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Design, Construction, and Evaluation of an Intelligent Frost Forecasting and Warning System

Nikrooz Bagheri[1]✉, Meisam Bagheri[2], Movahed Sepahvand[3]

[1] Agricultural Engineering Research Institute, Agricultural Research, Education and Extension Organization (AREEO), Karaj, Iran.
[2] Artificial Intelligence Researcher, Post Student, Shahid Beheshti University, Tehran, Iran.
[3] Agricultural Engineering Research Group, Lorestan Agricultural and Natural Resources Research and Education Center, Agricultural Research, Education and Extension Organization (AREEO), Khorramabad, Iran.

✉ Corresponding author: n.bagheri@areeo.ac.ir

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ABSTRACT

Every year, frost causes the loss of many agricultural products. There is numerous equipment to protect plants against frost. Late turning on these equipment causes inefficiency in raising the air temperature, and early turning them on will increases energy consumption and costs. Therefore, accurately forecasting frost is crucial for turning on the equipment on time. In this research, an intelligent radiation frost forecasting and warning system (IFFS) based on the Internet of Things (IoT) technology was designed and constructed. This system comprises a wireless sensor, computing, and intelligent forecasting based on deep learning methods and warning announcements to the farmer by a message. Intelligent forecasting based on forecasting dew point temperature for the next three hours according to the in-situ measurement of temperature and relative humidity of the air. The meteorological data of the studied regain from 2011-2021 were used to train the network. The IFFS Performance was evaluated. Based on the obtained results, the system accuracy in measuring temperature and relative humidity of the air was 99% and 98%, respectively. The F-score of the IFFS obtained 96%, and the system accuracy in the warning announcement obtained 100%. Finally, applying the IFFS for better protection of plants is recommended.

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INTRODUCTION

Climate change is the primary source of agricultural production risk (Fraisse et al., 2006), which has a tremendous negative effect on agricultural products (Hoogenboom, 2000a; Ding et al., 2021). Frost is one of the consequences of climate change and every year damages many crops, especially horticultural crops around the world (Chevalier et al., 2012).

Currently, numerous active methods, including machinery and equipment, are used to protect plants against frost. The efficiency of these methods depends on the time of turning on the equipment (Guillen-Navarro et al., 2021). Turning on the equipment late makes their use inefficient, and turning it on early increases energy consumption and costs. Therefore, it is necessary to forecast frost with the aim of timely use of active protection methods. In reality, forecasting frost occurrence has been introduced as one of the strategies to reduce damage to agricultural products (Fraisse et al., 2016).

In the past, weather forecasts were based on a statistical analysis of meteorological data. However, today artificial intelligence and expert decision-making systems have provided an excellent opportunity to provide more accurate forecasting models (Fraisse et al., 2006). Takle (1990) used an expert system to forecast frost. The minimum and maximum temperature of the previous day, cloud cover percentage, current dew point temperature, precipitation, and wind speed were used as input variables. The results showed that the accuracy of forecasting by the expert system was comparable with human forecasting methods. Hoogenboom et al. (1998, 2000) built an Automated Environmental Monitoring Network (AEMN). This system consisted of more than 70 meteorological stations in agricultural areas. The meteorological stations collected data related to air temperature, air relative humidity, soil temperature (at a depth of 5, 10, and 20 cm), wind speed and direction, and solar radiation. The accuracy of this system in recording air temperature, air relative humidity, wind speed, solar radiation, and soil temperature obtained ±0.5^{o} C, 2%, ±1.5%, ±5%, and ±0.4^{o} C, respectively. Robinson and Mort (1997) developed a neural network-based system for frost forecasting. The input variables included temperature, cloud cover, wind speed and direction, and air relative humidity.

