EDGESOIL 2.0 – Soil Analyzer Using Convolutional Neural Network and Camera Imaging in Agricultural Robotics

Roni Kasemi[1], Lara Lammer[2], Stefan Thalhammer[2] and Markus Vincze[2]

***Abstract*— Soil is the main building element of agriculture, and analyzing it is vital for having healthy crops and ample crop yield. But besides importance, analyzing soil is a laborious and time-consuming task. This paper presents EDGESOIL 2.0, a non-invasive, accurate, and real-time robotic system for soil pH prediction, which is one of the top four important soil parameters, together with nitrogen, phosphorus, and potassium levels. For implementation, we are using a mobile robot with the NVIDIA Jetson Nano module which is running a pH-estimator trained with a Convolutional Neural Network (CNN) on a novel dataset we built for this purpose. The EDGESOIL 2.0 predicts the pH value of the soil in real-time, using a live video stream from the webcam with an average of 7 FPS, and performing 400 predictions in 52 seconds. Predictions are performed while the robot is moving over the plowed field before the planting process starts. In order to achieve the best performance, we train the pH-estimator with different input modalities and validate each result using Mean Squared Error (MSE) and Standard Deviation (SD). We are able to achieve accurate results with the MSE value of 0.08, the SD value of 0.15, and with testing results from the field showing up to ± 0.3 deviation from the GT value during prediction, which is sufficient to comply with agricultural standards.**

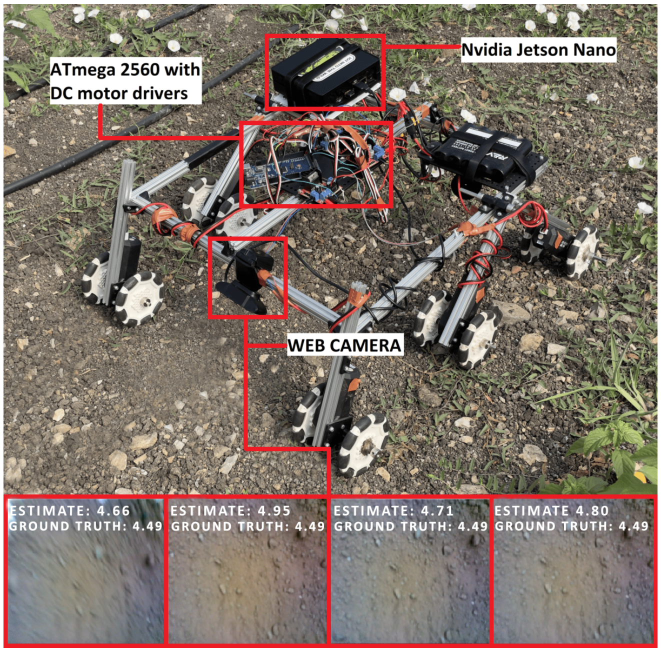

Fig. 1. **EDGESOIL 2.0** Presented is a cost-efficient mobile platform for performing online pH level analysis. At the bottom, frames and corresponding estimated pH-level, captured and processed in real time, are visualized.

I. INTRODUCTION

Soil analysis is crucial for ensuring crop health and maximizing crop yield, which are directly affected by soil parameters, such as pH, nitrogen, phosphorus, and potassium levels [1][2]. However, because of the laborious nature of the soil sample collection and time-consuming laboratory analysis procedure, soil analysis is seldom applied before crop sowing [3].

Diverse robotic systems have been proposed for performing tasks such as weed detection [4], plant disease classification [5], and fruit monitoring [6], [7], [8]. As compared to these tasks soil analysis presents a considerable challenge since exhaustive analysis of soil parameters requires sophisticated environmental measurements, or laboratory equipment [10], [11], [12], [13], [14], [15], [16], [17]. In [10] and [11] a continuous internet connection is assumed to correlate measurement with vast amounts of data of climatic parameters, satellite images, and mean annual temperatures, to name a few. This is especially challenging in rural areas and emerging countries since these environmental parameters are not always present. Methods for directly performing soil analysis are thus preferred. The works presented in [16] and [17] use time-consuming drilling mechanisms to collect soil samples, which in turn are analyzed in a laboratory. Similar approaches rely on measuring diverse soil parameters: the amount of organic soil matter [12], temperature and humidity [13], CO2 levels [14], and electrical resistivity [15]. As compared to these works, this paper focuses on analyzing the soil's pH value, because it is one of the most important parameters and therefore has been termed the ”master soil variable” by environmental soil science experts [1].

