From Raindrops to Insights: AI Empowers Hyperlocal Rain tracking in Ghana

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Abstract

This paper illustrates the development and application of an AI-based system aimed at addressing the critical need for accurate and accessible meteorological data among farmers in Northern Ghana. Due to climate change, irregularities in the rainy season pose a significant challenge to determining optimal crop planting times. Recognizing the importance of rainfall data for effective crop management, our system automates the process of data collection and interpretation using Computer Vision models. The innovation lies in the use of locally available resources: rain gauges made from plastic bottles. The system processes images of these gauges, shared via WhatsApp, to automatically measure and visualize the rainfall data. This solution not only enhances the scalability and reliability of the existing manual method but also represents a sustainable approach to addressing community-driven needs in regions with limited resources.

1 Introduction

Research findings indicate that the pace of climate change is exceeding initial predictions, posing significant challenges to socio-economic progress in developing countries [1]. Due to a mix of political and economic difficulties, and limited ability to adapt coupled with various societal pressures, Africa faces significant risks from climate change [2]. Among the regions affected by climate change, Africa is considered one of the most vulnerable due to a combination of factors. Although Africa contributes relatively less to climate change compared to other continents, it experiences significant challenges and risks associated with it [3]. This vulnerability stems from the continent's heavy reliance on rain-fed agriculture, which is particularly susceptible to changes in rainfall patterns and severe weather events.

Furthermore, Africa faces additional obstacles such as widespread poverty and limited adaptive capacity, which hinder its ability to cope with and recover from climate change impacts [3]. Therefore, in these regions, accurate and timely data on rainfall is crucial for effective agricultural management and strategies. However, conventional methods of weather reports or satellite-based weather data are either unavailable or not viable due to geographical and socio-economic factors.

In Northern Ghana, Farmers have historically identified the right time to begin sowing using a combination of ecological indicators, experience, and traditional knowledge, referred to as Indigenous Forecasting (IF) [4]. However, climate variability has disrupted such indicators and historical trends. Figuring out the right time to plant crops has thus become even more difficult. Farmers now rely on a combination of IF, meteorological data, and weather forecasts to determine when to begin planting. In the rural communities of Northern Ghana, meteorological data is spatially coarse and therefore difficult to use for farming, which requires more fine-grained weather data specific to each farm's location [5]. Reports from locals also suggest rainfall differs greatly from farm to farm, kilometre to kilometre [1].

The areas of interest lay in low-resource communities, so any forms of high-tech solutions in hardware and sensors are not a possibility [6]. To address the issue of limited localized meteorological data, a community of farmers from Nyankapala, Tingoli, and Tutamale in Northern Ghana has developed their own method using homemade rain gauges. These rain gauges enable them to collect rainwater, measure rainfall, and generate their own datasets to analyse rainfall patterns and predict optimal times to plant crops. Having such localized insight into the amount of rainfall can allow farmers to better manage their crops and sow the land. The farmers manually collect the data from the rain gauges and share the data through WhatsApp images. This manual process, however, is not reliable, efficient, or scalable. Therefore, this project aims to automate the data collection, processing, and pattern identification as much as possible.

This project aims to create a scalable approach, empowering farmers with data-driven decision-making and enhanced use of rain gauges for better agricultural practices. We do so by discussing the specifics of the current setup. Its challenges and the proposed solution are elaborated on in the following sections.

2 Background

A rain gauge is a device used to gather falling rainwater, and thus measure the amount of precipitation in an area. By correlating the amount of rainwater with actual rainfall metrics, or other indicators, rain gauges can be used to gather accurate and highly localized precipitation data [7]. However, data collection, such as collecting manual measurements of rain gauges, is often time-consuming and prone to errors.

