXVIII Int. Horticultural Congr. Sci. Horticulture People (IHC), Int. Symp.*, vol. 934, 2010, pp. 255–262.

[13] L. Manzocco, B. Quarta, and A. Dri, "Polyphenoloxidase inactivation by light exposure in model systems and apple derivatives," *Innov. Food Sci. Emerg. Technol.*, vol. 10, no. 4, pp. 506–511, Oct. 2009.

[14] S. Noichinda, K. Bodhipadma, C. Mahamontri, T. Narongruk, and S. Ketsa, "Light during storage prevents loss of ascorbic acid, and increases glucose and fructose levels in Chinese kale (Brassica oleracea var. Alboglabra)," *Postharvest Biol. Technol.*, vol. 44, no. 3, pp. 312–315, Jun. 2007.

[15] A. Draganić, I. Orović, S. Stanković, X. Zhang, and X. Wang, "Compressive sensing approach in the table grape cold chain logistics," in *Proc. 6th Medit. Conf. Embedded Comput. (MECO)*, Jun. 2017, pp. 1–4.

[16] A. Chaudhuri, I. Dukovska-Popovska, N. Subramanian, H. K. Chan, and R. Bai, "Decision-making in cold chain logistics using data analytics: A literature review," *Int. J. Logistics Manage.*, vol. 29, no. 3, pp. 839–861, Aug. 2018.

[17] E. Gogou, G. Katsaros, E. Derens, G. Alvarez, and P. S. Taoukis, "Cold chain database development and application as a tool for the cold chain management and food quality evaluation," *Int. J. Refrigeration*, vol. 52, pp. 109–121, Apr. 2015.

[18] W. R. Kim, M. M. Aung, Y. S. Chang, and C. Makatsoris, "Freshness gauge based cold storage management: A method for adjusting temperature and humidity levels for food quality," *Food Control*, vol. 47, pp. 510–519, Jan. 2015.

