From Cloud to Crop: A Predictive Platform for Weather and Apple Fruit Surface Temperature

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INTRODUCTION

Modern agriculture, especially high-value specialty crop prediction needs accurate, localized environmental prediction and data-driven automation technologies for production management. Among them, weather conditions and fruit surface temperature measurements are crucial for farmers as rapid shift in microclimate, solar radiation and temperature can lead to sunburn or frost damage, dehydration and yield loss especially during peak growing season. In order to overcome these limitations, we developed a web-based prediction platform that forecasts both weather and fruit surface temperature using deep learning. The system integrates:

- A Continuous Recurrent Neural Network GAN (C-RNN-GAN) [1] to generate short-term forecasts of key weather variables e.g., air temperature, humidity, wind, solar radiation
- Two different model, CNN-based (ResNet [2]) and RNN-based (LSTM [3]) to predict and benchmark apple fruit temperature from weather attributes.

The application allows user to input a specific datetime and select features of interest which is deployed through a python-based Flask server [4] and it returns both weather and FST prediction. This helps enabling timely interventions such as irrigation, shade management or harvest planning to protect our crops.

SYSTEM OVERVIEW

- **Web-based Architecture:** The system is implemented using Flask framework in python. This can provide a user-friendly web interface for submitting datetime and feature inputs via forms. The server manages input validation, model invocation and result rendering.
- **Dual Model Pipeline:** It integrates two section – a C-RNN-GAN for multivariate weather forecasting and ResNet/LSTM for predicting apple fruit surface temperature.
- **Data Processing and Prediction Flow:** Based on historical weather datasets, the models are trained and save in `.keras` format. Based on the requests, the server generates short-term weather forecasts and predict the apple fruit surface temperature.
- **Interactive Output:** The system displays the predicted values in an HTML table and graph. This modular and responsive design helps real-time agriculture decision making and can be extended to other crops or regions.