[1] Interview with resource team, North Ghana

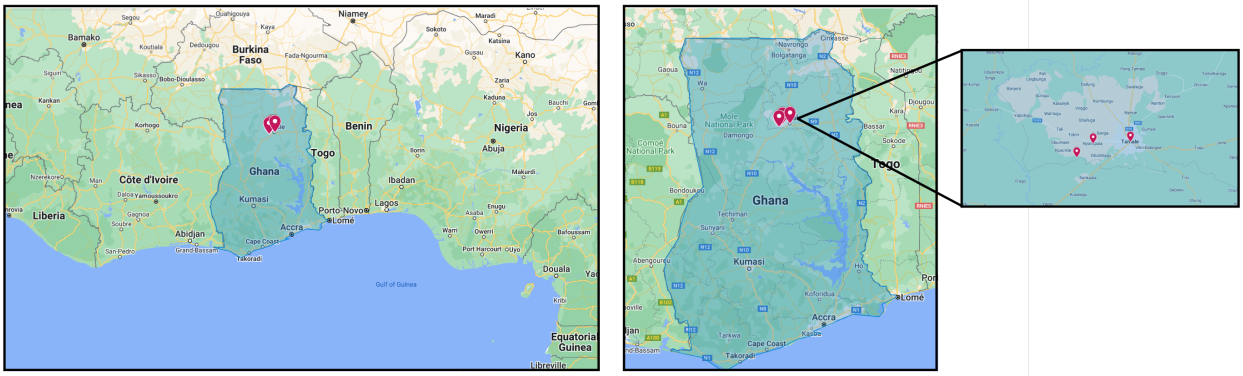

Figure 1: Location of communities in Northern Ghana, visualized in green, areas of communities in red.

To address these limitations, the integration of artificial intelligence (AI) technologies, specifically image recognition, offers promising opportunities for automating rainfall data collection and improving climate resilience in the Global South.
One recent example of utilizing AI technology for rainfall prediction is implementing artificial neural networks (ANN) [8]. ANN, inspired by the functioning of the human neurological system, offers a model for extracting meaningful spatial and temporal characteristics from historical rainfall patterns, particularly when dealing with complex and dynamic evolutions [8]. The use of ANN in rainfall forecasting takes advantage of its ability to identify nonlinear relationships and capture intricate patterns that may exist within historical rainfall data. By mimicking the human brain's processing capabilities, ANN can analyse the complex interactions between various meteorological factors and derive valuable insights for predicting future rainfall patterns [8]. The wide application of artificial neural networks (ANN) in hydrological problem-solving, such as rainfall forecasting, is facilitated by their ability to operate without the need for explicit knowledge of physical laws or assumptions commonly required in traditional statistical approaches. French et al. utilized ANN to develop a rainfall simulation model that effectively provided accurate forecasting information, including temporal and spatial distributions [9]. Similarly, Luk et al. employed ANN to forecast short-term rainfall in an urban catchment [10]. The empirical findings of these experiments demonstrated that the ANN model with a shorter lag exhibited superior performance in accurately forecasting the index [8].

Another example is using image processing methods for the deformation area of open-pit rock slopes under variable rainfall [11]. Proposed by Wei is a method based on the combination of the RGB color space and a support vector machine (SVM) to identify the rainfall areas [12]. In the upcoming section of the paper, we will review a similar approach to image recognition that has been employed in the development of our AI model.

3 Current Challenges and Proposed Solution

3.1 Context

The primary challenge faced by communities in Northern Ghana now is in scaling and analysing the data collected to detect trends in rainfall and thus identify the best time to plant crops. Currently, farmers in communities in Northern Ghana take pictures of handmade rain gauges, made by cutting the top off of a plastic water bottle (standardized to a 1-liter size with all/most bottles coming from the same water bottle brand).

These pictures are then sent using WhatsApp to resource persons in Ghana, who collect them, manually inspect the water level in each picture, match it to the area the picture was taken in, and then enter this data into a list of previous measurements. Currently, farmers in the communities of Nykapala, Tingoli, and Tamale (figure 1) have between 10-15 custom-made rain gauges that they mount on poles to keep them fixed during heavy winds during the rain. Local researchers, resource persons, and farmers now desire to scale this over multiple farms within those areas, new areas, and new regions of Ghana. The process currently implemented is shown in Figure 2.