In this paper, we a) investigate the observability of the pH value in RGB images, and b) present a modular edge device for predicting soil pH levels. Our findings confirm the findings of [18] that the soil's pH value correlates with the RGB image's saturation. Based on this confirmation, we have built EDGESOIL 2.0 as the continuation of our previous work EDGESOIL [19], which is also a robotic system, but with the task of classifying the soil type. We use a custom-tailored CNN architecture since we are passing as an input value the soil RGB images and alongside that the mean saturation value of those images in order to increase the performance of the CNN. Using a novel dataset and a custom-tailored CNN, we train a pH-estimator, which predicts the

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pH value of the soil in real-time without the need for an internet connection or depending on vast amounts of data, thus being suitable for farmers in emerging countries and also eliminating the laborious and time-consuming process of soil sample collection and laboratory analysis. Contributions of EDGESOIL 2.0 are listed as follows:

- Real-time and accurate pH-measuring robotic system with 97% of the predictions resulting below a threshold of 0.5 deviation of the ground truth pH value. The robotic system uses solely RGB images, which require no internet connection or databases.
- We identify a correlation between mean saturation values of soil images of agricultural land and the respective pH value of the soil. Using the mean saturation value as additional input to the pH-estimator leads to an error reduction of 68.5%, as compared to only using RGB.
- Novel dataset with soil images and their pH values[1]

The paper is structured as follows. Section 2 includes the related work and two different approaches used regarding soil analysis. Section 3 explains our approach and the method used to implement it. Section 4 analyses the dataset, how it is created, and what combinations of data are included. Section 5 presents in detail the results and evaluation of the results. Section 6 discusses the findings and the future work.

II. RELATED WORK

There are two main approaches used to analyze soil parameters, which are soil analysis using a) vast amounts of data collected from systems like GIS and satellite imagery, and b) sensor data and soil samples directly from the field.

Felegari et al. [10] approached the soil analysis problem by predicting total soil nitrogen using three machine-learning techniques. Instead of using any kind of robot or collecting soil images, the authors use different types of data like climate parameters, satellite data, topographic components, and soil samples. Using these data from different zones, they trained three different models using a Support Vector Machine, Boosted Regression Tree, and Random Forest algorithms. After validating each model using mean absolute error, root mean square error, and coefficient of determination, they concluded that Random Forest and Boosted Regression Tree algorithms were most successful in predicting total soil nitrogen value. A similar approach was used by Pham et al. [11] who also tried to estimate soil organic carbon, total nitrogen, and soil reaction values by using different environmental variables like land use and topographic wetness index. In this case, the authors used regression kriging and ordinary kriging methods for prediction, by concluding that the regression kriging method was more precise compared to others. The common point of these approaches and our paper is to analyze soil parameters, even though the used methodologies are totally different from ours since we do not depend on outside data and use our pH-estimator for prediction.

Zhou et al. [12] focus on mapping soil organic matter using drones to collect multispectral images and obtaining nine parameters out of the collected images, from which NLIrededge2 highly correlated with soil organic matter. After training with different models, the authors concluded that the random forest algorithm produced the best results when validated with coefficient of determination, root mean square error, mean bias error, and the ratio of performance to interquartile distance. A similar approach to ours was done by Iqbal et al. [13] who developed a mobile robot to analyze both soil and plant parameters. The robot is equipped with a depth camera to analyze the morphological traits of a plant and a manipulator with a sensor to detect the temperature and humidity of the soil. Another robotic system that analyzes a very specific soil parameter, soil respiration, was done by Jaffe et al. [14] who emphasizes that this parameter is important in agriculture but usually overlooked. The robot uses an arm-like mechanism that holds sensors for measuring temperature, humidity, and CO2 levels from the top of the soil, which after being measured are sent to the NVIDIA Jetson board via a radio module for further processing. Ünal et al. [15] also use a mobile robot, which uses using Wenner four-probe measurement method to determine the electrical resistivity (ER) of the soil in real time and store that information in a database. Besides measurement with different sensors, mobile robots are used also in soil sample collection [16][17] by including here other information such as location, satellite images of the field, and atmospheric conditions which are collected and sent to cloud storage. Very similar research to ours was done by Barman and Choudhury [18] who experimented with the correlation between soil pH values and the saturation of the soil images. The authors collected a total of 120 soil samples and 120 soil images in the laboratory, with a white background in order to extract the soil colors better. Then they proceeded to extract the saturation value of each soil image and the pH value of each soil sample, thus running the correlation analysis between those parameters, and they found out that these two values are highly correlated (0.859) with the pH values of the soil. What differs in our paper is that the images are acquired from both the agricultural land and laboratory conditions, thus creating a diverse mix dataset, since we find out that lighting conditions are changing drastically the final prediction results and the lighting in the terrain is not the same as in the laboratory. Also, we run the correlation test on a much larger dataset with 4800 images, which gives us a better overview.