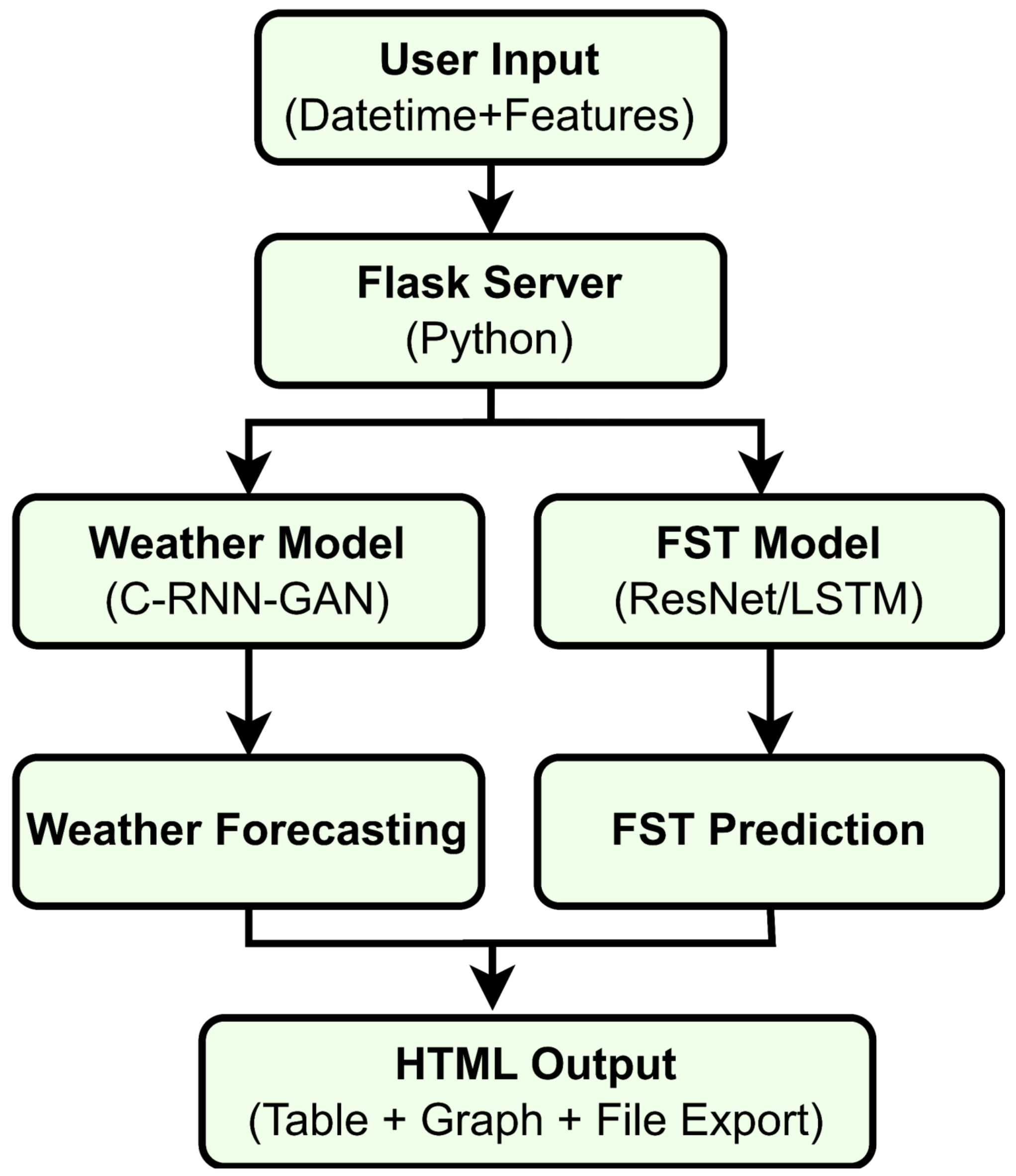

Figure 1: Workflow of the system

IMPLEMENTATION

The datasets are collected from AgWeatherNet for Quincy weather station. The weather attributes include air temperature, dew point, atmospheric pressure, relative humidity, solar radiation, wind speed, gust speed. There are prior work they have show that the fruit surface temperature from weather attributes [5]. We have trained our model using these data and these trained model are integrated with python Flask server. In figure 2 & Table 1, 2, we have show cased our implementation:

2024-11-17T01:15	Actual	Predicted
Air Temperature (◦c)	3.22	3.07
Dew Point (◦c)	1.67	1.42
Rel. Humidity (%)	89.50	90.19
Atm. Pressure (kPa)	100.51	100.61
Solar Radiation(w/m^2)	0.00	-3.50
Wind Speed (m/s)	2.77	2.16
Wind Gust (m/s)	4.83	4.68

Table 1: Weather Prediction for specific timestamp.

