Forecasting microclimates with a low-cost LoRa enabled weather station network

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***Abstract*—Farmers require accurate weather forecasting for a variety of reasons. Such as deciding if wind speed will be low enough to spray crops or whether there is a risk of spring frost and they should take appropriate action. This paper develops a low-cost weather station network built from widely available electronics for deployment in an agricultural setting. It then uses data from the network to train a LightGBM**

***Index Terms*—machine learning, smart farming, forecast, microclimate, IoT, LoRa, LightGBM**

I. Introduction

II. Related Work

A. LoRa based IoT in agriculture

IoT devices have seen widespread adoption in agriculture, with digital solutions offering the potential to improve yields even in remote areas. LoRa is an especially relevant technology in this context as the range of these devices enables data to be transmitted over long distances; additionally the low power of these devices allows for the use of gridless power solutions - such as solar-battery as used here.

There are relatively few papers examining the effectiveness of LoRa in agriculture but some notable examples include [1] where LoRa was used in an edge computing exercise. In this study the authors used CNN machine learning to create a compressed image that holds thousands of simulated climate readings. This image can then be sent over LoRa to a receiver node which can infer the readings of each node from this single image. While only one sensor node was created for the exercise they also tested the range of this device at a distance of 200m. This system would be useful in particularly large networks of LoRa devices where the low data transfer speed of LoRa would start to be a limiting factor.

The authors in [2] implement a LoRa based weather station prototype in India. The authors create a node that measures temperature, humidity and soil moisture in an experimental setting with no field deployment. Readings are then sent via LoRa to a receiver and can be read manually from the device's screen or viewed on an IBM dashboard.

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B. Weather forecasting microclimates with machine learning

General weather models operate at magnitudes between 1 and 10 km and microclimate predictions require models that operate at scales of roughly 100m or less. Using existing general forecast models for micro-scale predictions is computationally expensive [3], and these models have lower accuracy rates than predictions using machine learning due to the inherent complexity and non-linear nature of microclimates. Therefore a number of studies have focused on building bespoke models to predict very local forecasts using machine learning processes.

A 2021 study by Kumar et al [4] developed an ML framework called DeepMC as a part of a Microsoft Research initiative. Their model is able to predict a variety of climatic variables such as soil moisture, wind speed and temperature using inputs from weather station forecasts and IoT sensors. They were able to get up to 90% accuracy with a 12-120 hour forecast range.

Zanchi et al [5] used physical modelling of local terrain combined with deep learning (DL) to forecast the microclimate in the foothills of Lombardy. The objective was to predict the local conditions at the meter-scale as opposed to the 10km+ scale of regional and global weather forecasts. The initial model combined data about the morphology of the local terrain and weather forecast data to provide the input data for two feed-forward neural networks. These neural networks were trained to predict the local weather variables using data from 25 sensors deployed in the region being studied. The study demonstrated that local predictions were more accurate when using forecast data from local weather stations as opposed to global climate datasets, but accuracy good in both.

Blunn et al [3] ran a study focussed on predicting temperatures in urban environments during heatwaves, using data from eight heatwaves in London, UK. They used data from the UKV - a high-resolution weather forecasting model - and from citizen weather stations (CWS). The authors used a similar model training design to that in this study. A number of ML models were trained on UKV variables (i.e. a general forecast) and CWS variables (local sensor data) to bias correct the UKV readings and create a forecast prediction model that could predict the CWS readings accurately (mean average error: 0.12°C) compared with the general weather readings from UKV (mean average error: 0.64°C). The main points of difference to this paper are the use of only temperature versus a wider range of variables in this study, along with the use of custom weather stations here compared to public weather data.

A recent paper from Abdelmadjid et al 2025 [6] used online datasets from Kaggle (a public repository of various datasets) to develop an ML tool to predict changes in temperature and humidity within greenhouses in response to changes to external weather conditions. They used this data to test three ML models and three DL models and selected the LightGBM ML model and the LSTM DL model as the best performing models for prediction. The overall system design consisted of four LSTM models feeding into the LightGBM model. This design resulted in 98.45% accuracy for temperature predictions and 99.61% accuracy for humidity predictions. Due to these results LightGBM was also chosen for this experiment.