III. METHOD

EDGESOIL 2.0 consists of two main building blocks (see Figure 2), with the purpose of eliminating the time-consuming and laborious process of soil pH analysis, without depending on an internet connection or any other database. The first building block consists of the pH-estimator trained with CNN which is responsible for estimating the pH level of the soil by using only the RGB images collected from the webcam. The second building block consists of the

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[1] https://www.kaggle.com/datasets/ronikasemi/blackredmix

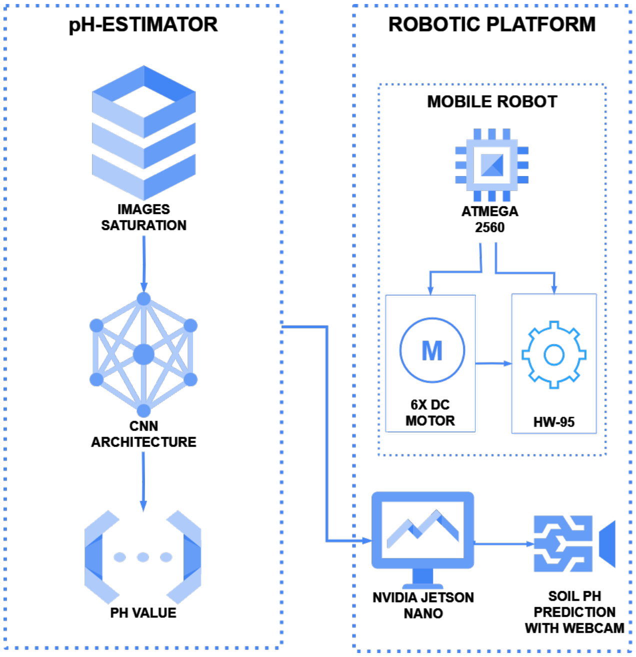

Fig. 2. **System Diagram**. Two main building blocks of EDGESOIL 2.0, with a platform including the mobile robot and NVIDIA Jetson Nano, which runs the pH-estimator trained from CNN.

robotic platform which includes the mobile robot and the Nvidia Jetson Nano[2] equipped with a webcam and running the pH-estimator, as an embedded device carried from the robot. The whole system is composed of easily available and low-cost components thus making it easily reproducible by researchers and practitioners. Compared to contemporary work it is easily available to the community and as such also in emerging countries.

pH-estimator. Since our main objective is to predict the soil pH value just from images, the Convolutional Neural Network architecture is best suited for developing our predictive model [20][21]. In order to fulfill our task, we developed a CNN architecture (see Figure 3) with common components such as convolutional layers, dense layers, batch normalization, and max pooling layers. The CNN contains four convolutional layers with filter sizes of 32, 64, 128, and 256. Training is supervised using MSE loss.

Following the convolutional layers are two dense layers with 512 and 256 neurons, each of them followed by batch normalization and max pooling layers. Besides those layers, our CNN architecture contains L2 regularization of 0.001, data augmentation, dropout of 0.5, learning rate adjustment of 0.001, Mean Squared Error as loss function supervising the training, and early stopping.

What differentiates our architecture from the traditional CNN is the dual input layer, since the traditional CNN architectures [20] usually only uses images as input data. In our case, we additionally pass the mean saturation of the corresponding soil image, and the RGB image itself to the network. Also, what makes our architecture specific is the concatenation feature [22], which happens between the output of the last dense layer and the scalar input, and merges the RGB image and scalar features for pH prediction.

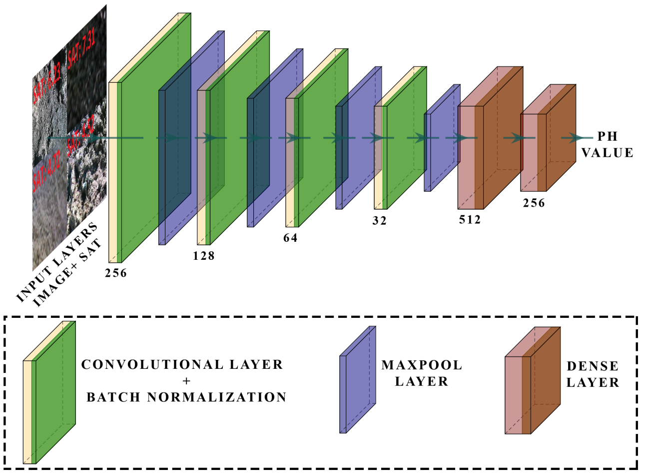

Fig. 3. **pH-estimator.** CNN architecture which trains the pH-estimator and contains six layers, with the input layer containing RGB soil images and their mean saturation value.