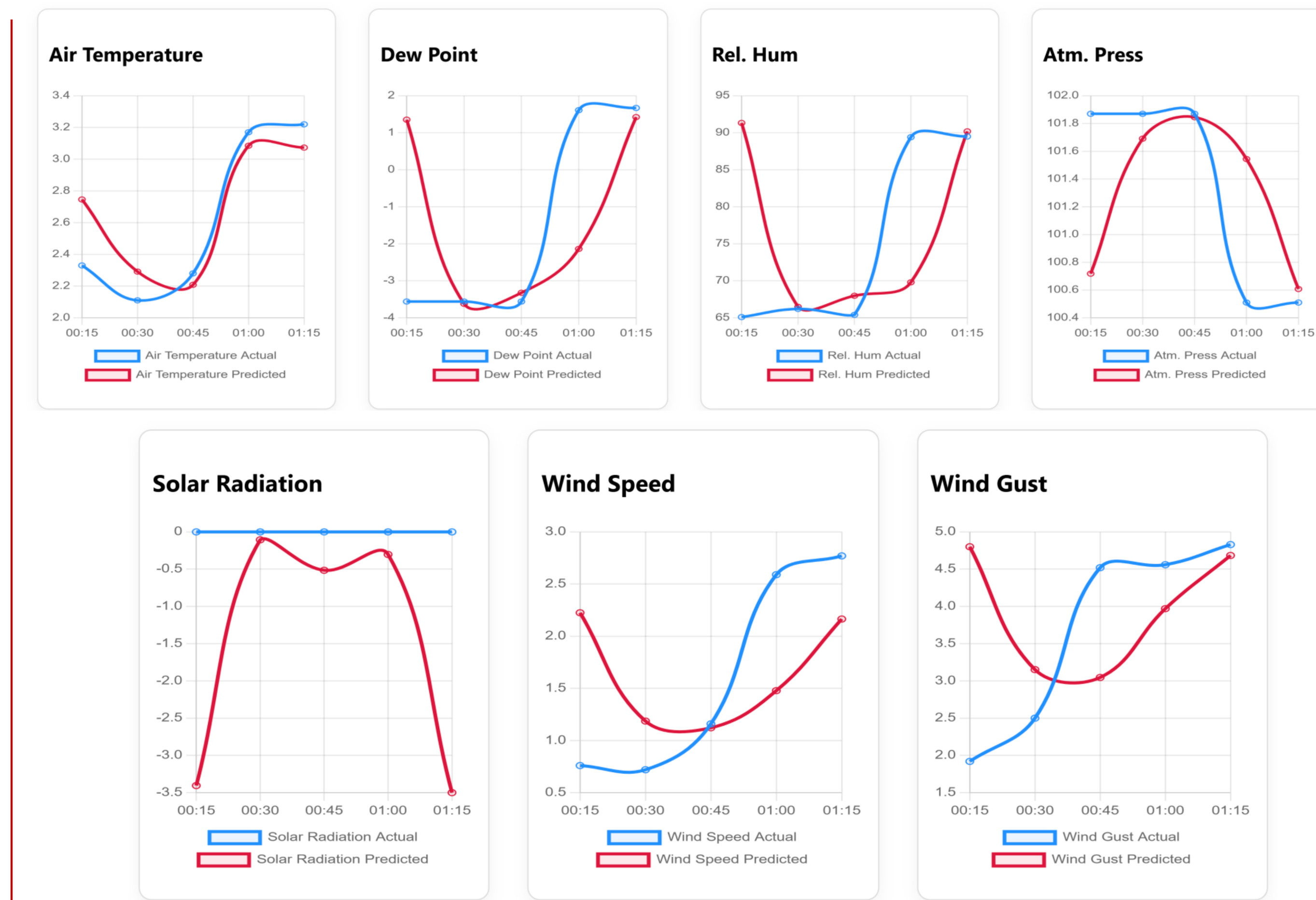

Figure 2: Interactive plots for weather prediction.

2024-11-17T01:15	Actual	Predicted	Difference
ResNet	6.67	6.68	-0.01
LSTM	6.67	6.78	-0.11

Table 2: Apple Fruit Surface Temperature prediction.

MODELS PERFORMANCE

For evaluating the performance of the models, we are using the following metric:

- Mean Absolute Error (MAE) = $\frac{1}{n}\sum_{i=1}^{n}(|y_i - \hat{y}_i|)$
- Root Mean Square Error (RMSE) = $\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$
- $R^2 = 1 - \frac{\sum(y_i-\hat{y}_i)}{\Sigma(y_i-\bar{y})^2}$

Attributes	MAE	RMSE	R^2
Air Temperature (◦c)	0.5446	0.7131	0.9804
Dew Point (◦c)	0.5805	0.8150	0.9735
Rel. Humidity (%)	1.4010	2.1400	0.9756
Atm. Pressure (kPa)	0.0919	0.1324	0.9765
Solar Radiation(w/m^2)	9.2337	20.3377	0.9564
Wind Speed (m/s)	0.1881	0.2700	0.8065
Wind Gust (m/s)	0.4573	0.6466	0.7767

Table 3: Performance for weather prediction model

Models	MAE	RMSE	R^2
ResNet	0.5823	1.2395	0.9344
LSTM	0.8335	1.3969	0.9167

Table 4: Performance for fst prediction models

From Table 3 and 4, the evaluation metrics indicates that the models well performing for predicting the weather attributes as well as fruit surface temperature.

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