



Design and Implementation a Low-Cost Automatic Weather Monitoring System using ESP-NOW

by

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A project report submitted in partial fulfillment of the requirements for the degree
of Bachelor of Science in Electrical and Electronic Engineering

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DECLARATION

This Final year Capstone Project report is submitted to the department of Electrical and Electronic Engineering, University of Liberal Arts Bangladesh in partial fulfillment of the requirements for the degree of Bachelor of Science. So, we hereby declare that this report is based on the work done by us. Materials of work found by other researchers are mentioned by reference. This project report, neither in whole, nor in part, has been previously submitted for any degree.

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SUPERVISOR'S CERTIFICATION / APPROVAL

This is to certify that the thesis entitled Design and Implementation a Low-Cost Automatic Weather Monitoring System using ESP-NOW, submitted by Sahin Miraz Khan (Student ID: 171016025) an undergraduate student of the Department of Electrical and Electronics Engineering has been examined. Upon recommendation by the examination committee, we hereby accord our approval of it as the presented work and submitted report fulfill the requirements for its acceptance in partial fulfillment for the degree of Bachelor of Science in Electrical and Electronics Engineering.

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Abstract

This study introduces an innovative, low-cost weather monitoring system designed to operate independently of internet infrastructure, making it particularly valuable for remote and underserved areas. The system provides real-time, localized weather data, measuring key parameters such as temperature, humidity, wind speed, wind direction, rainfall, and sunlight. Unlike traditional systems that often face limitations like high costs, internet dependency, and restricted accessibility, this solution offers a practical and scalable alternative tailored to resource-constrained environments.

One of the system's standout features is its ability to function without internet connectivity, powered sustainably by solar panels to ensure long-term operation. While the current implementation focuses on affordable sensors and efficient data processing, future integration of TinyML on microcontrollers is planned to enable local data processing, real-time weather predictions, and anomaly detection directly on the device. This will eliminate reliance on cloud infrastructure, improving reliability and scalability while reducing operational costs.

Initial results highlight the system's effectiveness, achieving significant cost savings—up to 30% less expensive than conventional solutions—while maintaining accuracy and functionality. Additionally, it is capable of measuring parameters that are often overlooked in existing systems, further enhancing its value. Future plans aim to incorporate high-precision sensors, expand deployment through distributed networks, and integrate Geographic Information Systems (GIS) for real-time spatial visualization. By collaborating with local communities and institutions, this system can drive widespread adoption, supporting sustainable development and enhancing resilience to climate change.

Ultimately, this solution represents a transformative step toward democratizing weather monitoring. By providing critical, localized weather data to underserved regions, it empowers communities to make informed decisions and contributes to global efforts to address the growing challenges posed by climate change.

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Chapter 1: Introduction

Monitoring local environments is a vital effort that provides invaluable insights into the challenges posed by climate change and how we can respond effectively. Environmental changes typically refer to alterations in the Earth's natural surroundings, driven by various factors such as human activities, climate change, natural disasters, and other natural processes. These changes can significantly affect ecosystems, biodiversity, water resources, and even human health [4]. By observing and analyzing these shifts, we gain a deeper understanding of the interconnectedness between natural systems and human activities, which is essential for developing strategies to mitigate environmental damage and adapt to inevitable changes.

The rapid shifts in weather patterns have made natural disasters increasingly frequent and severe. Each year, countless people endure the devastating impacts of these events. Since 1960, over 11,000 disasters triggered by natural hazards have been recorded globally, with the number rising steadily from an annual total of 33 disasters in 1960 to a peak of 441 disasters in 2000 [1]. Between 2000 and 2019, natural disasters claimed 510,837 lives and affected 3.9 billion people across the globe [2]. Alongside the staggering human cost, these disasters also have profound economic repercussions, particularly for developing nations. Beyond immediate damage to infrastructure and resources, these events often leave long-term impacts, such as decreased agricultural productivity, displacement of communities, and the disruption of local economies. Since the 1990s, natural disasters have caused economic losses totaling tens of billions of U.S. dollars [3]. This financial burden further exacerbates inequalities, as low-income countries lack the resources to recover quickly and effectively from such catastrophic events.

The disparity in the impact of disasters between high- and low-income countries is striking. Data from the Events Database (EM-DAT) reveals that, on average, over three times as many people die per disaster in low-income countries compared to high-income nations. While higher-income countries experienced 56% of recorded disasters, they accounted for only 32% of global disaster-related fatalities. Conversely, lower-income nations faced 44% of disasters but suffered a disproportionate 68% of the deaths [1]. This inequity underscores the urgent need for robust disaster management strategies and increased global cooperation. High-income countries often have the advantage of better infrastructure, advanced forecasting systems, and access to resources for post-disaster recovery, while low-income nations lack these critical tools. This gap highlights the importance of sharing technological advancements, financial aid, and expertise to improve disaster preparedness and resilience worldwide.

Environmental changes disrupt the delicate balance of ecosystems, causing harm to plant and animal species and threatening the stability of entire ecological networks. For example, deforestation leads to habitat loss, putting numerous species at risk of extinction. Similarly, ocean acidification damages marine ecosystems, disrupting food chains and threatening livelihoods dependent on aquatic resources [5]. These disruptions often create a cascade of negative effects, where the loss of one species impacts others within the same ecosystem, ultimately destabilizing the entire network. Biodiversity, which encompasses the variety of living organisms and the ecosystems they inhabit, is also under threat. Habitat destruction, climate change, and pollution contribute to biodiversity loss, as many species struggle to adapt to rapidly changing conditions [6]. Protecting biodiversity is not just an ecological concern but also a critical component of maintaining human well-being, as it supports food security, clean water, and natural resources vital for survival.

Addressing these environmental challenges requires sustainable solutions to safeguard the planet's health and livability for future generations. However, current weather monitoring systems face significant limitations. High costs associated with sensors, digital systems, communication devices, power sources, and trained personnel for maintenance and operation pose barriers. Additionally, limited coverage and insufficient data sharing with the public further hinder the effectiveness of these systems [7]. In many developing regions, the lack of resources and technical expertise makes it even more challenging to deploy and maintain advanced weather monitoring infrastructure. This situation underscores the importance of designing cost-effective, durable, and easily operable systems tailored to the needs of resource-limited areas.

Weather monitoring plays a crucial role in understanding and predicting environmental changes. A weather station is a system that measures key weather parameters, such as temperature, humidity, atmospheric pressure, light intensity, and rainfall. These stations come in various forms, including fixed ground-based stations, satellite image-based systems, and remote sensing technologies. By analyzing data from these systems, meteorologists can predict future weather conditions, a process known as weather forecasting. Such predictions enable proactive measures, including preparing for severe weather events, optimizing agricultural activities, and managing water resources efficiently.