Robotic Platform. The mobile robot is a six-wheeled model with enough traction power and flexibility to navigate easily on the field. For navigation, the robot uses a simple yet effective method [19], by calculating the distance with integrated encoders on the DC motors thus covering the field in vertical lines. The main control unit for reading the encoder data and moving the robot via HW-95 motor drivers is the ATmega2560 microcontroller[3], which is sufficient to perform those tasks, and also it is low-cost which is a great advantage for using it. While the robot is moving in the field, it is performing the pH prediction by using the webcam shown in Figure 1 and in real time by synchronizing the speed of the robot movement and processed frames per second (see Figure 7). The prediction is made from the pH-estimator running on NVIDIA Jetson Nano, which is powerful enough to run such a model, and yet it is very compact in size and power management which makes it very practical to be carried from almost any mobile robot.

IV. DATASET

The focus of EDGESOIL 2.0 is to predict the pH level of the soil just by using soil RGB images obtained from real-time video streaming from a webcam mounted on the agricultural robot and in order to design such a system, data collection is crucial. Since there is no other publicly available dataset for such a task, we created it including the RGB soil images and the ground truth (GT) which is the pH value measured for each collected soil sample. Also, the created dataset is made publicly available in order to be easily accessible to researchers and practitioners.

For images and soil sample collection, we chose a specific area in Southeast Europe, which has three types of soil - black, brown, and red - thus giving us diversity in soil

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[2] https://developer.NVIDIA.com/embedded/jetson-nano-developer-kit

[3] https://www.microchip.com/en-us/product/atmega2560

Fig. 4. **Data Collection**. Two top red boxes show the areas where soil data is collected. On the bottom of the image are five different fields, with a total of 5.6 hectares, where soil images and samples are collected.

types and pH values. In five different locations, as shown in Figure 4, we collected a total of 25,000 images, but also in each location, we collected four soil samples from different spots on that location, thus having 20 soil samples in total. Because the soil images are taken on the same day and time, the created dataset is biased regarding lighting conditions. To overcome this, we collected soil RGB images again from the soil samples in different lighting conditions simulated inside the laboratory and mixed the dataset with the original images taken from the field in order to create a more diverse dataset for training the pH-estimator. The importance of the lighting comes from the research findings of Barman [18] who states that the correlation coefficient is high between the saturation values of soil images and the pH value of those soil samples. Therefore, a diverse dataset in terms of lighting is very important, since it will impact drastically those image parameters, and as such the correlation cannot be considered only with one type of lighting condition. Besides the image collection, we measured the pH level of each soil sample with standard methodology [23] and labeled each sample with a measured value, thus creating the ground truth (GT) for the pH-estimator. With collected images, we create two different datasets named *BlackBrownRed* and *BlackRedMix*, each with different image content. The *BlackBrownRed* dataset includes brown-type soil images collected from the terrain lighting conditions and black and red-type soil images collected in the laboratory lighting conditions from the soil samples, with a total of 4800 images. The *BlackRedMix* includes only black and red type soil images, collected from terrain and laboratory lighting conditions, with a total of 3600 images. The reason why the number of images is less than the original 25,000 images collected is that after extensive experimentation, we observe that the same results are obtained with a much smaller number of images, thus speeding up the training process and producing a faster working model.

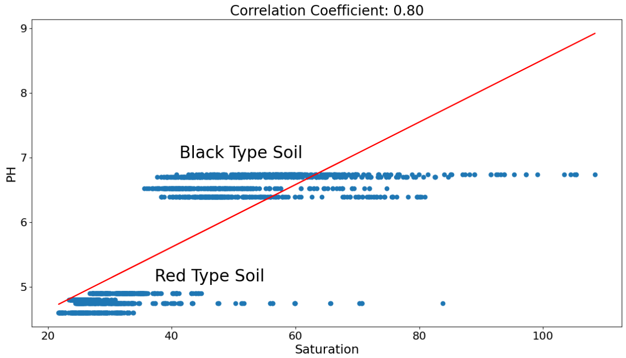

Fig. 5. **Correlation between Soil pH Values and Mean Saturation.** Correlation results, tested on the *BlackRedMix* dataset. Two groupings of data points represent two types of soil, with the black type of soil having higher pH values and the red type of soil having lower pH values.

V. EXPERIMENTS

This section presents the correlation between soil pH values and the mean saturation of soil images since we want to confirm the findings of Barman and Choudhury [18] who concluded that saturation values of the soil images are highly correlated (0.895) with the pH values of the soil. Confirming and replicating those findings is important in order to use the mean saturation of soil images for performance improvement of the pH-estimator. Following that are the implementation results of the pH-estimator, which then we evaluate with respect to its capacity for estimating the pH values from RGB images in the test set.