This system could forecast frost for the next 24 hours with acceptable accuracy. Hubbard et al. (2003) developed Kimball et al. research to provide a more accurate and less complicated method for forecasting and estimating dew point temperature. They showed that the combination of minimum and maximum temperature and the average temperature is the best input variable for estimating dew point temperature. The root means square error (RMSE) and means error (MAE) were obtained as 3.23 and 2.55, respectively. Jain et al. (2006) forecasted frost risk in three regions of Georgia using an artificial neural network. This system was able to forecast the temperature from 1 to 12 hours in the future. The data included meteorological variables such as air temperature, wind speed, rainfall, relative humidity, and solar radiation. The results showed that the rainfall variable does not affect the air temperature forecast, and the average error increases with the increase of the forecast period. Also, they estimated the most appropriate forecast interval to be 2-6 hours. The average error in forecasting one to 12 hours earlier was 0.6^{o} C and 2.5^{o} C, respectively. Prabha and Hoogenboom (2008) proposed a local-scale weather forecasting model for advective and radiation frost in peach and blueberry orchards. They found that the accuracy of forecasting dew point temperature depends on the time of day. Shank et al. (2008) used an artificial neural network to estimate air dew point temperature. They obtained an accuracy of about 0.8 for forecasting air dew point temperature within the next two hours. Smith et al. (2009) developed 12 artificial neural network models to forecast the air temperature in the next 1-12 hours. The average forecasting error ranged from 0.52^{o} C to 1.9^{o} C in forecasting one hour to 12 hours earlier. Chevalier et al. (2012) designed an expert system based on web-based fuzzy logic to prevent the frost of peach and blueberry crops. They used the regional meteorological data bank and an expert system to forecast frost from one to 12 hours in advance. Castanda-Miranda and Castano-Meneses (2017) used an artificial neural network to forecast frost in a greenhouse. The variables, including the temperature outside the greenhouse, outside and inside relative humidity, solar radiation, and wind speed, are used as network inputs. The accuracy of frost forecasting was 0.95. In 2020, these researchers succeeded in building an intelligent system based on the IoT to protect greenhouse tomatoes against frost. In this system, the weather station parameters, including temperature, relative humidity, wind speed, and solar radiation are used, and an artificial neural network and fuzzy (ANFIS) are used for forecasting the future temperature and frost. The probability of frost is announced to the greenhouse keeper through mobile phones and the internet. Also, in the frost condition, the sprinkler system will automatically turn on to increase the temperature of the environment. Guillen-Navarro et al. (2021) developed an IoT system to reduce frost damage to orchard trees. Ding and Tamura (2021) used a machine-learning method for forest forecasting. They applied time-series temperature data for developing a model and forecasting forest. The accuracy of the system was 0.6 in experiments.

Due to the lack of meteorological stations near agricultural fields and the uncertainty of meteorological data to predict frost, it is necessary to use local forecasting systems, the purpose of this research is to design and construct a local-scale intelligent system for frost forecasting.

MATERIALS AND METHODS

In this research, an intelligent system for local-scale frost forecasting was designed and constructed (Figure 1). This system calculates the current dew point temperature and forecasts the dew point temperature for the next three hours by deep learning. After forecasting frost, a warning message will be sent to the farmer by SMS. The implementation of the research is as follows:

Figure 1. The IFFS system

Identifying variables affecting the radiation frost

Based on documentary studies and the review of previous research, the variables affecting crop frost include minimum and maximum air temperature, dew point temperature, cloud cover, air relative humidity (Perry et al., 1998), wind speed and direction, and solar radiation. The most influential parameters in frost forecasting include air temperature, air relative humidity, and dew point temperature (Chevalier et al., 2012). So, based on the obtained results, these three variables can forecast frost with an accuracy of over 90%. Therefore, in this research, the air temperature, air relative humidity, and dew point temperature were used for local-scale forecasting of the radiation frost.

Design and construction of frost forecasting intelligent system

The IoT-based block diagram of the IFFS is shown in Figure 2. This system consists of four layers, including the perception layer, network layer, intelligent forecasting layer, and application layer. The task of the perception layer is to collect and store the air temperature and relative humidity data. The task of the network layer is to transfer the stored data from the perception layer to the intelligent forecasting layer. The intelligent forecasting layer is responsible for calculating the current dew point temperature and predicting the future dew point temperature based on the deep learning method. An application layer announces a warning to the farmer by SMS. More details are below:

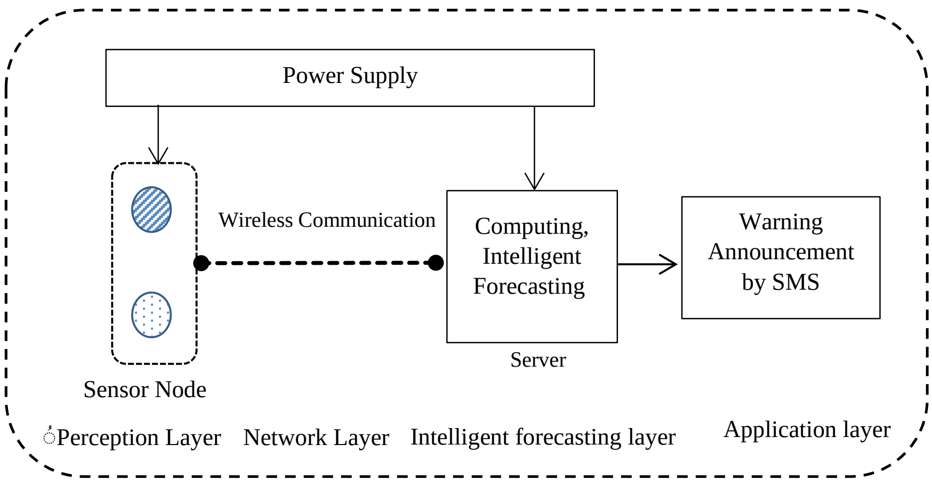

Figure 2. The IoT-based block diagram of the IFFS

The perception layer of the IFFS

The SHT35 digital sensor measures air temperature and air relative humidity. This sensor has high accuracy and the ability to work in an open environment and harsh weather conditions. This sensor is for simultaneous measurement of temperature (in the range of -40 to +125° C) and air relative humidity (in the range of 0-100%) with a digital output with an accuracy of ±0.2° C in temperature measurement, and an accuracy of ±1.5% in humidity measurement. The SHT35 sensor is fully calibrated, and its output is linear. The working voltage of the sensor is 2.4-5.5V. Reliability, high stability, and high signal-to-noise ratio are the characteristics of this sensor. The sensor needed a special board to connect to the circuit board, which connected to it. The sensor is set to measure and store the data every 60 seconds and transmit it to the intelligent forecasting layer through the wireless link. The Arduino UNO R3 board by Atmega 328 microcontroller (5V operating voltage, 40mA direct current) is applied to store and transfer the sensor data.

Due to the lack of electricity outdoors, a solar power bank provids the required electric power for the system. It includes the following components:

- Rechargeable 18650 lithium-ion battery with a voltage of 2.4 volts and a current of 3300 mAh
- An 18650 lithium-ion battery charger module (voltage 5 volts, current 1 A, USB output)
- Charge controller module
- Solar panel model Cl-650 with 24 cells and 4 watts capacity (CCLAMP Company, China) with fast charging capability.

The network layer of the IFFS

Wireless communication connected the perception (sensor node) to the intelligent forecasting layer. Among the types of communication protocols, the ZigBee communication protocol is chosen according to distance, environmental conditions, and cost. The Zigbee DRF 1605H CC2530CA module has a long-range antenna, a voltage of 2.6-3.6V, a maximum current consumption of 120mA, a frequency of 2.4GHz, a maximum range of 1600 m, with communication protocol: UART, a working temperature -40 to +85° C is used. The CC2530 Zigbee Module USB to UART Backplane (DRF1605-USB) board used to set up the Zigbee module and connect it to the USB port.

The intelligent forecasting layer of the IFFS

The Raspberry Pi 4 with 4 Gigabyte memory (5V, 3A) is used as hardware for data calculation and forecasting. It acts as a base station and is connected to the perception layer through a wireless communication protocol. Its operating system is Linux, and its programming language is Python. After transmitting the online sensor data to the Raspberry Pi, the current dew point temperature was calculated from equation (1) (Alizadeh, 2016):

$$T_{d=(0.1T-112)+(112+0.9T)(RH)^{0.125}} \quad (1)$$

Where, RH, Air Relative Humidity (%); T, Air Temperature (° C);Td, Dew Point Temperature (° C).

Frost was forecasted based on forecasting the future dew point temperature using the deep learning method and applying the gradient boosting algorithm. The frost threshold is set to a dew point temperature of 0° C. The threshold value changed according to the critical frost temperature of the plant. The GBM method by xgboost 1.6.1 library of PyPi implements the gradient boosting algorithm. The min-max scaler method is used to normalize the data, and the grid-search method is used to find the best grid parameters in training. Finally, the optimal parameters were obtained. Also, the num-boost-round parameter, which specifies the number of training repetitions, was considered 5.

For intelligent forecasting, time-series temperature and relative humidity data for April and May months during ten years (2011-2021) were gathered from the National Meteorological Organization. The time interval between data was 3 hours, and the total data was 4961. The data was separated into three categories: 65% of data for training, 10% of data for testing, and 25% of data for evaluation.

