Sugar Cane Yield Prediction Using Drone Data Processed by LSTM Algorithm

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***Abstract*—Sugarcane is an essential crop in southwestern Japan, particularly in Okinawa and Kagoshima, where it sustains local economies and supports large-scale sugar production. Traditional yield prediction relies on labor-intensive field surveys and is increasingly challenged by a shortage of skilled labor, resulting in potential inaccuracies. This work proposes an innovative approach to sugarcane yield prediction by combining Long Short-Term Memory (LSTM) models with Genetic Algorithms (GA) to optimize model performance. Drone-based data collection methods are also explored, leveraging aerial imagery to provide additional predictive features. The proposed model demonstrates the effectiveness of integrating time-series and spatial data, offering a scalable and accurate solution for improving yield forecasting and supporting efficient operations in sugarcane production.**

Keywords—Sugar cane yield prediction, 3D Map building, Drone navigation

I. Introduction

Japan's sugarcane industry occupies a significant land area, with a total of 23,200 hectares devoted to sugarcane cultivation. In Japan's southwestern regions, sugarcane serves as a crucial economic pillar for local communities, contributing to agricultural productivity, employment, and the broader regional economy. Sugar mills rely heavily on accurate crop growth surveys to plan and regulate their operations, adjusting activities and resource allocations based on anticipated yields. Therefore, large discrepancies between predicted and actual yields can lead to severe disruptions in mill operations, resulting in economic losses and resource inefficiencies.

Conducting accurate yield forecasts requires substantial labor resources, typically involving field visits and measurements by experienced surveyors. However, as the availability of skilled experts decreases, concerns are growing regarding the accuracy of current forecasting methods. This highlights the necessity for advanced technologies that can provide efficient, scalable, and high-precision data collection, particularly through drone-based monitoring systems [1]-[2]. Drones equipped with multispectral and RGB cameras offer new possibilities for collecting vast amounts of field data quickly and autonomously, capturing information about crop health, growth patterns, and other relevant features.

Several AI models for yield prediction are proposed [3] - [5]. Given the time-dependent nature of crop growth and weather conditions, yield prediction is well-suited to recurrent neural network (RNN)--based learning methods. RNN models, especially the Long Short-Term Memory (LSTM) model, are effective in capturing complex temporal relationships by accommodating both short-term and long-term dependencies within data [6] - [7]. The LSTM model has demonstrated superior accuracy over traditional machine learning approaches in yield prediction tasks, accounting for nonlinear crop growth trends that arise due to environmental fluctuations.

This work uses multimodal data to propose a robust sugarcane yield prediction model based on LSTM and Genetic Algorithms (GA). While the LSTM model processes temporal data, the GA is utilized to optimize key model parameters, such as learning rates and hidden layer configurations, further refining the model's predictive capacity. Additionally, the work explores the integration of drone-captured imagery, analyzing its utility as an input feature to improve model performance. This approach aims to establish an advanced, data-driven framework supporting sustainable sugarcane farming by improving yield accuracy and operational efficiency.

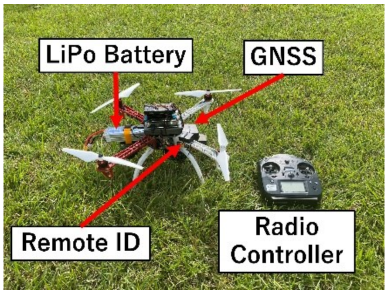
II. Developed Drone

A. Hardware

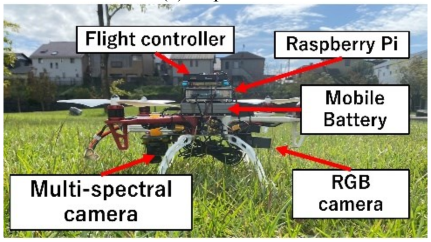
The hardware setup for the drone system is built around a modular and highly adaptable F450 frame, selected for its durability and compatibility with various sensors and payloads (Fig. 1). The Pixhawk 6C flight controller is employed for its precise aerial control capabilities, allowing for highly stable flight even under variable environmental conditions. The controller integrates multiple sensors, providing advanced flight modes, autonomous navigation, and flight stability, all essential for reliable data collection in field environments. A Raspberry Pi has been incorporated to handle onboard computations, enabling real-time processing and storage of data. Other peripheral devices can be also integrated.

Accurate geolocation is critical for mapping and data correlation, and this is achieved with a GNSS (Global Navigation Satellite System) module, which provides precise positional data for each captured image. This level of accuracy ensures that every image can be mapped accurately to specific areas within the field, facilitating spatial analyses and allowing for repeatability in longitudinal studies. The power requirements for such extended field operations are met by a high-capacity LiPo battery, selected for its energy efficiency and ability to sustain prolonged flight durations.