The challenge is that manually measuring and updating data for hundreds of such images received

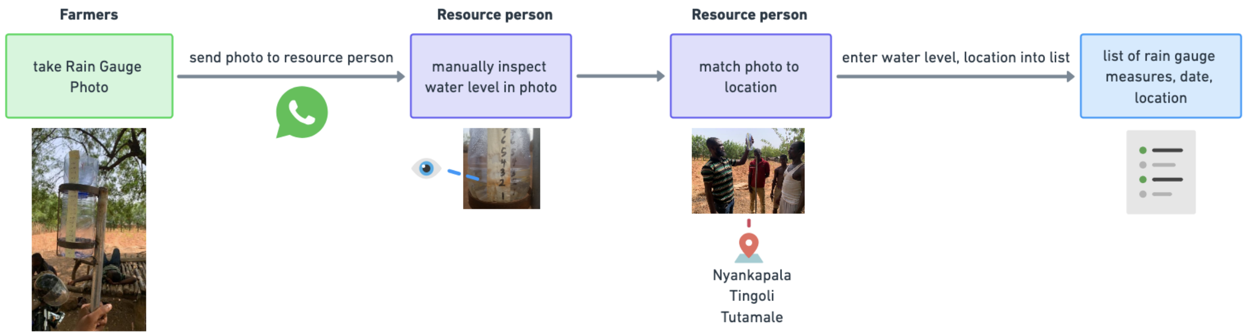

Figure 2: Current Implementation

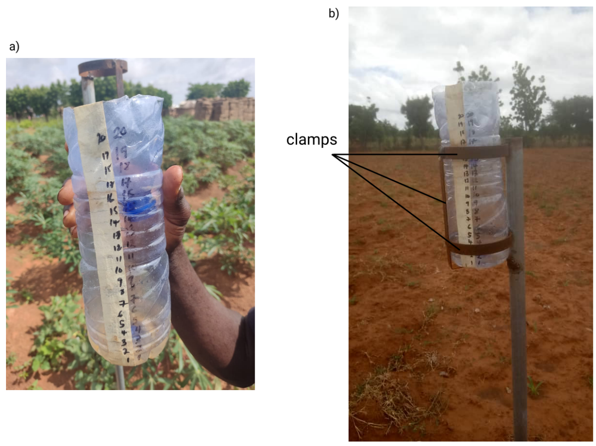

Figure 3: a) Custom-made rain gauge, created by cutting the top off of a 1l bottle, with markings for each centimeter. b) rain gauge fixed on pole, held firm by circular bands attached on the pole

every day from multiple sources is time intensive and prone to errors. Furthermore, specialized skills are required to analyse and derive patterns and trends every so often from the collected data.

The proposed solution is to automate the measurement of rainfall through rain gauges and the collation of data inputs (pictures) from farmers and to visually illustrate trends in the dataset to enable easy detection of the right time to begin sowing.

3.2 Challenges and Improvements

As elaborated on in Section 2, various AI-based methods have found success in automating data collection from images. However, the unique context of this application introduces novel challenges that we outline and propose solutions for below.

The rain gauges used in Northern Ghana are crafted from recycled plastic bottles. Unlike standardized printed markings, these rain gauges feature hand-drawn markings to indicate each centimetre, as printers are not easily accessible in the areas of the communities. Moreover, the environmental conditions on different farms contribute to the rain gauges being filled with or affected by mud and dust. Field reports have also indicated that the tape or marker used for the markings often gets blown off or erased by inclement weather.

These factors introduce diverse variations in the data that machine learning (ML) models must account for, as the clarity of the rain gauge and its markings can vary significantly in the images. Such environmental variability cannot be controlled, thus we train our ML model to be robust and accurately identify rain gauges under such challenging conditions.

Some rain gauges may have multiple markings (Figure 5a) due to rewriting caused by weather effects.

This can occasionally confuse the model, which is why we request locals to ensure only one set of markings on the tape or the bottle is visible in the photos.