Weather forecasting is categorized into four classes: nowcasting, short-term, medium-range, and long-term predictions. Nowcasting involves predicting current weather conditions, while short-term forecasting covers the next 72 hours. Medium-range predictions extend to forecasts for the next three to seven days, and long-term forecasting focuses on predictions for weeks, months, or even years into the future [8]. Each category of forecasting plays a unique role in addressing environmental challenges. For instance, nowcasting helps in issuing timely warnings for severe storms, while long-term forecasting provides valuable insights

into climate trends and global environmental changes. These tools are indispensable for planning and mitigating the effects of environmental changes, ensuring that individuals, organizations, and governments can act swiftly and effectively.

While commercial weather stations are widely available, they are often expensive and heavily reliant on the internet, which makes them unsuitable for rural areas where internet access is limited or non-existent. For instance, many advanced weather stations rely on cloud-based platforms for data storage and analysis, requiring uninterrupted internet connectivity. Without this connectivity, the stations' functionality is significantly compromised. Moreover, the high upfront costs and recurring maintenance expenses make them inaccessible to underprivileged communities. This economic and technological divide has left many rural areas under-equipped to monitor and respond to weather changes effectively. To bridge this gap, developing cost-effective and offline-compatible weather monitoring solutions is essential. Such systems should prioritize affordability, durability, and the ability to function without the need for constant internet access, ensuring inclusivity and equity in weather monitoring [7].

While commercial weather stations are widely available but they are often more expensive and heavily rely on internet which makes them unsuitable for rural areas where there is no internet connection. The cost analysis of some of these station are given below:

Table 1.1: Different price range of Weather Station.

Name	Wi-Fi based	Price
AMBIENT WEATHER WS-4000 SOLAR POWER ULTRASONIC WEATHER STATION	Yes	250 USD
Vantage Vue Weather Station with Weather Link Console	Yes	625.50USD
Tempest Weather Station	Yes	339.00 USD
AMBIENT WEATHER WS-2000 With WIFI Remote Monitoring	Yes	300 USD

The application of Short-term and medium-long term prediction is huge in daily life. Some of the common uses are given below:

Table 1.2: Different types of Weather Prediction technique.

Time Scale	Domains	Applications
Short Term	Agriculture	The timing for sowing and harvesting; Irrigation and fertilization plans [9].
	Energy	Predicts output for wind and solar energy [10].
	Transportation	Road traffic safety; Rail transport; Aviation and maritime industries [11].
	Construction	Project plans and timelines; Safe operations [12].
	Retail and Sales	Adjusts inventory based on weather forecasts [13].
	Tourism and Entertainment	Operations of outdoor activities and tourist attractions [14]
	Environment and Disaster Management	Early warnings for floods, fires, and other natural disasters [15].
Medium—Long Term	Agriculture	Long-term land management and planning [16].

	Insurance	Preparations for future increases in types of disasters, such as floods and droughts [17].
	Real Estate	Assessment of future sea-level rise or other climate-related factors [18].
	Urban Planning	Water resource management [19].
	Tourism	Long-term investments and planning, such as deciding which regions may become popular tourist destinations in the future [20].
	Public Health	Long-term climate changes may impact the spread of diseases [21].

Short-term weather prediction:

Short-term weather forecasting primarily targets weather conditions that span from a few hours up to seven days, aiming to deliver highly accurate and actionable information that empowers individuals to make timely decisions. For example, these forecasts enable people to decide whether to carry an umbrella, postpone outdoor activities, or plan agricultural operations. Short-term forecasts are indispensable for industries like aviation, where they ensure flight safety by predicting turbulence and weather-related delays. Similarly, emergency services rely on these forecasts to plan and execute timely responses to extreme weather events, such as flash floods, hurricanes, or severe snowstorms. The precision of these predictions supports not only individual decision-making but also large-scale logistical operations.

Key components of these forecasts include maximum and minimum temperatures, the likelihood and intensity of various forms of precipitation, such as rain, snow, or hail, wind speed and direction, levels of relative humidity or dew point temperature, and types of cloud cover, including sunny, cloudy, or overcast conditions [22]. In addition, short-term forecasts often include visibility distances during foggy or smoky conditions and warnings about extreme weather events like thunderstorms, tornadoes, and hurricanes. These elements are critical for day-to-day planning,

ensuring public safety, and maintaining economic stability in sectors vulnerable to weather fluctuations. For example, accurate precipitation forecasts can help farmers optimize irrigation schedules, while wind condition predictions aid in the efficient operation of wind turbines in the renewable energy sector.

The methodologies for generating these forecasts involve complex numerical simulations run on high-performance computers. These simulations use observational data collected from diverse sources, including satellites, ground-based weather stations, weather balloons, and radar systems, to create a comprehensive representation of current atmospheric conditions. Advanced statistical techniques further enhance the accuracy of predictions, employing pattern recognition and probability calculations based on historical weather data. Moreover, the integration of machine learning and artificial intelligence is revolutionizing forecasting by enabling the identification of subtle patterns and trends that traditional models may overlook. These technologies allow meteorologists to refine predictions continually, improving reliability and precision.

Despite their growing sophistication, short-term forecasts face inherent limitations. The quality of input data, the resolution of numerical models, and sensitivity to initial atmospheric conditions all influence the accuracy of predictions. For instance, localized phenomena, such as sudden wind shifts or isolated thunderstorms, are challenging to predict due to their unpredictable and transient nature. Nevertheless, short-term weather forecasts remain indispensable, playing a pivotal role in transportation safety, disaster preparedness, agriculture, and recreation. By providing timely and actionable insights, these forecasts significantly enhance our ability to adapt to and mitigate the impacts of rapidly changing weather conditions.

Medium-to-long-term climate prediction:

Medium-to-long-term climate forecasting (MLTF) focuses on projecting climate conditions over extended periods, ranging from several months to multiple years. Unlike short-term weather forecasts, which emphasize immediate atmospheric conditions, MLTF provides a broader perspective, offering insights into long-term climate patterns and trends. These forecasts are typically categorized into medium-term predictions, which span from a single season up to a year, and long-term predictions, which extend over years, decades, or even longer [23]. While short-term forecasts are essential for daily decision-making, MLTF emphasizes understanding systemic shifts in Earth's climate, offering strategic guidance for planning and policy-making.

MLTF predictions typically include variables such as average temperature and precipitation, ocean-atmosphere interactions like El Niño or La Niña events, the likelihood of extreme weather phenomena such as droughts or floods, and

projections of hurricane activity [24]. Additionally, these forecasts provide insights into broader climate trends, such as global warming, sea-level rise, and localized climatic shifts. For instance, accurate projections of El Niño events can guide fisheries in managing resources, while predictions of prolonged droughts can inform water conservation strategies and agricultural planning. By understanding these long-term patterns, policymakers and scientists can design adaptive strategies to address critical challenges like food security, energy demand, and resource management.