A. *Correlation between Image Parameters and the pH Value*

In order to prove the association between soil pH value and the scalar parameters such as mean saturation and mean hue of the soil images we run the correlation test. The reason for such analysis is to find any related parameter with pH value, in order to enhance the CNN model by using it as an extra input layer. Pearson correlation (r) [24] is used to measure the relationship between the mentioned scalar values and pH values of the soil, which is formulated as:

$$r = ((x_i - \hat{x})(y_i - \hat{y}))/(\sqrt{\sum(x_i - \hat{x})^2 * \sum(y_i - \hat{y})^2}) \qquad (1)$$

Where x_i and y_i are the individual data points, $\hat{x}$ and $\hat{y}$ are the means of the x and y variables, respectively.

We applied the correlation test for both *BlackRedMix* and *BlackBrownRed* datasets, and the corresponding pH values of soil images on those datasets. The results show that there is a high correlation (0.8) between the mean saturation of images from the *BlackRedMix* dataset and pH values of the black and red type of soil, which also proves the findings in [18]. The results are shown in Figure 5 which are seen as two groups of data points with the upper data points representing the black type of soil with higher pH values, and lower data points representing the brown type of soil with lower pH values. Also, for each specific pH value on the Y axis, we have a range of corresponding mean saturation values on the X axis of the graph. This is happening since we have large numbers of soil images collected from each of the five fields (see Figure 4), and the pH value of the soil does not change if the soil type is the same. The reason for having a range of saturation values corresponding to the same pH value is that the dataset is created in different lighting conditions, so the image of the same soil is taken in different light intensities, different angles, and different distances, in order to create a diverse dataset and not be biased and dependent on the mentioned conditions. Since saturation is directly affected by those conditions [25], this causes a range of saturation values to exist for a given pH value. Based on the results, it is seen that with the increasing pH values of the soil, the mean saturation values of that soil image are also increasing.

Besides the saturation, we test if there is a correlation between soil pH values and other soil image parameters such as mean hue, mean red, mean green, and mean blue values of soil images. We find no significant correlation between those values and thus continue with only the mean saturation values as extra input beside the image datasets for improving the performance of the pH-estimator.

B. *Soil Analysis Evaluation*

Building on the findings of the previous section, we evaluate the system for soil pH value analysis on an edge device. We present experiments that demonstrate that using the mean saturation value as additional input to our pH-estimator reduces the pH value regression error. Following that, a runtime analysis and a real-world test run of EDGESOIL 2.0 on previously unseen agricultural land is provided.

1) Implementation Details: In order to achieve the best performance, we trained the pH-estimator with different input modalities and analyzed the results for each one. First, we split the dataset into 80% training and 20% testing, which is followed by data augmentation and normalization. Data augmentation includes rotation, shift, shear, zoom, and flipping, then each pixel intensity is normalized to a range of [0, 1]. Also, the soil images in the dataset are resized with a shape 300x300x3 before the training process starts.

RGB - Refers to using RGB images as input to the pH-estimator. For training, we test separately two datasets, *BlackBrownRed* and *BlackRedMix* with the first dataset taking 6 to 8 hours for training and the second one 5 to 6 hours.

RGBS - Refers to additionally pass the mean saturation value of each soil image, alongside the RGB images to the pH-estimator, since we proved that the pH value of soil and mean saturation of soil images are highly correlated (see Figure 5). The concatenation feature is implemented because the input is of a dual nature, and again two datasets are tested, with similar training time as mentioned above.

2) pH-estimator Evaluation: For the evaluation of four pH-estimators trained with different input combinations, we use Mean Squared Error (MSE) and Standard Deviation (SD) on a test set, which are the most suited evaluation techniques for regression models [26]. For the calculation of MSE, we use the equation:

TABLE I

EVALUATION OF FOUR DIFFERENT OUTPUTS PRODUCED FROM THE COMBINATION DATASET AND INPUT MODALITIES, WITH THE MSE AND SD RESULTS FOR EACH OUTPUT.