For data acquisition, the drone is equipped with a dual-camera setup. An RGB camera (DJI Action 2 Power Combo) captures high-resolution visible-spectrum images, providing detailed color data that can aid in identifying crop structure, canopy cover, and other visual characteristics of the crop. Additionally, a Survey3W OCN multispectral camera captures spectral bands beyond the visible range, essential for assessing plant health indicators such as chlorophyll content and stress levels. This multispectral data allows the drone to capture valuable insights into the physiological condition of the sugarcane, which can be critical for yield prediction and disease detection. A mobile battery has been integrated to power the additional components. For regulatory compliance and safety, an AERO-D-X1 remote ID system has been incorporated, allowing for real-time drone tracking and identification.



(a) Top view



(b) Side view

Fig. 1 Robot hardware

B. *Software*

To achieve efficient and comprehensive data collection, an advanced autonomous flight system was implemented for the drone. This system enables full coverage of the designated agricultural fields by automating the aerial photography process. The flight altitude was set at 20 meters, balancing image resolution with coverage area to capture high-quality imagery while maximizing the area surveyed in each pass.

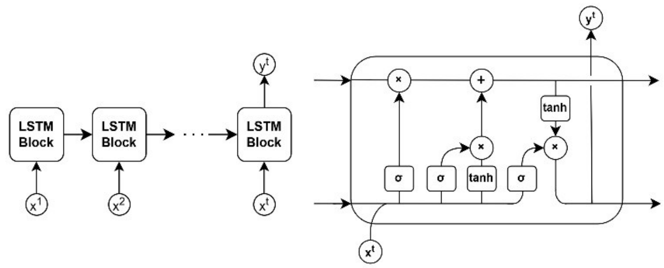
The optimal shooting locations are determined considering the camera's viewing angle, overlap requirements, and the topography of the target area. This method minimizes data gaps. With these factors, an optimal flight path was generated that linked each calculated shooting position in a continuous and efficient sequence. Additionally, it has a return-to-home feature, programmed to activate in case of low battery levels, connectivity loss, or emergencies, protecting both the drone and data.

The drone is configured to trigger the camera at preset intervals along the flight path, to stream the captured data. This synchronization of movement and image capture ensures consistent data spacing which is critical for post-processing tasks, such as developing 3D maps from captured images.

III. Yield Prediction Model

The LSTM model, a recurrent neural network architecture well-suited for time-series data, is implemented using a many-to-one configuration, specifically chosen to predict final sugarcane yield based on a sequence of inputs over time (Fig. 2). This many-to-one structure is highly effective in yield prediction tasks because it allows the model to integrate into a single vector multimodal chronological series of data points, such as environmental conditions, plant growth, and meteorological factors. The LSTM's recurrent structure captures dependencies across time steps, a critical feature given that sugarcane growth is influenced by cumulative environmental conditions and seasonal variations.

To improve the model's predictive accuracy and efficiency, a Genetic Algorithm (GA) is integrated into the model to perform automated feature selection and optimization of hyperparameters. GA searches for optimal solutions by iteratively evolving a population of candidate configurations. In this work, GA is applied to identify the most relevant input variables, such as temperature, rainfall, sunlight, plant growth stage, and soil quality, enabling the model to focus only on data that significantly impacts sugar cane yield. By excluding less influential variables, GA helps prevent overfitting and improves the model's generalization capability.



(1) Many-to-one (2) LSTM Block

Fig. 2 LSTM

Beyond feature selection, GA also plays a crucial role in optimizing the LSTM model's hyperparameters, including the number of hidden layers, the size of each layer, the learning rate, and dropout rates. These hyperparameters influence the model's learning dynamics and the ability to capture complex, nonlinear relationships within the data. For instance, selecting the appropriate number of hidden layers and units allows the model to balance computational efficiency with the capacity to learn intricate patterns in the input data. The learning rate, another critical hyperparameter, determines the step size during model training; an optimized learning rate accelerates convergence while avoiding oscillations or divergence in the loss function. Dropout rates are also tuned to mitigate overfitting, ensuring the model generalizes well to unseen data. GA initializes a population of LSTM configurations, each with random values of hyperparameters. Over successive generations, GA evaluates the performance of each configuration using a fitness function. In our implementation, the fitness is the model's prediction accuracy measured as mean square error (MSE) of the validation dataset. The best-performing configurations are selected for crossover and mutation, creating a new generation of configurations that inherit the best traits of their predecessors while introducing variability. This evolutionary process iterates until convergence or until a pre-specified level of prediction accuracy is reached.

IV. Results

A. DSM Creation and Comparison with Measured Values

To validate the accuracy of the Digital Surface Model (DSM), orthophoto measurements generated by Open Drone Map were cross-referenced with actual measurements from four randomly selected sugarcane fields located in Tokunoshima island (Fig. 3).