The presence of poles and clamps used to secure the rain gauge can sometimes obstruct the view of the markings or water surface level. For instance, if the water surface is positioned behind the horizontal clamps, it becomes more challenging for the ML algorithm to differentiate between an empty bottle and a hidden water surface.

The angle at which the bottle is captured in the picture poses another challenge for accurately detecting the water level. To ensure precise measurements, the water surface must align perfectly horizontally with the bottle's markings. Therefore, it is recommended to place the rain gauge on a flat surface, such as the ground, to avoid unintentional tilts caused by holding the bottle for the picture.

Determining the exact location from which each rain gauge originates presents a unique challenge. Image compression in messaging applications like WhatsApp often results in the loss of metadata, including location data. As a result, image metadata can't be relied on to track the image's origin. Location sharing or manually entering locations introduces additional inconvenience and learning curves.

To address this, each farm and sender is assigned a unique ID, which is also written onto the bottle. This can then be detected by the model and matched to a location. This idea was developed based on valuable feedback and discussions with resource persons.

Initially, we encountered a challenge where assigning numeric IDs led to confusion within the ML model between the numbers representing the location ID and the water level. To overcome this, we made the decision to use alphabetic letters for location identification, effectively eliminating any ambiguity. However, implementing this approach requires training an additional model capable of recognizing handwritten alphabets. This presents an opportunity for future work and further enhancement of our system, as outlined in Section 9.

The date and time of the picture being taken can, however, be retrieved from metadata. This can be used to analyse trends in rainfall patterns.

In our approach, we create a video tutorial explaining the requirements for a good picture for the model, with our solutions for each challenge: 1. Place the bottle on a flat surface (this eliminates the water level being hidden beneath clams, or tilted water levels) 2. Ensure only one set of markings is available on the bottle (this eliminates confusion for the model) 3. Place your unique ID on the bottle (to capture location data)

An AI model is then developed to detect water levels and the ID-based location.

Finding trends over weeks or months of data, collating information from several pictures of rain gauges each day from several areas and farms, and storing this in a way that is easily visually represented, retrievable, and can also be accessed by local resource persons and farmers, is the challenge that lies ahead.

A method of correlating the rain gauge readings to real rainfall requirements for each farm, and thus learning when real-world rainfall is sufficient and regular enough to begin planting seeds and sowing, is also the next necessary step.

Considering the unique context of the application, the study area, and the potential lack of familiarity with technology among users and data collectors, our model and approach have been specifically designed to minimize the learning curve and prioritize user-friendliness. The specific model and proposed application flow are elaborated on next.

3.3 Demonstration Video

Given the lack of standardization of the images, we have created a short demonstration video on how the rain gauges need to be placed for the image. Using a certain baseline for the images, helps the model detect more accurately. The script of the video includes: it should not be too dark outside, the entire bottle needs to be in the image, centered, the bottle needs to be placed on a flat surface, and remove any old numbers. Unfortunately, due to time constraints and limited data, we were unable to train the models for detecting ID's. Nonetheless, the video does acknowledge this aspect, as it is an opportunity for further exploration in the future.

4 Design

In order to ensure that the resulting application is as user-friendly as possible, we use a series of models that require very little manual preprocessing. This approach was created through discussions with stakeholders in Ghana. The initial interviews provided the requirements for creating a successful application.