Input	Dataset	MSE	SD
RGB	BlackBrownRed	0.26	0.26
	BlackRedMix	0.16	0.24
RGBS	BlackBrownRed	0.15	0.20
	BlackRedMix	**0.08**	**0.15**

$$MSE = \sum (y_i - \hat{y}_i)^2 / N \tag{2}$$

Where N is the number of data points, y_i is observed values, and $\hat{y}_i$ is predicted values. For SD, we used the following equation:

$$SD = \sqrt{\sum (x_i - \mu)^2 / N} \tag{3}$$

Where N is the size of the population, x_i is each value from the population, and μ is the population mean. When we compare the evaluation results from four input modalities, the best results are obtained from the RGBS (see Table I) which uses the *BlackRedMix* dataset and mean saturation values of the soil images from the dataset as input for CNN architecture. We can see an improvement in MSE results for 68.5% with the passing of mean saturation value alongside the image dataset as an input. The improvement is also backed up by the high correlation coefficient (see Figure 5) between the mean saturation of soil images and the pH values of the soil, which shows that the pH values of soil increase with the increasing of the mean saturation values of soil images. The cause for this is the difference in color for each type of soil which directly affects the mean saturation of the soil image [25] thus resulting in a correlation between mean saturation and pH values of soil.

3) Runtime Analysis: We evaluate the runtime of the EDGESOIL 2.0 by measuring the frames per second (FPS) that are processed during deployment. On average, the pH-estimator computing on the NVIDIA Jetson Nano achieves a seven FPS and performs 400 pH measurements in 52 seconds (see Figure 7). The frame rate and the number of measurements are sufficient to achieve the desired pH information since the aim is to collect the accurate pH value and not to increase the number of measurements per second.

4) Real-world Experiments with EDGESOIL 2.0: Besides the runtime performance, the EDGESOIL 2.0 is also tested in a real-world scenario. We present results on soil images captured outside the agricultural land used for dataset creation. In both cases, for black and red types of soil, the deviation on pH value prediction maximally deviates with 0.3 from ground truth (see Figure 8). This deviation is considered a low error for agricultural standards [27]. This experiment

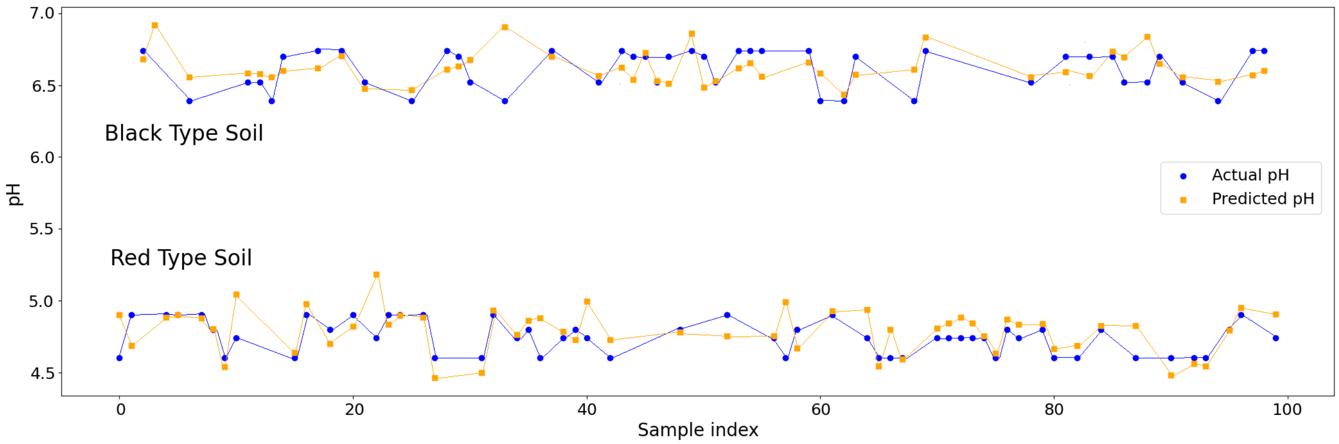

Fig. 6. **MSE Result of RGBS.** MSE evaluation results from the *BlackRedMix* dataset show actual pH values compared to predicted pH values from the pH-estimator for 100 data samples.

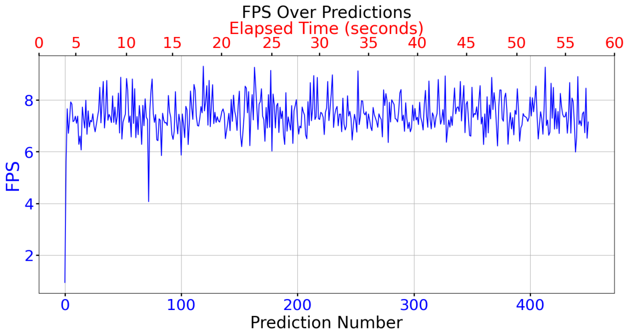

Fig. 7. **Runtime Evaluation of EDGESOIL2.0.** Runtime evaluation shows that EDGESOIL 2.0 is running the video stream at an average of 7 FPS and is performing 400 pH predictions for less than a minute.

provides a verification that the accuracy achieved on the test data transfers well to new data.