The methodologies behind MLTF are diverse and robust, utilizing a combination of statistical, dynamical, and integrated modeling approaches. Statistical models rely on historical data and seasonal patterns, while dynamical models use complex mathematical equations rooted in physical laws to simulate atmospheric and oceanic processes. Integrated models combine multiple approaches and data sources to enhance accuracy and reliability. These methodologies often leverage cutting-edge technology, including high-performance computing, satellite data, and machine learning algorithms, to analyze vast datasets and improve the predictive power of models. However, the inherent complexity of the climate system poses challenges to achieving high accuracy. Multi-scale interactions between atmospheric, oceanic, and terrestrial processes, combined with socio-economic factors such as human activities and policy changes, contribute to the uncertainty of long-term predictions.

Despite these challenges, MLTF remains an invaluable tool for strategic planning and policy development. It plays a critical role in sectors like resource management, disaster risk reduction, agricultural planning, and energy policy. For example, accurate seasonal rainfall projections help farmers determine optimal planting schedules, while predictions of rising sea levels guide coastal infrastructure planning. Furthermore, MLTF informs global and regional climate action strategies, contributing to the design of mitigation and adaptation measures to combat climate change effectively. By providing a long-term perspective, these forecasts support sustainable development and resilience-building in the face of evolving environmental challenges.

This paper is organized as follows: Section 2 reviews the relevant literature, laying the groundwork for the study. Section 3 describes the materials and methods employed, detailing the data collection processes, modeling approaches, and analytical frameworks used. Section 4 presents and discusses the results, comparing the proposed methodologies with existing systems and highlighting the advancements achieved. Finally, Section 5 concludes the paper by summarizing the findings and proposing future research directions to enhance the accuracy and applicability of medium-to-long-term climate forecasting.

Chapter 2: Literature Review

Early weather prediction systems relied on serial communication, which served as the foundation for basic weather monitoring. As research progressed, more advanced systems emerged, incorporating GSM and Ethernet modules alongside sensors for measuring humidity, temperature, rainfall, solar radiation, and UV radiation [25]. These advancements enabled more reliable and accurate data collection, which improved weather predictions. The introduction of the Zigbee protocol and Arduino further revolutionized the field, allowing for systems capable of measuring barometric pressure, dew point, air temperature, wind speed, wind direction, and relative humidity [26], [27]. Researchers also leveraged Zigbee technology to develop mini weather stations tailored for agriculture, enabling farmers to monitor microclimatic conditions effectively. These systems were connected to a central station that processed data and generated early warnings for extreme weather events, such as frost or high winds, providing users with sufficient time to implement protective measures [28].

The rise of the Internet of Things (IoT) marked another leap forward in weather systems, offering enhanced functionality and reducing data storage and infrastructure costs by leveraging cloud-based services for efficient database management [29]. However, the reliance on internet connectivity in designs like those presented in [26] and [29] limited their effectiveness in areas with unreliable or no internet access. This limitation prompted further innovation in weather monitoring systems, focusing on alternative solutions for remote regions.

The evolution of the semiconductor industry introduced wireless sensor networks (WSNs) into weather monitoring, enabling the creation of versatile, low-power systems. One notable application was a data acquisition system designed to determine irrigation requirements based on weather conditions and soil percolation data [30]. Cleaner energy sources, such as solar panels, were also integrated into weather monitoring stations, making them more sustainable. However, these solar-powered systems faced challenges during cloudy or rainy conditions due to insufficient backup power storage [31].

Automatic Weather Stations (AWS) became a cornerstone of modern meteorology, offering automated observation and data transmission capabilities [32], [33]. In

AWS, measurement devices collect data via data acquisition units, which can either process the data locally or transmit it to centralized processing hubs for analysis. Advanced variations of AWS, such as Automatic Weather Observing Systems (AWOS) or Automatic Surface Observing Systems (ASOS), integrate multiple measurement devices, interfaces, and transmission units for seamless functionality. AWS systems can be classified into real-time AWS, which provide instantaneous data and alert users about extreme weather conditions, and offline AWS, which store data for later retrieval and analysis. Real-time AWS systems typically feature wireless communication modules like GSM/GPRS, enabling wide-range data transmission and user notifications in emergencies [34].

The introduction of Low-Cost Automatic Weather Stations (LCAWS) represented a significant milestone in weather monitoring technology. By utilizing commercially available components and open-source IoT platforms, LCAWS achieved substantial cost reductions without sacrificing autonomy or functionality. Notable components like the ESP8266 microcontroller, with its built-in Wi-Fi capabilities, have been widely adopted in DIY projects and small-scale IoT applications due to their ability to connect to wireless networks and support TCP and UDP protocols. These features make ESP8266 ideal for creating cost-effective, internet-connected weather monitoring systems [36].

Innovations continued with systems like the one developed by Reddy et al., which integrated IoT to monitor air quality and issue warnings for harmful gas levels. Similarly, Kumari et al. designed an IoT-based environmental monitoring system using a Raspberry Pi running on Android to measure soil, water, and air parameters through sensors [37]. Addressing the challenges of internet dependency in remote areas, ESP-NOW, a wireless communication protocol by Espressif, was introduced [38]. This protocol enables devices to communicate directly without Wi-Fi, making it ideal for remote weather stations with unstable or unavailable internet connectivity. Supporting broadcast, unicast, and multicast communication methods at data rates of 1 Mbps or more, ESP-NOW provides a robust solution for rural applications.

Building on these advancements, the integration of the ESP-NOW protocol with solar-powered weather stations has enabled the creation of reliable, low-cost

systems for rural areas. By combining sustainable energy sources with cutting-edge communication technology, these designs address the dual challenges of affordability and accessibility, paving the way for widespread adoption in underserved regions. Such innovations highlight the continuous evolution of weather monitoring systems to meet the demands of diverse environments and applications.

Machine Learning (ML) algorithms are showing their potential for extracting knowledge from large amounts of data. Traditionally, ML algorithms have been executed in supercomputers, where performance prevails over energy efficiency. There are variety of current models that are used for forecasting. Some of the common models are given below:

Table 2.1: Different types of Machine Learning Model.