III. Methodology

A. IoT hardware

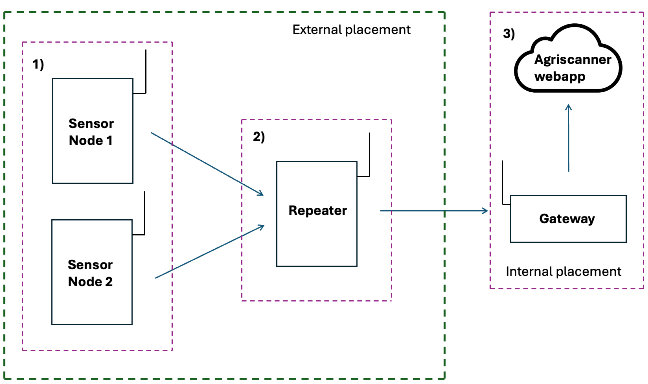

Fig. 1. Network diagram of the system

The design of the hardware consisted of two sensor nodes, a repeater and a gateway. The purpose for each is outlined below:

1) Sensor node: Collects temperature, humidity, wind speed and soil moisture data every 6 seconds. These readings are then averaged and sent as a single packet each minute to the repeater. Figure 2
2) Repeater: Receives LoRa signals from the sensor nodes and then immediately re-transmits these to boost range.
3) Gateway: A hub that receives LoRa signals and then transmits weather data using WIFI.

All components were commercially available, and assembling the final hardware required only basic tools. Each device used the iLabs Challenger RP2040 microcontroller, which provided the necessary computing power and included built-in LoRa capability for wireless communication. The gateway node was additionally equipped with a Raspberry Pi to enable WIFI connectivity and remote access via VNC Viewer.

Fig. 2. Sensor node

B. Webapp design

Weather data was sent to a purpose built webapp

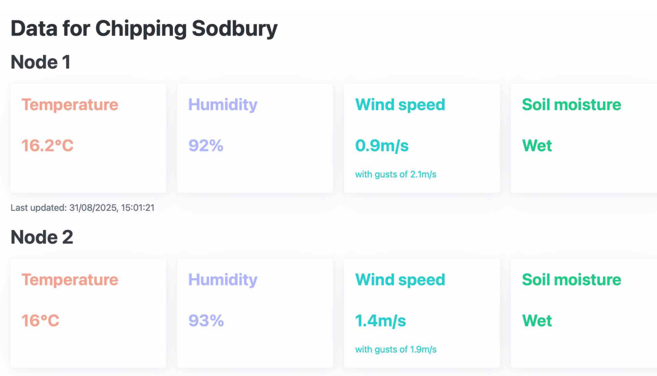

Fig. 3. Webapp main dashboard

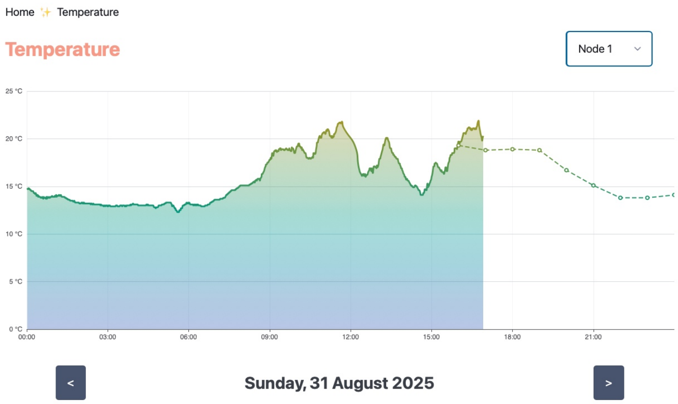

Fig. 4. Webapp temperature page showing current and predicted weather

TABLE I
TABLE TYPE STYLES

Table Head	**Table Column Head**		
	Table column subhead	***Subhead***	***Subhead***
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[a]Sample of a Table footnote.

C. Training and deployment of Machine learning algorithm

IV. RESULTS

A. Machine learning performance

B. Range and cost

V. CONCLUSION

A. Example figure and table

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