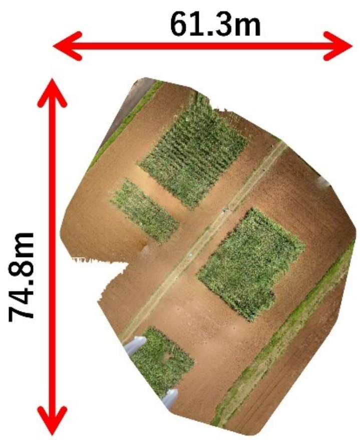


Fig. 3. Sugar cane fields.

The orthophotos provided a high-resolution, top-down view of each field, corrected for perspective distortions and topographic variations. This allows for precise distance measurements and spatial mapping within the field. Comparisons between DSM-derived heights and manually measured pseudostem lengths were conducted, as these heights serve as a proxy for sugarcane growth and health.

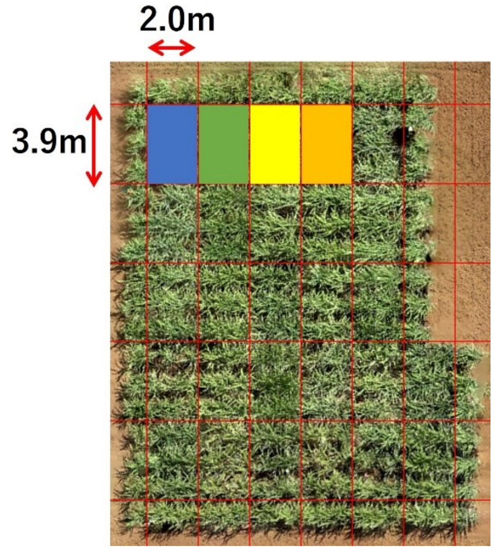


Fig. 4. Segments of divided model.

To ensure a robust analysis, the DSM was divided into segments aligned with the survey plots, where crop measurements were already recorded (Fig. 4). Within each plot, the work focused on the upper 20% of height data points, calculating their average to generate a representative crop height while minimizing the impact of outliers (Fig. 5). This approach allowed for a more accurate reflection of sugarcane height, reducing bias from areas with irregular vegetation or lower growth, and helping to isolate data that most accurately correlated with the pseudostem length data from ground surveys. This correlation was quantified using calculated coefficients, which provided insights into the degree of alignment between DSM-derived crop height data and field measurements, thus evaluating DSM's effectiveness as a yield predictor. Strong correlations between these data sets indicated that DSM height data could be a reliable, non-invasive predictor for sugarcane growth stages and overall yield potential.

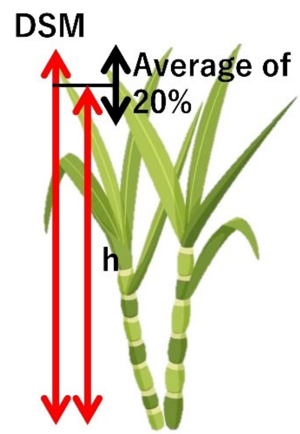


Fig. 5. Calculated data points.

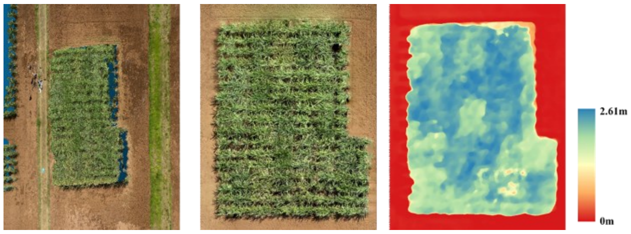


Fig. 6. 3D map generated and sugar cane height prediction

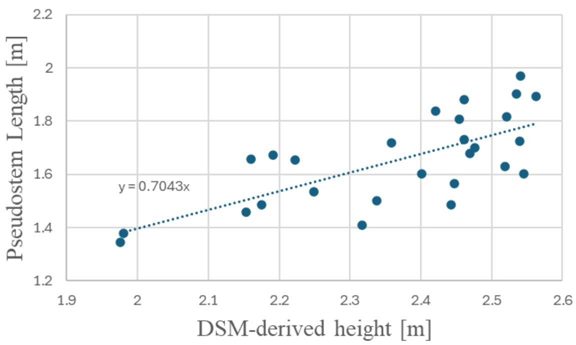


Fig. 7. Pseudostem length and DSM-derived height

B. Data Selection and Accuracy Comparison for Yield Prediction

The Kagoshima Prefectural Agriculture Development Center conducted comprehensive growth surveys from 2016 to 2023, collecting data on variables crucial for sugarcane yield analysis, such as pseudostem length, stem count, and sugarcane variety, with measurements taken consistently from July to October. This rich dataset provided an in-depth view of growth dynamics across different seasons and environmental conditions. Complementing these field measurements, meteorological data from the Japan Meteorological Agency—including average temperature, total rainfall, and daily sunshine hours—were integrated into the dataset as additional predictive factors, given their direct impact on crop development.