Name	Description
CNN (Convolutional Neural Network)	CNN. A specific type of ANN is the Convolutional Neural Network (CNN), designed to automatically and adaptively learn spatial hierarchies from data [39]. CNNs comprise three main types of layers: convolutional, pooling, and fully connected [40]. The convolutional layer applies various filters to the input data to create feature maps, identifying spatial hierarchies and patterns. Pooling layers reduce dimensionality, summarizing features in the previous layer [41]. Fully connected layers then perform classification based on the high-level features identified [42]. CNNs are particularly relevant in meteorology for tasks like satellite image analysis, with their ability to recognize and extract spatial patterns [43]. Their unique

	structure allows them to capture local dependencies in the data, making them robust against shifts and distortions [44].
LSTM (Long Short-Term Memory)	LSTM. Long Short-Term Memory (LSTM) units are a specialized form of recurrent neural network architecture [45]. Purposefully designed to mitigate the vanishing gradient problem inherent in traditional RNNs, LSTM units manage the information flow through a series of gates, namely the input, forget, and output gates. These gates govern the retention, forgetting, and output of information, allowing LSTMs to effectively capture long-range dependencies and temporal dynamics in sequential data [45]. In the context of meteorological forecasting, the utilization of LSTM contributes to a nuanced understanding of weather patterns as it retains relevant historical information and discards irrelevant details over various time scales [45]. The pioneering design of LSTMs and their ability to deal with nonlinear time dependencies have led to their outstanding robustness, adaptability, and efficiency, making them an essential part of modern predictive models [45].
Random Forest	Random forest. A technique used to adjust or correct biases in predictive models, particularly in weather forecasting or climate modeling. Random Forest (RF) is a machine learning algorithm used for various types of classification and regression tasks. In the context of bias correction, the Random Forest algorithm would be trained to identify and correct systematic errors or

	biases in the predictions made by a primary forecasting model.
Probabilistic Deep Learning	Probabilistic deep learning models in weather forecasting aim to provide not just point estimates of meteorological variables but also a measure of uncertainty associated with the predictions. By leveraging complex neural networks, these models capture intricate relationships between various features like temperature, humidity, and windspeed. The probabilistic aspect helps in quantifying the confidence in predictions, which is crucial for risk assessment and decision-making in weather-sensitive industries.
Generative Adversarial Network	Generative Adversarial Networks (GANs) are a class of deep learning models composed of two neural networks: a Generator and a Discriminator. The Generator aims to produce data that closely resembles a genuine data distribution, while the discriminator's role is to distinguish between real and generated data. During training, these networks engage in a kind of “cat-and-mouse” game, continually adapting and improving—ultimately with the goal of creating generated data so convincing that the Discriminator can no longer tell it apart from real data.
Graph Neural Network	Graph Neural Network (GNN) are designed to work with graph-structured data, capturing the relationships between connected nodes effectively. They operate by passing messages or aggregating information from neighbors and then updating each node's representation accordingly. This makes GNNs exceptionally good at handling problems like social network analysis,

	molecular structure analysis, and recommendation systems.
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Machine Learning (ML) algorithms are increasingly demonstrating their potential to extract valuable knowledge from massive datasets, driving innovation across diverse domains [46]. Traditionally, these algorithms have been executed on supercomputers, where performance takes precedence over energy efficiency [47]. However, as the landscape of computing evolves, new approaches are emerging that balance performance, energy efficiency, and practicality. For example, edge and fog computing paradigms have introduced a decentralized model where initial computations are carried out close to the data capture devices. This decentralization offers several advantages, including (1) significant energy savings by reducing the need to transmit and process data in the cloud, (2) highly responsive applications and services tailored for mobile environments, (3) scalability enabled by the distribution of processing units, (4) enhanced privacy protection for IoT systems, and (5) improved resilience against intermittent connectivity issues [48]. These innovations are particularly important for IoT devices, which operate under strict power constraints due to their reliance on batteries or energy harvesters. Such limitations necessitate the development of ultra-low-power architectures, especially for energy-intensive components like wireless transmitters and processing units [49].

One of the most promising advancements in this area is Tiny Machine Learning (TinyML), an emerging field at the intersection of ML, IoT, and computing platforms [50]. TinyML aims to leverage microcontroller units (MCUs)—compact, ultra-low-power hardware components ubiquitous across IoT ecosystems—for implementing deep learning (DL) tasks locally on devices. These MCUs serve a broad spectrum of functions, from sensor data collection and actuation to information transfer and reception, all within power budgets as low as a few milliwatts [51]. The TinyML paradigm enables DL tasks to be executed directly on devices, eliminating the need for extensive computational resources or large datasets, which significantly benefits edge AI and IoT applications [52].

This shift is fueling rapid growth across fields such as smart manufacturing, smart healthcare, and autonomous systems, with industry experts predicting a

transformative impact on edge AI markets. ABI Research, a global tech market advisory firm, estimates that 2.5 billion devices equipped with TinyML chipsets will be shipped by 2030. These devices prioritize advanced automation, low costs, minimal data transmission latency, and ultra-power-efficient AI chipsets. Known as edge AI or embedded AI, these chipsets perform AI inference directly on the board. While training for these devices often depends on external resources like gateways, on-premises servers, or the cloud, the ability to perform real-time data analysis and interpretation on-device brings significant advantages in latency, privacy, and cost-effectiveness [52], [53].

TinyML has garnered significant interest from leading technology companies, driving innovation and adoption in the industry. Google, for instance, has introduced TensorFlow Lite, a platform designed for running neural network (NN) models on IoT devices [54]. Similarly, Microsoft has developed EdgeML [55], and ARM has released the Cortex Microcontroller Software Interface Standard Neural Network (CMSIS-NN), an open-source library aimed at enhancing NN performance on Cortex-M processors [56]. Additionally, STMicroelectronics has developed X-Cube-AI, a package that facilitates the execution of DL models on STM32 microcontrollers [57]. These tools and platforms empower developers to build efficient TinyML solutions tailored for various applications.

Microcontroller units (MCUs) are particularly well-suited for TinyML due to their small size ($\sim 1 \text{ cm}^3$), low power consumption (1 mW), and affordability (\$1). MCUs integrate a CPU, digital and analog peripherals, embedded flash (eFlash) memory for program storage, and Static Random-Access Memory (SRAM) for handling intermediate data. This combination of features makes MCUs an ideal hardware platform for TinyML applications, enabling compact, energy-efficient, and cost-effective implementations of AI models [52].

The potential of TinyML continues to expand as developers and researchers push the boundaries of what is possible with ultra-low-power devices. By reducing dependency on centralized resources and enabling localized intelligence, TinyML is poised to revolutionize IoT ecosystems, fostering innovation and scalability in fields that demand efficient and responsive solutions.

Chapter 3: Materials and Methods

Hardware Materials:

An effective weather station must measure important parameters such as wind speed, wind direction, rainfall, temperature, humidity, altitude, barometric pressure, and light intensity. The overview of the proposed system can be seen in Fig. 1.