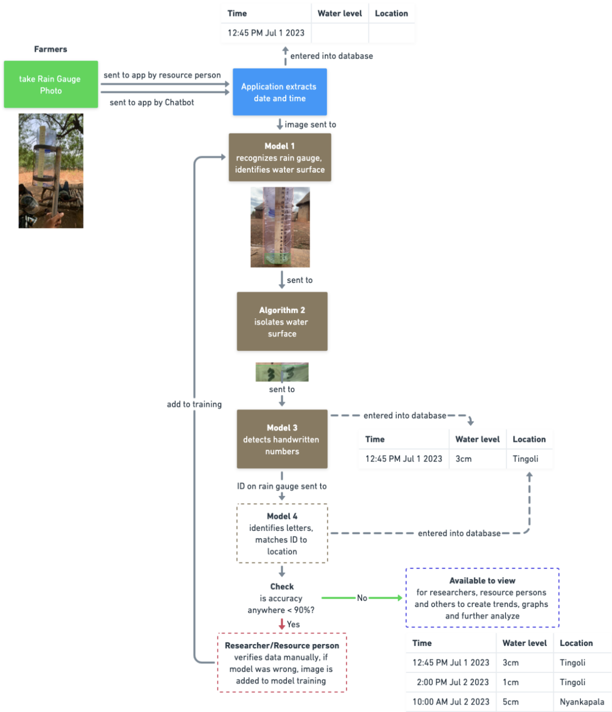

Figure 4: Proposed Flow

The outputs of the AI models involved in the application have been designed to create direct and understandable metrics:

- water-level: the level of water in the rain gauge,
- location: the location from which the rain gauge originates
- date-time: the date and time the picture was taken

A secondary algorithm is then used to process a series of such data to unearth trends and predict the time to begin sowing or to convey this information to local users (such as farmers) and researchers.

The data received by the ML model is an image. Each image containing a rain gauge contains the following: water bottle cut open at the top, water surface, numbered measurement tape vertically placed on the bottle, and ID. The model must therefore be able to recognize all of these.

We employ a multistep process involving several AI models and algorithms. This process is illustrated by the flow diagram in Figure 4.

Images of the rain gauge are sent by WhatsApp or other messaging platforms to a Chatbot, which collects the images and sends them to a series of AI models.

An initial algorithm extracts the date and time the photo was taken. The first AI model is trained to identify the rain gauge itself and highlight the water surface within. This result is passed to an algorithm that isolates the numbers at the water surface. A third model which specializes in digit recognition then identifies the numbers in this isolated image of handwritten digits. A fourth model recognizes alphabetical IDs. All data extracted by the models is then entered into a database. A final algorithm captures patterns or trends in rain data such as increases, decreases, sudden changes, etc.

Due to a smaller dataset size, pre-trained models are used in all cases and fine-tuned. The YOLO model which was pre-trained on a dataset consisting of images of water bottles was fine-tuned on user-collected images of rain gauges to learn their visual characteristics and accurately detect their presence [13].

5 Implementation

5.1 Model 1 - Rain Gauge and Water surface recognition

Addressing the challenge of water surface detection assuming a variance of user image qualities, we opted to fine-tune the pre-trained object detection model, YOLOv8n. Known for its high performance and efficiency, this ML model enables rapid prediction generation, which is crucial for our use case. A notable obstacle was the lack of available training data, specifically images of community-used rain gauges. Both in terms of quantity and diversity, the data was inadequate to effectively train our model, considering the range of image object detection factors such as water content, angles, lighting conditions, seen objects, bottle types, colors, and reflections. Therefore, we expanded our dataset using images of homemade rain gauges found online and synthetically generated images from image generators, introducing varied image attributes. This data augmentation process was essential to enhance the model's generalization capability.

After formulating our training dataset, we undertook manual annotation using specialized annotation software. We marked bounding boxes around the relevant image objects - the rain gauge and the water surface near the measurement point(see Figure 5). This step allows the model to generate bounding box coordinates, enabling the cropping of images at the water level(see Figure 6). Subsequently, a digit classification model can interpret the cropped images to estimate the water measurement.

Figure 5: Rain gauge and surface detection

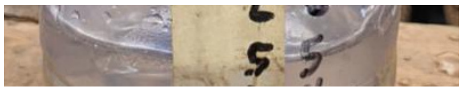

Figure 6: Crop of surface

5.2 Model 2 - Crop of digit

To extract the number near the water surface, we fine-tune the YOLOv5s [14] pre-trained model, and the training data for this model is the crop images of the water surface which are part of the output of the last model, the example that can be seen in Figure 6. And because our next step is planning to use a CNN based on the MNIST dataset, for better input image quality, while we crop the digit, we draw the box around the digit as 34x34 pixels which will be resized to 28x28 in the next step(the input image size of the original MNIST CNN is 28x28 pixels), the result of the cropped digit could be seen as Figure 8.