[19] S. Li, L. Xu, and S. Zhao, "The Internet of Things: A survey," *Inf. Syst. Frontiers*, vol. 17, no. 2, pp. 243–259, 2015.
[20] P. Schulz, M. Matthe, H. Klessig, M. Simsek, G. Fettweis, J. Ansari, S. A. Ashraf, B. Almeroth, J. Voigt, I. Riedel, A. Puschmann, A. Mitschele-Thiel, M. Muller, T. Elste, and M. Windisch, "Latency critical IoT applications in 5G: Perspective on the design of radio interface and network architecture," *IEEE Commun. Mag.*, vol. 55, no. 2, pp. 70–78, Feb. 2017.
[21] T. Geng and Y. Du, "The business model of intelligent manufacturing with Internet of Things and machine learning," *Enterprise Inf. Syst.*, pp. 1–19, Feb. 2020, doi: 10.1080/17517575.2020.1722253.
[22] F. Tian, "A supply chain traceability system for food safety based on HACCP, blockchain & Internet of Things," in *Proc. Int. Conf. Service Syst. Service Manage.*, 2017, pp. 1–6.
[23] Q. Gao, S. Guo, X. Liu, G. Manogaran, N. Chilamkurti, and S. Kadry, "Simulation analysis of supply chain risk management system based on IoT information platform," *Enterprise Inf. Syst.*, vol. 14, nos. 9–10, pp. 1–25, 2019.
[24] L. Wang, S. K. Kwok, and W. H. Ip, "A radio frequency identification and sensor-based system for the transportation of food," *J. Food Eng.*, vol. 101, no. 1, pp. 120–129, Nov. 2010.
[25] A. Rong, R. Akkerman, and M. Grunow, "An optimization approach for managing fresh food quality throughout the supply chain," *Int. J. Prod. Econ.*, vol. 131, no. 1, pp. 421–429, May 2011.
[26] M. M. Aung and Y. S. Chang, "Temperature management for the quality assurance of a perishable food supply chain," *Food Control*, vol. 40, pp. 198–207, Jun. 2014.
[27] R. Badia-Melis, L. Ruiz-Garcia, J. Garcia-Hierro, and J. Villalba, "Refrigerated fruit storage monitoring combining two different wireless sensing technologies: RFID and WSN," *Sensors*, vol. 15, no. 3, pp. 4781–4795, Feb. 2015.
[28] X. Xiao, Q. He, Z. Fu, M. Xu, and X. Zhang, "Applying CS and WSN methods for improving efficiency of frozen and chilled aquatic products monitoring system in cold chain logistics," *Food Control*, vol. 60, pp. 656–666, Feb. 2016.
[29] R. Accorsi, E. Ferrari, M. Gamberi, R. Manzini, and A. Regattieri, "A closed-loop traceability system to improve logistics decisions in food supply chains: A case study on dairy products," in *Advances in Food Traceability Techniques and Technologies*. Amsterdam, The Netherlands: Elsevier, 2016, pp. 337–351.
[30] Y. P. Tsang, K. L. Choy, C. H. Wu, G. T. S. Ho, H. Y. Lam, and P. S. Koo, "An IoT-based cargo monitoring system for enhancing operational effectiveness under a cold chain environment," *Int. J. Eng. Bus. Manage.*, vol. 9, Dec. 2017, Art. no. 1847979017749063.
[31] J. Wang and H. Yue, "Food safety pre-warning system based on data mining for a sustainable food supply chain," *Food Control*, vol. 73, pp. 223–229, Mar. 2017.
[32] G. Alfian, M. Syafrudin, and J. Rhee, "Real-time monitoring system using smartphone-based sensors and NoSQL database for perishable supply chain," *Sustainability*, vol. 9, no. 11, p. 2073, Nov. 2017.