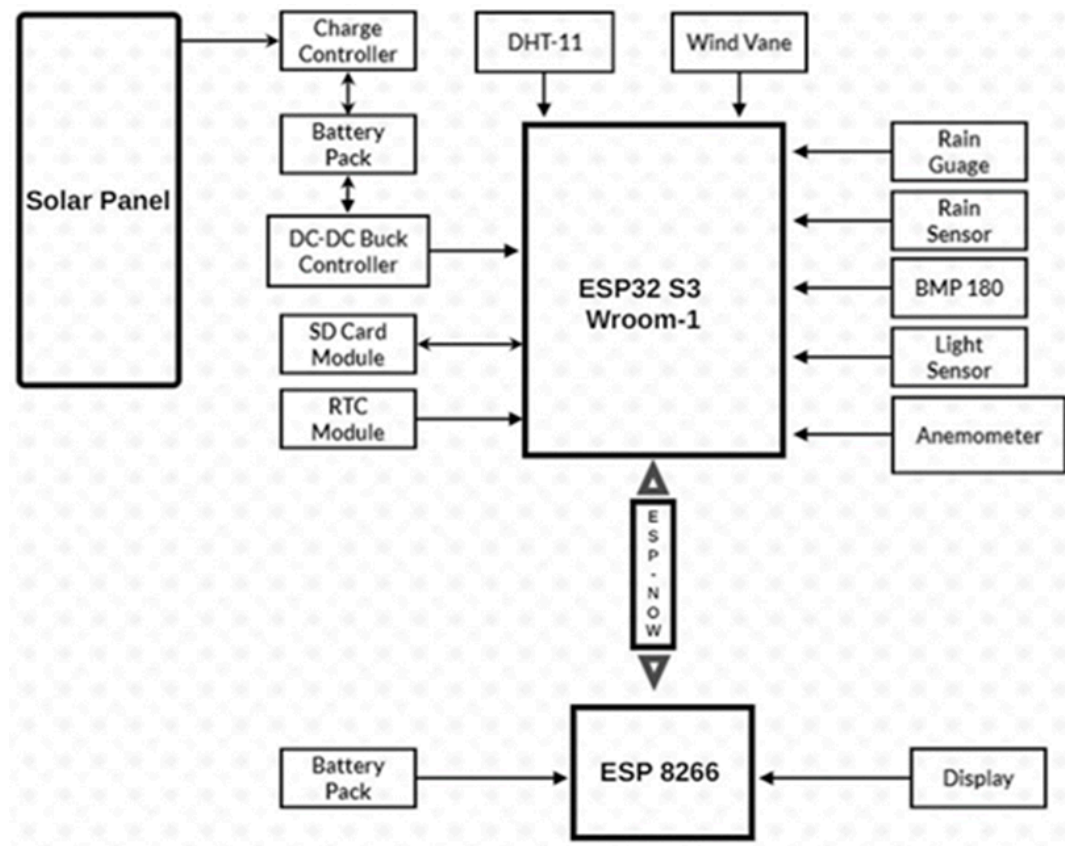


Fig. 1. Overview of the proposed system.

Our system is a solar-powered weather monitoring station based on the ESP32-S3 WROOM-1 microcontroller, which collects data from various sensors. A solar panel charges a rechargeable battery pack, which powers the system through a DC-DC buck controller. The system utilizes a real-time clock (RTC) module for timed data acquisition. An SD card module for data storage is also integrated, ensuring that the collected weather data is saved for future analysis. The ESP NOW communication protocol connects the ESP32-S3 with an ESP8266, which is

responsible for powering a 3.5-inch thin film transistor (TFT) display that shows real-time weather data. The range of this protocol is 220 meters under ideal conditions.

A. Sensors, Modules and Microcontroller

The weather station was constructed using low-cost components, considering energy efficiency, resolution and range. The selected sensors, as presented in Table I, include an anemometer [58] for wind speed, wind vane [59] for wind direction, rain sensor for detect weather it is raining or not, rain gauge [60] for rainfall detection, DHT-11 [56] for temperature and humidity, BMP180 [61] for altitude and barometric pressure, and BH1750 [62] for light intensity.

Table3.1: Specification of Selected Sensors.

Parameter	Model	Current	Res.	Range
Temperature and Humidity	DHT-11	2.5 mA	1	0 - 50 °C
Anemometer	WindMaster _{ISS7}	55 mA	0.01	0 - 50 m/s
Rain Gauge	ARG314	50 μ A	0.1	0 - 500 mm/hr

Barometric Pressure and Altitude Sensor	BMP180	5 μ A	0.02	300 - 1100 hPa
Sunlight Sensor	BH1750	0.12 mA	-	1 - 65535 lx
Wind Vane	OSA-16	2.5 mA	1	0 - 360 °

Based on the comparison of microcontrollers as shown in Table 2, the ESP32-S3 WROOM-1 [63] emerged as the most suitable choice for this work, particularly due to its superior microprocessor, clock speed and memory which offer greater potential for future expansion, compared to ESP-8266 [64] and Arduino Nano 33 BLE [65].

Table 3.2: A Comparison of Various Microcontrollers.

Model	Processor	Clock Speed	Memory	Connectivity
ESP-32-S3 WROOM 1	Xtensa® dual-core 32-bit	240 MHz	384 KB	Wi-Fi HT20

ESP-8266	Xtensa® single-core 32-bit L106	80 MHz	384 KB	Wi-Fi HT20
Arduino Nano 33 BLE	nRF52840	64 MHz	1 MB	Bluetooth 5

The ESP32-S3 uses deep sleep mode with timed intervals for data collection. However, the rain sensor can wake the system upon detecting the first raindrop, to start weather monitoring. An SD card module is integrated for data storage. Additionally, a 3.5-inch TFT touchscreen display unit powered by an ESP-8266 [64], enables real-time remote monitoring via the ESP-NOW protocol.

B. Printed Circuit Board

Fig. 2 shows the schematic diagram of the weather monitoring station, detailing the connections between the ESP32-S3 WROOM-1 microcontroller and key components. These include the buck converter for power regulation, the environmental sensors, RTC module for accurate timekeeping and SD card module for data storage.