5.3 Model 3 - Digit recognition

For the construction of the digit classification model, we tailored the renowned MNIST dataset, which is a classic set of 70,000 28x28 pixel images of handwritten digits from 0-9, often used in ML and image

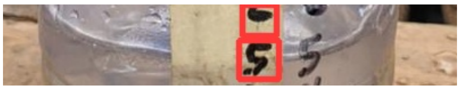

Figure 7: Raingauge and surface detection

Figure 8: Crop of surface

processing fields. However, considering our specific application where rain gauge measurements span from 1-20, a modification of the original dataset was required. We conducted a process of permuting and concatenating digit images to create two-digit images. This operation effectively doubled the dataset size, yielding a total of 140,000 samples.

Subsequently, we trained a Convolutional Neural Network (CNN) - a type of neural network especially effective in processing grid-like data such as images - on our custom dataset. The model resulted in an accuracy of around 84% on the validation set, but when we test it with the real data from the local community in Ghana, the performance and accuracy are not well, in most situations, we can not get the accurate result, so this model should be ameliorated in the future work.

6 Evaluation, Testing, and Validation

6.1 Evaluating models

Each AI model underwent evaluation using a comprehensive test dataset comprising rain gauge images that the models had never encountered before.

To assess the model's performance, we focused on two key aspects. Firstly, we examined whether the model correctly identified the rain gauge within the image. Secondly, we verified whether the model accurately highlighted the relevant area of the water surface in the images.

As creating a dataset with a hundred diverse rain gauges and differing water levels from real users and resource persons in Ghana was challenging initially, a workaround was used. Multiple pictures of a few bottles, filled to different water levels, and taken from different angles, were captured to generate a portion of the dataset. Additionally, we incorporated images of water bottles and homemade rain gauges found online to augment the dataset (figure 9).

Figure 9: Annotated dataset used by models

However, we observed that this approach led to certain challenges. When the model was trained on larger datasets, it exhibited a tendency to overfit, resulting in the identification of numerous false positives (figure 11). Conversely, when trained on smaller datasets, the model's performance was compromised, leading to lower accuracy levels (figure 10).

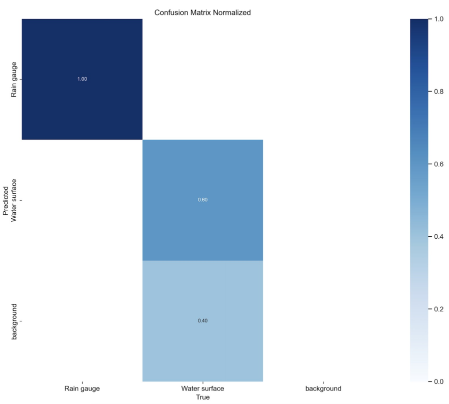

Figure 10: Evaluation of Model trained on small dataset

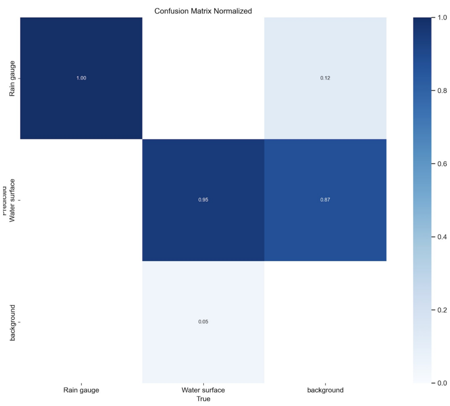

Figure 11: Evaluation of Model trained on large dataset

However, this is an issue that will decrease with time as the number of users increases, and the dataset of the model expands. Currently, we include a check in the application that requests a human to verify the model's prediction if its confidence for a prediction is lower than 90%. This number was chosen as all models had accuracies higher than 90% on average.

The algorithm within the application that extracts the date and time from the image was tested by the messaging platform, such as WhatsApp or Telegram, and was determined to be accurate.