[33] P. D. Ganjewar, S. Barani, S. J. Wagh, and S. S. Sonavane, "Food monitoring using adaptive Naïve Bayes prediction in IoT," in *Proc. Int. Conf. Intell. Syst. Design Appl.* Cham, Switzerland: Springer, 2018, pp. 424–434.
[34] S. Mercier and I. Uysal, "Neural network models for predicting perishable food temperatures along the supply chain," *Biosyst. Eng.*, vol. 171, pp. 91–100, Jul. 2018.
[35] Y. P. Tsang, K. L. Choy, C. H. Wu, G. T. S. Ho, and H. Y. Lam, "Blockchain-driven IoT for food traceability with an integrated consensus mechanism," *IEEE Access*, vol. 7, pp. 129000–129017, 2019.
[36] G. Alfian, M. Syafrudin, U. Farooq, M. R. Ma'arif, M. A. Syaekhoni, N. L. Fitriyani, J. Lee, and J. Rhee, "Improving efficiency of RFID-based traceability system for perishable food by utilizing IoT sensors and machine learning model," *Food Control*, vol. 110, Apr. 2020, Art. no. 107016.
[37] H. Feng, W. Wang, B. Chen, and X. Zhang, "Evaluation on frozen shellfish quality by blockchain based multi-sensors monitoring and SVM algorithm during cold storage," *IEEE Access*, vol. 8, pp. 54361–54370, 2020.
[38] A. Popa, M. Hnatiuc, M. Paun, O. Geman, D. Hemanth, D. Dorcea, L. Son, and S. Ghita, "An intelligent IoT-based food quality monitoring approach using low-cost sensors," *Symmetry*, vol. 11, no. 3, p. 374, Mar. 2019.
[39] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, and J. Vanderplas, "Scikit-learn: Machine learning in Python," *J. Mach. Learn. Res.*, vol. 12, pp. 2825–2830, Nov. 2011.
[40] A. Géron, *Hands-on Machine Learning With Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems*. Newton, MA, USA: O'Reilly Media, 2019.
[41] N. Shukla, *Machine Learning With TensorFlow*. Shelter Island, NY, USA: Manning Publications, 2018.
[42] Y. P. Tsang, K. L. Choy, C. H. Wu, G. T. S. Ho, C. H. Y. Lam, and P. S. Koo, "An Internet of Things (IoT)-based risk monitoring system for managing cold supply chain risks," *Ind. Manage. Data Syst.*, vol. 118, no. 7, pp. 1432–1462, Aug. 2018.
[43] A. Mohsin and S. S. Yellampalli, "IoT based cold chain logistics monitoring," in *Proc. IEEE Int. Conf. Power, Control, Signals Instrum. Eng. (ICPCSI)*, Sep. 2017, pp. 1971–1974.
[44] R. Nukala, A. Shields, U. McCarthy, and S. Ward, "An IoT based approach towards global food safety and security," in *Proc. 14th IT&T Conf.*, 2015, pp. 10–17.
[45] M. Tu, M. K. Lim, and M.-F. Yang, "IoT-based production logistics and supply chain system—Part 1," *Ind. Manage. Data Syst.*, vol. 118, no. 1, pp. 65–95, Feb. 2018.
[46] E. Manavalan and K. Jayakrishna, "A review of Internet of Things (IoT) embedded sustainable supply chain for industry 4.0 requirements," *Comput. Ind. Eng.*, vol. 127, pp. 925–953, Jan. 2019.
[47] P. Štefanič, M. Cigale, A. C. Jones, L. Knight, I. Taylor, C. Istrate, G. Suciu, A. Ulisses, V. Stankovski, S. Taherizadeh, G. F. Salado, S. Koulouzis, P. Martin, and Z. Zhao, "SWITCH workbench: A novel approach for the development and deployment of time-critical microservice-based cloud-native applications," *Future Gener. Comput. Syst.*, vol. 99, pp. 197–212, Oct. 2019.