The application layer of the IFFS

A warning is sent announced to the farmer by SMS in frost conditions. A SIM800C SIM (Subscriber Identity Module) card shield with a GSM shield antenna is used to send the SMS. This shield was compatible with Raspberry Pi. Its communication protocol was serial UART, voltage 5-18V, working temperature from -25° C to +85° C, and data transfer rate of 2400-115200 bits per second. To prevent entering rain, snow, or moisture into the system, as well as to prevent animal damage, devices were placed in waterproof and resistant boxes.

The performance evaluation of the IFFS

The evaluation of the performance of the IFFS was carried out in three stages as follows:

Evaluation of the performance of the IFFS in measuring the temperature and relative humidity of the air

To evaluate the accuracy of the IFFS, the temperature and relative humidity sensor data were compared with the meteorological reference data. So, the IFFS was placed next to the accurate temperature and relative humidity sensors of the meteorological organization's synoptic station for five days (120 hours). Data is recorded and stored every hour. Then, the gathered data were compared.

Evaluation of the accuracy of IFFS in forecasting

To evaluate the IFFS frost forecasting accuracy, the confusion matrix of the results presented and the accuracy, sensitivity, specificity, and the F-Score obtained based on the below formulas (Cadenas et al., 2020):

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad \text{(Cadenas et al., 2020)} \quad (2)$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \quad \text{(Cadenas et al., 2020)} \quad (3)$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} \quad \text{(Cadenas et al., 2020)} \quad (4)$$

$$\text{F} - \text{Score} = \frac{\text{2TP}}{2TP+FP+FN} \quad \text{(Hand et al., 2021)} \quad (5)$$

Where, TP (True Positive), Forecasted Frost; FP (False Positive), Forecasted False Frost; FN (False Negative), Frost Not Forecasted; TN (True Negative), No Frost.

Evaluation of the accuracy of the system in warning announcement

To evaluate the IFFS warning announcing accuracy, the system was placed in an orchard under different weather conditions in March and May. Then, the performance of the IFFS in sending SMS in frost conditions was evaluated.

RESULTS AND DISCUSSION

To evaluate the performance of the IFFS, the hardware is located in the orchard near the trees. The distance between the sensor node and Raspberry Pi could be a maximum of 1000 meters, and the height of the sensor from the ground level should be 1.5-2 meters. The results are presented as follows:

Evaluation of the performance of the IFFS in measuring the temperature and relative humidity of the air

In Figure 3, the result of comparing the IFFS data with the meteorological reference sensor data is shown. Based on the figure, the correlation between air temperature data recorded by the IFFS and the air temperature data recorded by the meteorological sensor was 0.99. The results confirm the accuracy of the temperature sensor. Also, the result of comparing the air relative humidity recorded by the IFFS with the air relative humidity recorded by the meteorological sensor is shown. Based on the figure, the data of the air relative humidity recorded by the IFFS had a correlation of 0.98 with the air relative humidity data of the meteorological reference sensor. Therefore, the sensor has sufficient accuracy to measure the air's relative humidity in actual conditions.

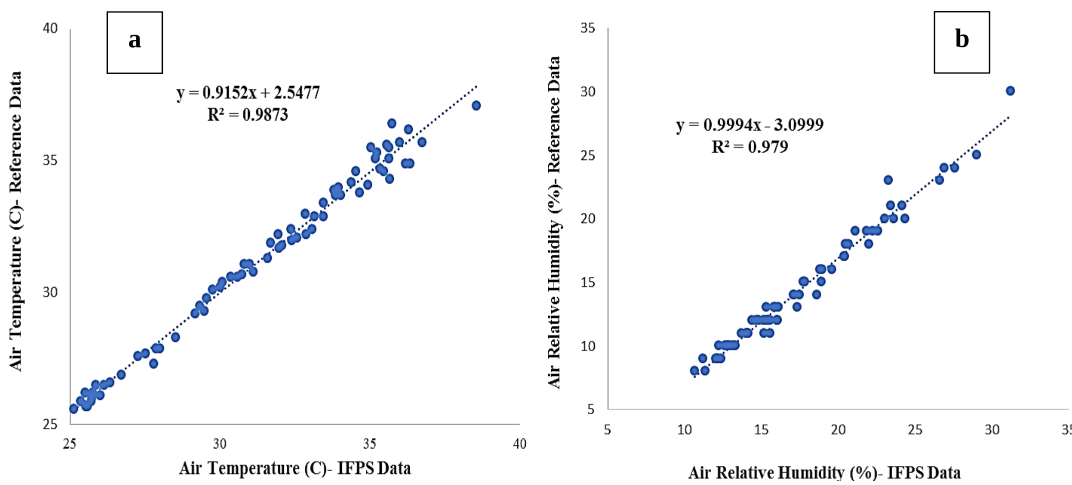

Figure 3. Comparing the air temperature (a) and air relative humidity (b) recorded by the IFFS with the data recorded by the reference sensor