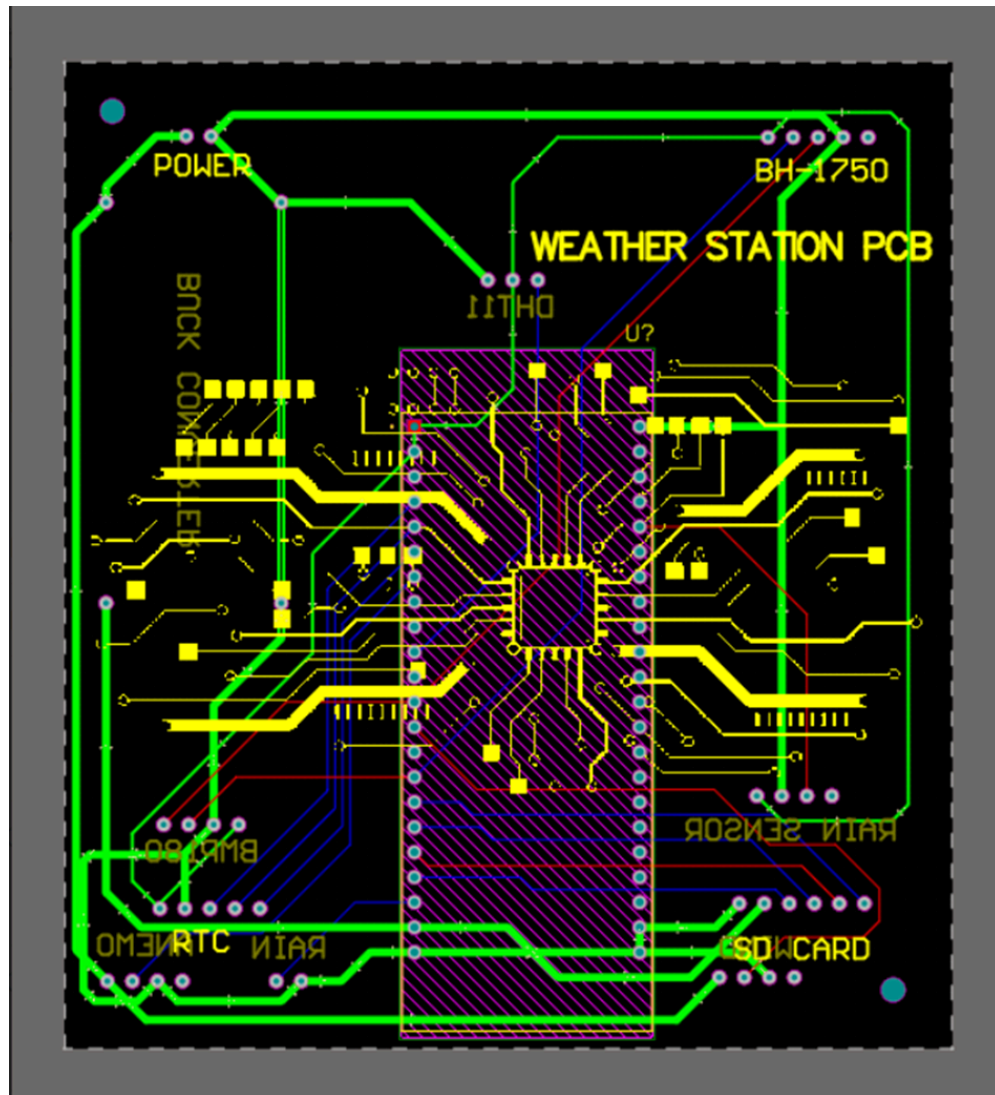


Fig. 3. Weather Station PCB layout

Two double-layer printed circuit boards (PCBs) were designed using Altium PCB design software to securely mount all components, minimizing noise and the risk of disconnection. Figure 2 The upper red one is the top layer and the upper blue one is the bottom layer of the PCB for the sensors, modules and microcontroller after applying polygon pours to minimize noise. All the power traces are 1mm wide to ensure proper power can be drawn by each of the components. And all the signal traces routed are 0.254mm wide though all the sensor data output singles are in 5V. The lower red one is the top layer and the lower blue one is the bottom layer of the battery pack PCB after applying polygon pour. Being a maximum 12V battery pack, all the traces are routed in 1.5mm thickness. 90° banding traces are avoided in both cases while routing to ensure proper thickness can form on the manufacturing

etching process. All the traces are 45° angles so that traces can be made in proper thickness in the manufacturing copper deposition process. For print the PCB 1.4mm fiber glass was chosen after solder mask and print silkscreen which became 1.6mm to enhance the durability of the PCB.

C. 3D Printed Protection Box

To protect the circuit board from uncertain weather and rain fall, a 3D printed box is designed using Fusion360 software, as shown in Fig. 3, and fabricated with a 3D printer. To make it non heat resistive the box is made from acrylonitrile butadiene styrene (ABS) filament with 0.5 mm nozzle.



Fig. 4. Design of the 3D printed protection box.

It features five windows with curved shields on the left, right, and front sides, allowing air to flow freely to get actual temperature and humidity while preventing rainwater from entering. In addition, the box has a 30 mm level surface for halo light intensity sensor and a 55 mm, 35-degree angled surface for the solar panel to get maximum sunlight exposure. Inside the box there is sufficient space to mount both the circuit board and battery pack.

D. Power Management

Power management is a critical component of the weather station design, particularly for deployment in remote areas. The proposed system is powered primarily by solar energy, with additional backup from a rechargeable battery system. The backup power consists of three 18650 lithium-ion rechargeable batteries connected in series, each providing 6400 mAh and 3.7 V. This configuration results in a battery pack with a total capacity of 6400 mAh at 11.1 V. These batteries are charged with the help of a TP4056 charger powered by three 80 × 80 mm solar panels, each generating approximately 5 V and 800 mA.



Fig. 5. Power Consumption in an oscilloscope.

In this system, the anemometer and wind vane are directly connected to the power supply and constantly draw current. The microcontroller is powered via a buck-boost converter which provides a stable 5V output and the rest of the sensors are powered via the microcontroller. The sensors in the system activate every 10 minutes to take measurements. In each 10- minute cycle, the system transitions through active, transmission, and sleep modes. During transmission, the microcontroller, sensors, anemometer and wind vane draw a current of 1.5A for 17.7 microseconds, followed by an active period of 58.6 microseconds where they

consume 620 mA. Once in sleep mode, the system consumes an average of 240 mA per second due to the anemometer and wind vane. The time spent in sleep mode is calculated to be 599.9999237 seconds using (1):

$$T_{\text{sleep}} = T_{\text{period}} - T_{\text{execution}} \quad (1)$$

Consider the supply voltage (V_{supply}) of 5 V and 6 readings per hour (N), the energy consumed for a particular mode (E_{mode}) in one day or 24 hours (H) was calculated using (2) and summarized in Table III:

$$E_{\text{mode}} = I_{\text{mode}} \times V_{\text{supply}} \times T_{\text{mode}} \times N \times H \quad (2)$$

TABLE 3.3 Energy consumption in different operating modes

Operating Modes	Current Consumption (A)	Duration (seconds)	Energy Consumption (Joules/day)
Transmit	1.50	17.7×10^{-6}	0.019116
Active	0.620	$58.6 \times 10^{-}$	0.02615904
Sleep	0.240	599.9999237	103679.986815
Total			103680.032

The total power consumption per day is 103680.032 joules, which is converted to 28.8 watt-hours per day (Wh/day) using

These batteries are charged with the help of a TP4056 charger powered by three 80×80 mm solar panels, each generating approximately 5 V and 800 mA. Considering the charge controller's efficiency of 95%, the solar output was calculated to be 11.4 W using (6):

$$\text{Solar Output} = V \times I \times N_{\text{solar panels}} \times \text{Efficiency}_{\text{charger}} \quad (6)$$

With a 50% DoD, the battery capacity is discharged by 35.52 Wh. The charge time can be estimated by using (7):

$$T_{\text{charging (hours)}} = \text{Discharged Battery Capacity (Wh)} / \text{Solar Output}_{(W)} \quad (7)$$

The calculated charging time is approximately 3.11 hours. Therefore, the backup duration of 1.23 days provides enough time for the solar panels to recharge the batteries, ensuring that the system operates mainly on renewable energy with minimal power consumption.