[48] H. Hromic, D. L. Phuoc, M. Serrano, A. Antonic, I. P. Zarko, C. Hayes, and S. Decker, "Real time analysis of sensor data for the Internet of Things by means of clustering and event processing," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Jun. 2015, pp. 685–691.
[49] Y. Omura, A. Mallik, and N. Matsuo, *MOS Devices for Low-Voltage and Low-Energy Applications*. Hoboken, NJ, USA: Wiley, 2017.
[50] A. Kreho, J. Hadzajlic, and E. Sokic, "Design of active visual marker for high speed object tracking by frame subsampling," in *Proc. XXVII Int. Conf. Inf., Commun. Automat. Technol. (ICAT)*, Oct. 2019, pp. 1–6.
[51] P. Foltýnek, M. Babiuch, and P. Šuránek, "Measurement and data processing from Internet of Things modules by dual-core application using ESP32 board," *Meas. Control*, vol. 52, nos. 7–8, pp. 970–984, Sep. 2019.
[52] A. Maier, A. Sharp, and Y. Vagapov, "Comparative analysis and practical implementation of the ESP32 microcontroller module for the Internet of Things," in *Proc. Internet Technol. Appl. (ITA)*, Sep. 2017, pp. 143–148.
[53] M. L. A. T. M. Hertog, I. Uysal, U. McCarthy, B. M. Verlinden, and B. M. Nicolaï, "Shelf life modelling for first-expired-first-out warehouse management," *Phil. Trans. Roy. Soc. A, Math., Phys. Eng. Sci.*, vol. 372, no. 2017, Jun. 2014, Art. no. 20130306.
[54] P. Jin, K. Wang, H. Shang, J. Tong, and Y. Zheng, "Low-temperature conditioning combined with methyl jasmonate treatment reduces chilling injury of peach fruit," *J. Sci. Food Agricult.*, vol. 89, no. 10, pp. 1690–1696, Aug. 2009.
[55] B. Zhang, W.-P. Xi, W.-W. Wei, J.-Y. Shen, I. Ferguson, and K.-S. Chen, "Changes in aroma-related volatiles and gene expression during low temperature storage and subsequent shelf-life of peach fruit," *Postharvest Biol. Technol.*, vol. 60, no. 1, pp. 7–16, Apr. 2011.
[56] J. Wang, H. Wang, J. He, L. Li, M. Shen, X. Tan, H. Min, and L. Zheng, "Wireless sensor network for real-time perishable food supply chain management," *Comput. Electron. Agricult.*, vol. 110, pp. 196–207, Jan. 2015.
[57] H. Q. Nguyen, B. Q. Ta, N. Hoivik, E. Halvorsen, and K. E. Aasmundtveit, "Carbon nanotube based gas sensor for expiration detection of perishable food," in *Proc. 13th IEEE Int. Conf. Nanotechnol. (IEEE-NANO)*, Aug. 2013, pp. 675–678.
[58] A. M. Taye, S. Tilahun, D. S. Park, M. H. Seo, and C. S. Jeong, "Effects of continuous application of CO_2 on fruit quality attributes and shelf life during cold storage in cherry tomato," *Horticultural Sci. Technol.*, vol. 35, no. 3, pp. 300–313, 2017.
[59] S. Palani, P. Tkalich, R. Balasubramanian, and J. Palanichamy, "ANN application for prediction of atmospheric nitrogen deposition to aquatic ecosystems," *Mar. Pollut. Bull.*, vol. 62, no. 6, pp. 1198–1206, Jun. 2011.
[60] K. Suzuki, *Artificial Neural Networks: Architectures and Applications*. Norderstedt, Germany: Books on Demand, 2013.
[61] J. V. Tu, "Advantages and disadvantages of using artificial neural networks versus logistic regression for predicting medical outcomes," *J. Clin. Epidemiol.*, vol. 49, no. 11, pp. 1225–1231, Nov. 1996.