Evaluation of the performance of IFFS in frost forecasting

The confusion matrix of the test data is shown in Figure 4. Also, the results of measuring accuracy, sensitivity, specificity, and F-Score are presented in Table 1. Based on the figure, out of 495 data used for the testing model, 390 data forecasted non-frost conditions (True Positive), 75 data forecasted freezing conditions (True Positive), 20 data forecasted frost (False Positive), and 10 data forecasted non-frost (False Negative).

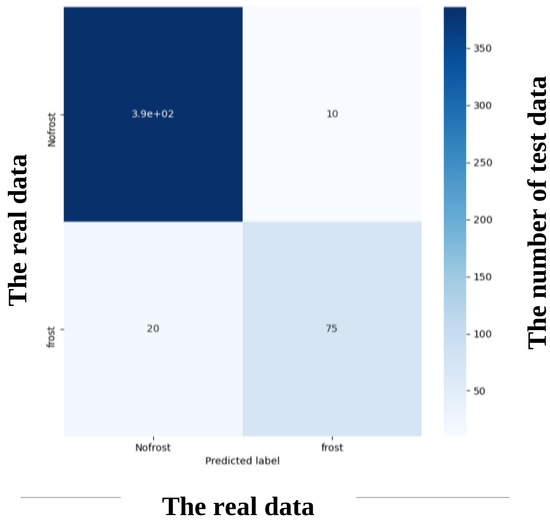

Figure 4. The confusion matrix of the test data

Based on the results of Table 1, the accuracy of the IFFS forecasting model was 94% and 94% of frost and non-frost events forecasting were correct. The false positive error was about six percent. The sensitivity of the IFFS forecasting model was also 88.2%. In other words, more than 88% of forecasted frost results were corrected, and the false negative error was about 12%. Also, the specificity of the IFFS obtained 0.95 which means 95% of the results of forecasting non-frost events were corrected. Also, the F-score was equal to 96%, which shows the high accuracy of the forecasting model.

Table 1. The results of the confusion matrix of test data

Accuracy	**Sensitivity**	**Specificity**	**F-Score**
0.939	0.882	0.951	0.963

Evaluation of the performance of the IFFS in warning announcement

The result of the evaluation of the performance of the IFFS in warning announcements is presented in Table 2. In all frost situations, a warning message is sent to the farmer. Also, in all non-frost situations, a warning message was not sent to the farmer. The results indicated an accuracy of 100% in warning announcements.

Table 2. The performance of the IFFS in warning announcement

Frost Forecasting		**Warning Announcement**	
Frost	No Frost	Sending SMS	Not Sending SMS
√	-	√	
√	-	√	-
-	√	-	√
√	-	√	-
-	√	-	√
-	√	-	√
√	-	√	-
√	-	√	-
√	-	√	-
-	√	-	√

This system is designed in such a way that it announces warning messages in two situations:

- When forecasting the frost in the next three hours
- When the sensor node does not send data to the Raspberry PI according to the schedule (due to battery or sensor failure).

CONCLUSION

In this research, an intelligent system for local-scale forecasting of radiation frost and warning announcements to farmers is designed and constructed. This system is based on IoT and consists of 4 layers, including a perception **layer**, network layer, intelligent forecasting layer, and application layer. Intelligent Frost forecasting was carried out using the deep learning method by gradient boosting algorithm. The 10-year meteorological data (from 2011-2021) was used to train the network. When frost forecasts within the next three hours, the system sends a warning SMS to the farmer.

The performance evaluation result showed that the accuracy of the IFFS in measuring air temperature and air relative humidity was 0.99, and 0.98, respectively. Also, the F-score obtained 0.96, and the accuracy in announcing the warning was 100%. Due to the acceptable accuracy of the system, the IFFS recommended forecasting radiation frost. This system is recommended to forecast radiation frost of all agricultural products by having at least ten years of data on air temperature, air relative humidity, and dew point temperature of the region.

To get better results in using this system, farmers must do the following work:

- Always keep the mobile phone on while using the IFFS.

- Considering the plant protective equipment must start working before the air temperature reaches the critical value, operators should turn on equipment at least 30 minutes before starting the forest.

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