6.2 Validation of Application

We conducted user feedback sessions with users and local resource persons and demonstrated the application to them. The feedback received was overwhelmingly positive, with resource persons expressing satisfaction with the system's ease of use, understandability, transparency, and accuracy. A Telegram-based Chatbot API was developed that could immediately process images and return data about the water level of the rain gauge, however, Telegram was found to be unusable by the local community due to a lack of familiarity, unavailability, and learning curve. Therefore, a Whatsapp-based API is being developed as part of future work.

Based on discussions and feedback from users, the data from the models will currently be routed to an Excel spreadsheet that will be used to analyse trends. This will be a transition to a database and app in the future. Throughout the development process, we kept the needs and requirements of the community at the forefront. The solution was designed to address the unique challenges faced by farmers in monitoring rainfall and making informed decisions regarding planting and sowing. By automating data collection from rain gauges, our system significantly reduced the manual effort needed to interpret rain gauge data and will contribute to reducing the uncertainty caused by climate variability. The direct and understandable metrics provided by the system, such as water level, location, and date-time, proved to be highly valuable in facilitating data-driven decision-making.

To ensure the robustness and generalization of our solution, extensive testing was carried out under varying environmental conditions. We evaluated the system's performance across different rain gauge designs, image qualities, and environmental factors such as dust and mud. Our models demonstrated a remarkable ability to adapt to diverse contexts, accurately identifying rain gauges and interpreting the markings and water surface levels, even identifying rain gauges accurately from photos taken in the night (figure 12).

The stakeholders were happy with the idea to create a tutorial video that instructs the farmers how they should take the photo and what they should consider whilst doing it.

We recognize the social and ethical implications of deploying AI-based systems in local communities. Our solution aims to empower farmers and resource persons by providing them with valuable insights to support agricultural practices. By aligning planting activities with rainfall patterns, our system has the potential to enhance agricultural productivity and contribute to more sustainable, efficient farming

Figure 12: Illustration of accurate identification of the rain gauge even during nighttime

practices. We have also taken measures to ensure data privacy, security, and fairness. We implement safeguards to anonymize data by storing only the location, date, and time of rain-related measurements, without storing phone numbers or other personally associated data sent by users taking rain-gauge pictures. The models, training dataset, and data are open source and public, thus ensuring transparency.

7 Reflection

The manual process of measuring and updating data from numerous images received daily is time-consuming and prone to errors. Variations in the rain gauges, such as hand-drawn markings, mud, dust, and tape erosion, introduce challenges for machine learning models. However, whilst developing the algorithms, the discovery was made that these challenges can be overcome when enough data is collected. The angle at which the bottle is captured can impact detection accuracy, next to the presence of enough light. Additionally, the absence of location metadata in image compression hampers tracking the origin of each rain gauge. The approach taken resulted in the recognition of the water bottles, water surface, and measurements by finding the number on the tape. Pretrained models, such as YOLOv5s and digit recognition models, are fine-tuned using user-collected images of rain gauges. Clear instructions provided through a demonstration video help ensure high-quality images for accurate detection and analysis and increase the dataset.

8 Limitations

It can be very valuable for local farmers in Northern Ghana to use computer vision (CV) to detect the amount of rainfall in the rain gauges. However, it is important to take the limitations of this method into consideration, explore alternative approaches, and identify any possible extensions that might enhance effectiveness. Several considerations to keep in mind are, for example, regarding the overall use of CV for rainfall detection. Namely, the quality of the images captured by local farmers in Northern Ghana heavily varies due to factors such as lighting, camera capabilities, and user expertise. Poor image quality influences the accuracy of the algorithms detecting the amount of rainfall [15]. E.g., during the testing of our model, we discovered that in darker environmental conditions, the algorithm is not able to detect the bottle nor the amount of water inside it. The self-made rain gauges currently lack standardized calibration in image quality, creating measurement errors, which in turn also play a role in the accuracy estimation. Another limitation to consider is the positioning of the rain gauges in the images. The rain gauges need to be positioned in such a way that the detection algorithm can properly identify the bottle and not mistake another object for the rain gauge. The orientation and position of the rain gauges also have to correspond in all the images, as inconsistencies can affect the accuracy of the algorithms as well [16]. We had the additional intention of integrating a WhatsApp Chatbot API in response to the farmers' sent images. This API would have provided farmers with information on the ideal timing for planting or irrigating crops based on the amount of water in the rain gauges. Due to both time and financial constraints, this is something for future work. Lastly, Northern Ghana has a significant amount of land