Each of these variables was evaluated as a potential input for the yield prediction model, with the target variable set as stem weight—a key indicator of sugarcane yield. However, not all variables contribute equally to prediction accuracy. By iterating through combinations of input variables, the GA identified which factors most strongly influenced the model's accuracy, allowing the model to prioritize high-impact variables, such as pseudostem length and temperature, while discarding less influential data, such as less variable weather factors.

Once the optimal set of variables was selected, the LSTM model was trained on this refined dataset to maximize predictive power while minimizing overfitting. This careful curation of inputs improved the model's performance, as extraneous data could introduce noise and reduce prediction accuracy.

C. DSM Accuracy

The accuracy of the Digital Surface Model (DSM) was evaluated through comparisons between the DSM-derived measurements and actual field data, including point clouds, orthophotos, and DSM images (Fig. 6). To verify spatial precision, the orthophoto-based measurements were cross-referenced with field-obtained distances, which revealed minor discrepancies, with the maximum error reaching 1.8 meters. While this deviation was within acceptable limits for the scale of sugarcane fields, it underscored the importance of refining mapping accuracy for even better data fidelity in future applications.

The DSM's ability to reflect crop height accurately was quantified by calculating the correlation coefficient between DSM-derived heights and pseudostem length measurements obtained from manual surveys. The observed correlation coefficient of 0.704 demonstrated a strong positive relationship, indicating that DSM-derived height data closely approximated actual crop growth and could serve as a reliable predictor for sugarcane yield. This positive correlation validated the DSM as a valuable input for the yield prediction model, providing a non-invasive alternative to traditional crop measurement methods. By capturing crop height with high precision, the DSM also enabled a better understanding of growth patterns across different regions within the field, allowing for targeted analysis and yield management strategies.

In addition to height validation, the DSM provided spatial insights into crop density and structural uniformity, which are crucial for yield estimation. Differences in DSM-derived crop height across the field highlighted areas of inconsistent growth, likely due to varying soil conditions, water availability, or sunlight exposure. These spatial variations underscored the DSM's utility in identifying zones that may require intervention to maximize yield potential, thus improving precision agriculture applications in sugarcane fields.

D. GA-Optimized Data Selection and Yield Prediction Model Accuracy

In optimizing the LSTM yield prediction model, the Genetic Algorithm (GA) played a pivotal role in selecting the most predictive variables and refining model configurations. Through multiple iterations, GA identified an optimal hidden layer configuration of 64 nodes, with a learning rate of 0.0001, which enabled the model to effectively capture the complex, nonlinear relationships within the dataset. This setup facilitated efficient learning while avoiding overfitting, which is critical for generalizing the model to diverse field conditions and seasonal changes.

The GA-driven analysis revealed that excluding stem count as an input variable improved the model's accuracy. Although initially considered important, stem count showed a weaker correlation with final yield compared to other metrics, such as pseudostem length. Pseudostem length proved to be a more reliable indicator of growth and biomass, likely due to its closer relationship with sugarcane height and overall structural mass. By eliminating less predictive variables, the model was streamlined, focusing on the data inputs that held the strongest predictive power, which minimized noise and improved model robustness.

Among the models tested, the GA-optimized LSTM model consistently outperformed other configurations, achieving a prediction error rate of 7.6%. This low error rate indicated a high level of predictive accuracy, especially given the complexity of factors affecting crop yield. The significant accuracy improvement provided by GA-optimized input selection and hyperparameter tuning demonstrates the efficacy of combining LSTM with GA for yield prediction tasks. This hybrid approach allows the model to adapt to diverse and evolving environmental factors, providing farmers with a powerful, data-driven tool for anticipating yield outcomes. Additionally, this model has potential applications for broader agronomic studies, where similar yield forecasting methods could be applied to other crop types, further demonstrating the adaptability and robustness of the GA-optimized LSTM architecture.

V. CONCLUSIONS

This work developed a sugar cane yield prediction model using a combination of LSTM and GA, aimed at assisting in the prediction of sugar cane yield. The GA-optimized model achieved a prediction error rate of 7.6%, demonstrating the potential of LSTM+GA for accurate yield prediction. The Digital Surface Model (DSM) derived from drone-captured images strongly correlated with pseudostem length, supporting its use as a valuable input for the yield prediction model. Future research may explore alternative data extraction methods from DSM, including advanced statistical techniques and Convolutional Neural Networks (CNNs) to refine model performance and generalizability further.

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