Chapter 4: Results and Discussion

A. Assembly and Deployment of the System

All the sensors placed in front of the 3D printed non heat resistive box to get accurate measurement. The most important and expensive part of this system is the microcontroller along with the modules placed in the middle to prevent damages from heat and water from the rainfall. Three 18650 rechargeable batteries, which power up the system, are placed in back of the box.



Fig. 6. PCBs placed inside the 3D printed protection box.

B. Data Collection and Validation

Data were recorded every ten minutes, resulting in six readings for each hour. For a period of fifty-nine hours, the mean value of these readings was calculated and presented in Figure 5. By averaging the data over shorter periods, the collected dataset provides a more accurate representation of temperature, humidity, wind

speed, and rainfall in an area, which helps to capture localized weather pattern that broader datasets may overlook.

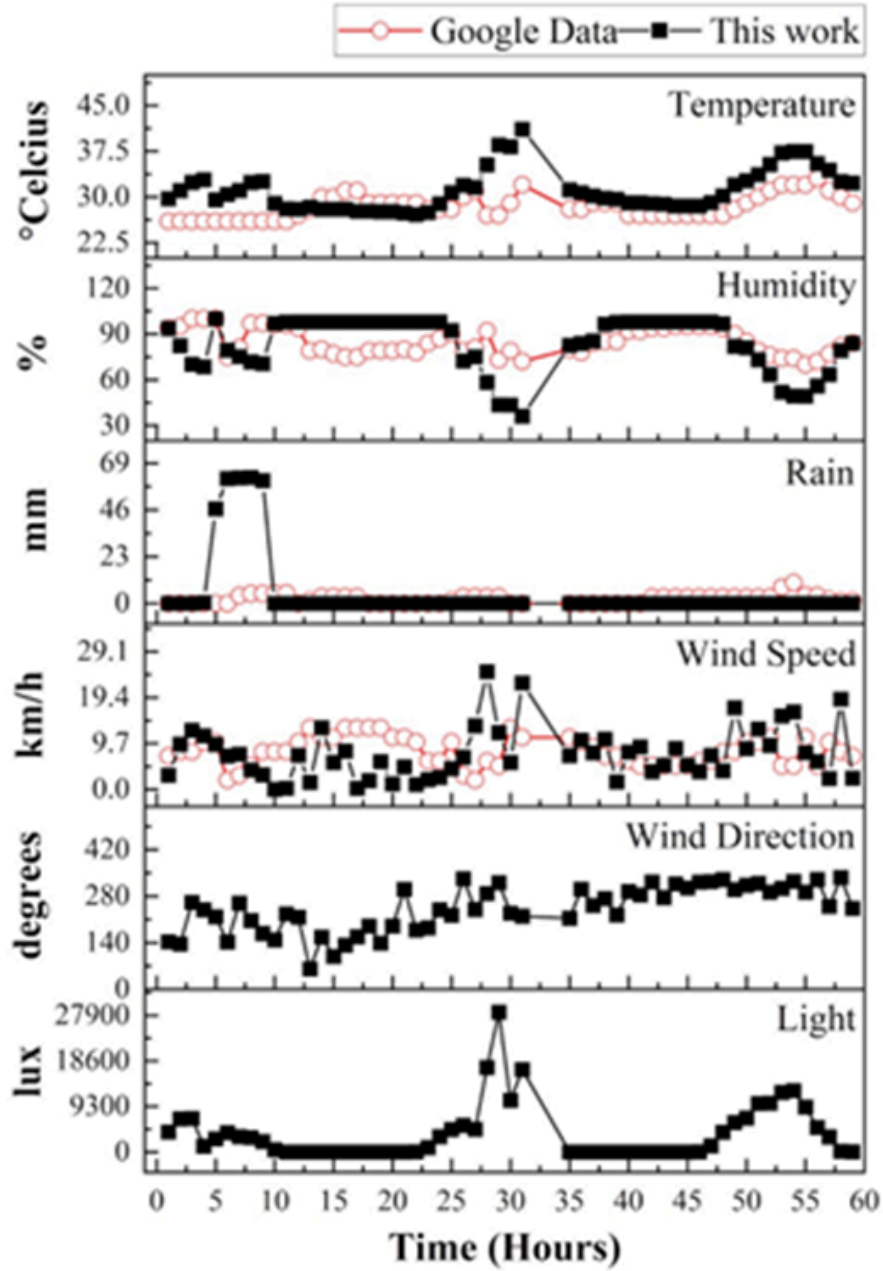


Fig. 7. Comparison of data collected by the designed weather station and Google data.

The mean values of these readings were compared with Google data. The variation between the two datasets as a percentage of the station data was calculated using (8):

$$\text{Difference} = (\text{Google data} - \text{Station data}) / \text{Station data}$$

After comparing the station data with the Google data, a significant difference emerges for every parameter. For the temperature at hour 31, the station recorded

41.08°C, whereas Google recorded 32°C, resulting in a variation of -22.14%. On the other hand, at hour 12, the station recorded 28°C and Google recorded 27°C; the smallest variation occurred at -3.57%. The average temperature variation was -8.54%. However, at hour 3, humidity was measured by the station at 70.17% and 100% by Google, which reflects a variation of 42.46%. Similarly, at hour 14, 98% was recorded by the station and 80% by Google, yielding a -22.45% variation. The average variation for humidity is -6.83%. A dramatic difference can be observed in the rainfall data. At hour 5, the station recorded 46.45 mm; in contrast, Google recorded 0 mm. This results in a 100% variance, and the average variance is 75%. A -267.79% variance arises from the station wind speed at hour 28, which was 24.86 km/h, compared to Google's 6.80 km/h. Nevertheless, at hour 9, the variance was 56.26% when the station's wind speed was 3.08 km/h and Google's speed was 4.8 km/h. The average variation for wind speed is -57.14%. Google does not provide wind direction and light intensity data, but the system measures these as well. The maximum wind direction recorded by the station was 289.9° and the minimum was 148.07°; additionally, the maximum light intensity was 28517.2 lux at hour 27.