VI. CONCLUSIONS

In this paper, we present a non-invasive, accurate, and real-time pH soil measuring method using only RGB images on a mobile robot. Prediction is performed using a pH-estimator which runs on a NVIDIA Jetson Nano and is trained on CNN with input combinations of soil image dataset and the scalar values of mean saturation of each soil image. A total of 400 pH predictions are performed for 52 seconds, with only ±0.3 deviations in pH value compared to GT. Also, validation results such as MSE 0.08 and SD 0.4 show that the model is accurate at the pH prediction task.

Future work will investigate how to expand the pH prediction for more types of soil and also predict other soil parameters by using only machine vision, which would give the farmers better overall information about their land.

REFERENCES

[1] Neina, D., 2019. The role of soil pH in plant nutrition and soil remediation. Applied and environmental soil science, 2019, pp.1-9.

[2] Zhong, W., Gu, T., Wang, W., Zhang, B., Lin, X., Huang, Q. and Shen, W., 2010. The effects of mineral fertilizer and organic manure on soil microbial community and diversity. Plant and soil, 326, pp.511-522.

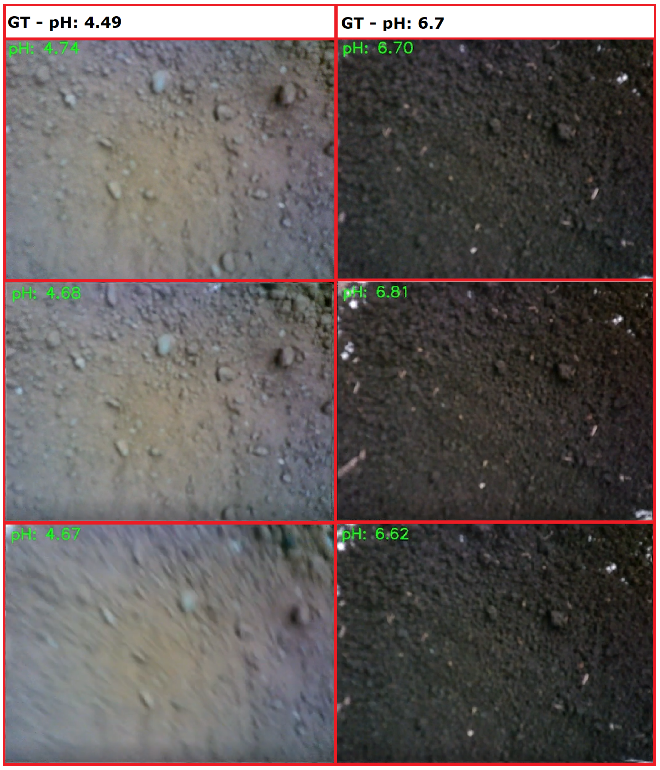

Fig. 8. **EDGESOIL 2.0 Performance of pH Prediction on Terrain.** EDGESOIL 2.0 performs soil pH prediction on the black and red types of soil on the terrain conditions. On the top left of each frame is shown the predicted pH value, which is compared to the GT value on the top.

[3] Kasemi, R., Lammer, L. and Vincze, M., 2022. The gap between technology and agriculture, barrier identification and potential solution analysis. IFAC-PapersOnLine, 55(39), pp.314-318.

[4] Raffik, R., Mayukha, S., Hemchander, J., Abishek, D., Tharun, R. and Kumar, S.D., 2021, October. Autonomous Weeding Robot for Organic Farming Fields. In 2021 International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA) (pp. 1-4). IEEE.

[5] Karpyshev, P., Ilin, V., Kalinov, I., Petrovsky, A. and Tsetserukou, D., 2021, January. Autonomous mobile robot for apple plant disease detection based on cnn and multi-spectral vision system. In 2021 IEEE/SICE international symposium on system integration (SII) (pp.

157-162). IEEE.

[6] Doddamani, S.T., Karadgi, S. and Giriyapur, A.C., 2022. Multi-Label Classification of Cotton Plant with Agriculture Mobile Robot. In Data Intelligence and Cognitive Informatics: Proceedings of ICDICI 2021 (pp. 759-772). Singapore: Springer Nature Singapore.

[7] Choi, T., Would, O., Salazar-Gomez, A. and Cielniak, G., 2022, May. Self-supervised representation learning for reliable robotic monitoring of fruit anomalies. In 2022 International Conference on Robotics and Automation (ICRA) (pp. 2266-2272). IEEE.