[62] M. Puri, A. Solanki, T. Padawer, S. M. Tipparaju, W. A. Moreno, and Y. Pathak, "Introduction to artificial neural network (ANN) as a predictive tool for drug design, discovery, delivery, and disposition: Basic concepts and modeling," in *Artificial Neural Network for Drug Design, Delivery and Disposition*. Amsterdam, The Netherlands: Elsevier, 2016, pp. 3–13.
[63] N. García-Pedrajas, C. Hervás-Martinez, and D. Ortiz-Boyer, "Cooperative coevolution of artificial neural network ensembles for pattern classification," *IEEE Trans. Evol. Comput.*, vol. 9, no. 3, pp. 271–302, Jun. 2005.
[64] X. Yao and Y. Liu, "Making use of population information in evolutionary artificial neural networks," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 28, no. 3, pp. 417–425, Jun. 1998.
[65] S. F. Silva, C. A. R. Anjos, R. N. Cavalcanti, and R. M. D. S. Celeghini, "Evaluation of extra virgin olive oil stability by artificial neural network," *Food Chem.*, vol. 179, pp. 35–43, Jul. 2015.
[66] A. A. Mohammed and V. Umaashankar, "Effectiveness of hierarchical softmax in large scale classification tasks," in *Proc. Int. Conf. Adv. Comput., Commun. Informat. (ICACCI)*, Sep. 2018, pp. 1090–1094.
[67] C. Nwankpa, W. Ijomah, A. Gachagan, and S. Marshall, "Activation functions: Comparison of trends in practice and research for deep learning," *Arxiv*, vol. abs/1811.03378, 2018.
[68] S. Sharma, "Activation functions in neural networks," *Towards Data Sci.*, vol. 6, pp. 1–7, Sep. 2017.
[69] P. Sibi, S. A. Jones, and P. Siddarth, "Analysis of different activation functions using back propagation neural networks," *J. Theor. Appl. Inf. Technol.*, vol. 47, no. 3, pp. 1264–1268, 2013.
[70] R. Miikkulainen, J. Liang, E. Meyerson, A. Rawal, D. Fink, O. Francon, B. Raju, H. Shahrzad, A. Navruzyan, N. Duffy, and B. Hodjat, "Evolving deep neural networks," in *Artificial Intelligence in the Age of Neural Networks and Brain Computing*. Amsterdam, The Netherlands: Elsevier, 2019, pp. 293–312.
[71] O. San and R. Maulik, "Neural network closures for nonlinear model order reduction," *Adv. Comput. Math.*, vol. 44, no. 6, pp. 1717–1750, Dec. 2018.
[72] S. Agatonovic-Kustrin and R. Beresford, "Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research," *J. Pharmaceutical Biomed. Anal.*, vol. 22, no. 5, pp. 717–727, Jun. 2000.
[73] T. T. Rogers and J. L. McClelland, *Semantic Cognition: A Parallel Distributed Processing Approach*. Cambridge, MA, USA: MIT Press, 2004.
[74] S. Haykin and N. Network, "A comprehensive foundation," *Neural Netw.*, vol. 2, no. 2004, p. 41, Feb. 2004.
[75] S. S. Haykin, *Neural Networks and Learning Machines*, S. Haykin, ed. New York, NY, USA: Prentice-Hall, 2009.
[76] FAO. (May 22, 2020). *International Year of the Potato*. [Online]. Available: http://www.fao.org/potato-2008/en/aboutiyp/index.html
[77] N. Cromme, A. B. Prakash, N. Lutaladio, and F. Ezeta, *Strengthening Potato Value Chains: Technical and Policy Options for Developing Countries*. Rome, Italy: Food and Agriculture Organization of the United Nations, 2010.
[78] A. Devaux, P. Kromann, and O. Ortiz, "Potatoes for sustainable global food security," *Potato Res.*, vol. 57, nos. 3–4, pp. 185–199, Dec. 2014.
[79] I. Iancu, "A Mamdani type fuzzy logic controller," *Fuzzy Logic: Controls, Concepts, Theories and Applications*. London, U.K.: IntechOpen, 2012, pp. 325–350.
[80] C. M. Bishop, *Neural Networks for Pattern Recognition*. London, U.K.: Oxford Univ. Press, 1995.
[81] J. Brownlee, *Machine Learning Mastery With Python: Understand Your Data, Create Accurate Models, and Work Projects End-to-End*. Adelaide, SA, Australia: Machine Learning Mastery Pty, 2016.
[82] F. Farhadi, "Learning activation functions in deep neural networks," Ph.D. dissertation, École Polytechnique de Montréal, Montreal, QC, Canada, 2017.
[83] B. C. Zapata, *Android Studio Application Development*. Birmingham, U.K.: Packt Publishing, 2013.
[84] T. Hagos, "Android studio," in *Learn Android Studio 3*. Berkeley, CA, USA: Apress, 2018, pp. 5–17.
[85] N. Shahid, T. Rappon, and W. Berta, "Applications of artificial neural networks in health care organizational decision-making: A scoping review," *PLoS ONE*, vol. 14, no. 2, Feb. 2019, Art. no. e0212356.
[86] L. Deng, G. Hinton, and B. Kingsbury, "New types of deep neural network learning for speech recognition and related applications: An overview," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process.*, May 2013, pp. 8599–8603.
[87] F. Amato, A. López, E. M. Peña-Méndez, P. Vanhara, A. Hampl, and J. Havel, "Artificial neural networks in medical diagnosis," *J. Appl. Biomed.*, vol. 11, no. 2, pp. 47–58, 2013.
[88] B. Widrow, D. E. Rumelhart, and M. A. Lehr, "Neural networks: Applications in industry, business and science," *Commun. ACM*, vol. 37, no. 3, pp. 93–106, 1994.
[89] Y. Huang, L. J. Kangas, and B. A. Rasco, "Applications of artificial neural networks (ANNs) in food science," *Crit. Rev. Food Sci. Nutrition*, vol. 47, no. 2, pp. 113–126, Apr. 2007.
[90] Y. Singh and A. S. Chauhan, "Neural networks in data mining," *J. Theor. Appl. Inf. Technol.*, vol. 5, no. 1, pp. 1–6, 2009.

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