and the amount of rainfall can vary across the different regions. Considering this factor, we aimed to incorporate the precise location of each rain gauge, which could have been obtained from the metadata of images sent on WhatsApp by the local farmers. However, due to privacy reasons, Whatsapp does not disclose this metadata. To overcome this limitation, our demonstration video includes instructions on implementing a system in which each rain gauge is assigned a unique ID, each ID corresponds to a specific location. This approach allows the local farmers to associate the rain gauges with their specific locations and obtain relevant information, to help them in their crop management.

Possible solutions or extensions to the other above-mentioned limitations would be to integrate multiple factors and data sources. Using a combination of CV to detect the amount of rainfall, together with weather forecasts and satellite images, the accuracy and reliability of the rainfall estimation would improve. Another solution is to train the model on a larger and more diverse data set. Currently, we have very a limited amount of images, which affects the accuracy of the detection algorithm. Using machine learning in combination with more data can improve the algorithm drastically. Lastly, given the short period, we have thought of a solution to standardize the way images are taken by making a demonstration video. This might help the farmers in creating the gauges and images in such a way that help the algorithm to detect the amount of rain much better. To further extend this, local farmers can be better supported if their feedback is collected and user studies are conducted. This way, more user-specific challenges can be addressed as well.

9 Future Work and Extensions of the Current Solution

While significant progress has been made in the implementation of the CV model for processing rainfall data, there are several areas that warrant further attention and exploration. In this section, potential avenues for future work to enhance the effectiveness and impact of the AI-powered rainfall data processing system in Northern Ghana are discussed.

Firstly, improving Prediction Accuracy. Despite the successful recognition of water bottles and surfaces by the CV model, there is room for improvement in rainfall prediction accuracy. Future research should focus on refining the model's algorithms and incorporating advanced machine-learning techniques to enhance its predictive capabilities. Additionally, exploring the integration of other relevant data sources, such as soil moisture and atmospheric conditions, could further enhance the accuracy of rainfall predictions. Next, the limited rain season in Northern Ghana poses a significant challenge for data collection. Future efforts should aim to extend the duration and coverage of rain data collection, potentially through the deployment of additional rain gauges in strategic locations. Researchers recently conducted an effort to combine rain gauges with high Spatio-temporal satellite-based rainfall data for various applications in Ghana [17]. A potential collaboration with these researchers could benefit both parties, since this project is able to create a network of low-cost rain gauges in the area of interest, including the CV model to process the data. Furthermore, the project must be scaled up so that it is sustainable for the future. As the system progresses, efforts should be made to scale up its implementation and ensure its long-term sustainability. This can be achieved through continued collaboration with governments, local communities, and relevant stakeholders. Establishing policies that support the adoption of AI-powered agricultural systems and investing in digital infrastructure and connectivity will be essential for widespread deployment and usage.

To summarize, while the collaboration with spatial-temporal satellite rainfall data has shown promise, future work should concentrate on refining the predictive accuracy, expanding data collection efforts, improving user experience, scaling up implementation, and assessing the socioeconomic impact.

10 Conclusion

In conclusion, this paper presents an innovative AI-based solution for automating rain gauge data collection in the context of Northern Ghana. By addressing the unique challenges of the environment, low-resource context, and user-friendliness, our approach offers a practical and efficient method for accurately detecting rainfall patterns. The successful collaboration with local stakeholders, including farmers and researchers, has been instrumental in ensuring the relevance and applicability of our solution in empowering local agricultural practices, enhancing decision-making, and contributing to sustainable development.

We believe that our solution holds great promise for empowering agricultural practices and sustainable development in the region and beyond.

11 Acknowledgement

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