[8] Chen, Y., Lin, J., Du, X., Fang, B., Sun, F. and Li, S., 2022, May. Non-destructive fruit firmness evaluation using vision-based tactile information. In 2022 International Conference on Robotics and Automation (ICRA) (pp. 2303-2309). IEEE.

[9] Bini, D., Pamela, D. and Prince, S., 2020, March. Machine vision and machine learning for intelligent agrobots: A review. In 2020 5th International conference on devices, circuits and systems (ICDCS) (pp. 12-16). IEEE.

[10] Felegari, S., Moravej, K., Sharifi, A., Golchin, A. and Karami, P., 2023. Prediction of total soil nitrogen variations using three machine learning approaches and remote sensing data.

[11] Gia Pham, T., Kappas, M., Van Huynh, C. and Hoang Khanh Nguyen, L., 2019. Application of ordinary kriging and regression kriging method for soil properties mapping in hilly region of Central Vietnam. ISPRS International Journal of Geo-Information, 8(3), p.147.

[12] Zhou, J., Xu, Y., Gu, X., Chen, T., Sun, Q., Zhang, S. and Pan, Y., 2023. High-Precision Mapping of Soil Organic Matter Based on UAV Imagery Using Machine Learning Algorithms. Drones, 7(5), p.290.

[13] Iqbal, J., Xu, R., Halloran, H. and Li, C., 2020. Development of a multi-purpose autonomous differential drive mobile robot for plant phenotyping and soil sensing. Electronics, 9(9), p.1550.

[14] Finegan, H., Jaffe, S., Leon, A., Lytle, K., Morgan, E., Greene, C., Meyer, A., Brinkman, B., De Wekker, S., Yochum, H. and Bezzo, N., 2019, April. Development of an autonomous agricultural vehicle to measure soil respiration. In 2019 Systems and Information Engineering Design Symposium (SIEDS) (pp. 1-6). IEEE.

[15] Ünal, I., Kabaş, Ö. and Sözer, S., 2020. Real-time electrical resistivity measurement and mapping platform of the soils with an autonomous robot for precision farming applications. Sensors, 20(1), p.251.

[16] David, C.N.A., Yumol, J.V., Garcia, R.G. and Ballado, A.H., 2021, November. Swarm Robotics Application for Gathering Soil Samples. In 2021 IEEE 13th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM) (pp. 1-6). IEEE.

[17] Łukowska, A., Tomaszuk, P., Dzierżek, K. and Magnuszewski, Ł., 2019, May. Soil sampling mobile platform for Agriculture 4.0. In 2019 20th International Carpathian Control Conference (ICCC) (pp. 1-4). IEEE.

[18] Barman, U. and Choudhury, R.D., 2019. Prediction of soil pH using smartphone based digital image processing and prediction algorithm. Journal of Mechanics of Continua And Mathematical Sciences, 14, pp.226-249.

[19] Kasemi, R., Vincze, M. and Lammer, L., EDGESOIL: LOW-COST SOIL SENSOR AND EDGE AI FUSION IN AGRICULTURAL ROBOTICS.

[20] Krizhevsky, A., Sutskever, I. and Hinton, G.E., 2017. ImageNet classification with deep convolutional neural networks. Communications of the ACM, 60(6), pp.84-90.

[21] - Zhang, X., Wu, F. and Li, Z., 2021. Application of convolutional neural network to traditional data. Expert Systems with Applications, 168, p.114185.

[22] - Du, C., Wang, Y., Wang, C., Shi, C. and Xiao, B., 2020. Selective feature connection mechanism: Concatenating multi-layer CNN features with a feature selector. Pattern Recognition Letters, 129, pp.108-114.

[23] Buck, R.P., Rondinini, S., Covington, A.K., Baucke, F.G.K., Brett, C.M., Camoes, M.F., Milton, M.J.T., Mussini, T., Naumann, R., Pratt, K.W. and Spitzer, P., 2002. Measurement of pH. Definition, standards, and procedures (IUPAC Recommendations 2002). Pure and applied chemistry, 74(11), pp.2169-2200.

[24] Cohen, I., Huang, Y., Chen, J., Benesty, J., Benesty, J., Chen, J., Huang, Y. and Cohen, I., 2009. Pearson correlation coefficient. Noise reduction in speech processing, pp.1-4.

[25] Lin, C., Mottaghi, S. and Shams, L., 2023. The effects of color and saturation on the enjoyment of real-life images. Psychonomic Bulletin & Review, pp.1-12.

[26] Chicco, D., Warrens, M.J. and Jurman, G., 2021. The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. PeerJ Computer Science, 7, p.e623.

[27] Gallagher, P.A. and Herlihy, M., 1963. An evaluation of errors associated with soil testing. Irish Journal of Agricultural Research, pp.149-167.