C. Comparative Performance Analysis

A comparative performance analysis of the proposed system with several existing systems is summarized in Table X. The proposed weather monitoring system shows various noticeable advantages over the compared systems in terms of features and functionality.

Table 4.1: Comparison of Proposed and Existing system.

Features	[1]	[2]	[17]	[18]	[19]	This Work
Temperature	Yes	Yes	Yes	Yes	Yes	Yes
Humidity	Yes	Yes	Yes	Yes	Yes	Yes
Precipitation Detection	Yes	No	No	No	No	Yes
Remote Operation (No Internet/Wi-Fi)	No	No	No	No	No	Yes
Low Cost	No	No	Yes	No	Yes	Yes
Sunlight Measurement	No	No	No	No	No	Yes
Local Storage	No	No	No	No	No	Yes
Renewable Energy	No	No	Yes	No	No	Yes
RTC	No	No	No	No	No	Yes

This study presents a practical and cost-effective solution for real-time weather monitoring, particularly suited for remote and resource-limited areas. By utilizing microcontrollers, sensors, and the ESP-NOW communication protocol, the system offers a decentralized approach to capturing localized weather data. Its ability to operate without internet connectivity and reliance on solar power ensures sustainable functionality, even in off-grid environments, while maintaining affordability and accessibility.

The social and environmental benefits of this system are significant. It empowers rural communities with reliable weather information, enabling smarter decisions in agriculture and disaster preparedness, while also contributing valuable data for global climate resilience initiatives. Its modular and scalable design supports diverse applications, including environmental monitoring, disaster management, and microclimate research, making it a transformative tool for democratizing access to localized weather data.

Looking ahead, this proof-of-concept paves the way for future enhancements. By addressing current limitations and integrating additional features—such as high-precision sensors or advanced analytics—the system can evolve to meet a broader range of needs. This development aligns with the vision of making accurate, real-time weather data accessible to even the most underserved communities, fostering sustainable development and resilience in the face of climate challenges.

Future advancements in this weather monitoring system emphasize enhancing its functionality, accuracy, and scalability. A critical area for improvement is the integration of advanced data processing capabilities using machine learning (ML). Deploying TinyML on the microcontroller will enable localized analysis of weather data, allowing the system to provide precise forecasts without internet connectivity. Additionally, TinyML will facilitate real-time anomaly detection, offering critical early warnings for extreme weather events, which could be life-saving in disaster-prone regions.

Upgrading to high-precision, industry-standard sensors is another priority. While the current sensors are reliable, advanced options would improve data quality, particularly for applications requiring rigorous accuracy, such as scientific research or environmental policy development. Expanding the system's capabilities to include measurements like air quality, soil moisture, and barometric pressure could transform it into a comprehensive environmental monitoring tool for diverse applications.

Scaling the system into a distributed network of monitoring nodes is also a critical goal. A network of units across a region could provide granular data on localized weather patterns and microclimates, supporting climate change studies and

improving predictive models. Aggregated data from these networks could train advanced machine learning systems, further enhancing forecasting and analytical insights.

To address challenges in data transmission, incorporating communication protocols such as LoRaWAN or satellite technology is planned for future iterations. These upgrades would allow long-range data transfer, making the system viable even in the most geographically remote locations. Integrating cloud platforms for real-time data storage and visualization, paired with user-friendly mobile and web applications, would enhance accessibility and usability for a wide range of users.

Incorporating Geographic Information Systems (GIS) would enable real-time mapping of weather data, offering spatial insights into trends and patterns. This would be particularly valuable for researchers, policymakers, and disaster management teams, providing actionable intelligence for informed decision-making.

Collaboration will play a vital role in scaling the system. Partnerships with government agencies, research institutions, and non-profit organizations could provide funding, technological resources, and local insights. Tailoring the system to meet specific community needs—such as supporting precision farming initiatives or monitoring fragile ecosystems—will ensure its relevance and impact.

Sustainability will remain central to future enhancements. Optimizing energy efficiency through low-power hardware and improved energy management systems will further reduce the system's environmental footprint while ensuring reliable operation during extended periods of low sunlight or extreme conditions.

The system also holds potential as an educational tool. Involving local communities in its deployment and maintenance can promote awareness of weather monitoring and climate change. Workshops and training sessions could empower individuals to interpret and act on weather data, fostering a culture of informed decision-making at the grassroots level.

While all systems measure temperature and humidity, only the proposed system and [1] are capable of detecting precipitation. Like [17], [19], the proposed system is low-cost while providing greater autonomy and functionality, making it more efficient and ideal for off-grid conditions. Compared to other systems, the proposed system stands out by operating remotely without any internet or Wi-Fi, making it suitable for remote areas without connectivity. Additionally, it includes sunlight measurement, local data storage, renewable power management, and a real-time clock—features absent in all other systems. These distinctive features enable the system to deliver comprehensive and accurate weather data under challenging conditions, ensuring its effectiveness in diverse applications. The inclusion of renewable power management and local data storage ensures continuous operation,

even during prolonged power outages or extreme weather scenarios, further enhancing its reliability.

In conclusion, this real-time weather monitoring system represents a paradigm shift in how localized weather data is captured and utilized. Its innovative design and forward-looking development potential highlight its role as a critical enabler for sustainable development and climate resilience. By bridging the gap between technology and underserved communities, this solution has the power to transform lives, enhance resilience, and safeguard the environment for future generations.

Chapter 5: Conclusion

This study presents a practical and cost-effective solution for real-time weather monitoring, particularly suited for remote and resource-limited areas. By utilizing microcontrollers, sensors, and the ESP-NOW communication protocol, the system offers a decentralized approach to capturing localized weather data. Its ability to operate without internet connectivity and reliance on solar power ensures sustainable functionality, even in off-grid environments, while maintaining affordability and accessibility.

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Future enhancements could include leveraging machine learning algorithms to analyze weather patterns and predict extreme weather events with greater accuracy. Integrating IoT platforms for centralized data aggregation and visualization would further enhance the system's functionality, enabling seamless data sharing among stakeholders. Furthermore, incorporating long-range communication technologies, such as LoRaWAN or satellite connectivity, could extend the system's reach to even more remote regions, ensuring no community is left behind.

The potential for customization adds another layer of versatility. By adapting the system to monitor specific environmental parameters, such as air quality, soil moisture, or water levels, it could serve broader purposes beyond weather monitoring. This adaptability makes it an invaluable tool for addressing diverse challenges in environmental management and sustainability.

Collaboration with government agencies, non-governmental organizations, and private entities could accelerate the system's deployment and impact. These partnerships could facilitate large-scale implementation, funding opportunities, and

knowledge sharing, further enhancing the system's capabilities and reach. Educational initiatives could also be integrated, training local communities to maintain and utilize the system effectively, thereby fostering self-reliance and technical empowerment.

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Chapter 6: Future Work

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