Design of an Embedded Machine Learning Based System for an Environmental-friendly Crop Prediction Using a Sustainable Soil Fertility Management

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***Abstract*— Most of the existing precision agriculture solutions recommend the use of fertilizers as a remedy to poor soil fertility and to boost yields. Such solutions cause environmental degradation in the long run mainly due to the overuse of fertilizers. There is therefore, a need for a system to ensure that farmers can practice precision farming in terms of a sustainable soil management approach so as to attain high yields while at the same time conserving the environment. In this research, a design and simulation of an embedded machine learning based system to predict the best crop to grow with minimal use of fertilizers with an aim of conserving the environment is presented. The system senses different real time soil parameters on a daily basis, integrates them with forecast weather information and uses embedded machine learning technique to determine which crop would grow best under the existing soil conditions so as to minimize fertilizer use. In addition to crop prediction, the system helps farmers to monitor the soil nutrients evolution so that action can be done on real time. The results are either displayed on the device or sent to the farmer's mobile phone. This is a move from the existing solutions that depend on cloud analytics and do not consider the change of soil conditions on time in making the predictions and decisions since this is expensive when done at the cloud. The implementation of the proposed solution is expected to not only lead to high productivity and reduced costs but also conserve the environment**.

Keywords— *Internet of Things, Precision Farming, Embedded Machine learning (ML), Environmental conservation, Deep learning, Crop prediction*

I. INTRODUCTION

The demand for agricultural products has mainly been increasing due to the fast growing population and urbanization [1]. To give way for infrastructural development, the increase in population has led to more agricultural land being converted into nonagricultural fields. Adverse changes in climate and wastage of natural resources have also had negative impacts on agriculture [2]. This has led to the application of new technologies to help mitigate the problems leading to the growing popularity of precision agriculture.

Internet of Things (IoT) is used in precision agriculture [3], [4] to help in the optimization of resources, assisting farmers to make informed decisions so as to achieve high productivity and yields. With solutions that deal with soil parameters, farmers are mostly advised on the fertilizers to add which may lead to overuse of chemicals and fertilizers; thus causing environmental degradation in the long run. These fertilizers are usually chemicals that, in most cases, kill important microorganisms in soil that convert dead animals and plants into organic matter that is rich in nutrients. Nitrogen- and phosphate-based synthetic fertilizers leach into groundwater and make it toxic, causing water pollution. More to that, chemical fertilizers make the top soil acidic leading to crop burn and hence lower crops yields [5]

Besides, soil fertility is one of the most important elements that determine the growth and ultimate production of crops. Thus, it is one of the primary factors considered in developing precision farming solutions. To begin with, the three main crop nutrients are nitrogen (N), phosphorus (P) and potassium (K) together often referred to as NPK. There are also other important nutrients such as calcium, magnesium and sulphur, among others, but are needed in small quantities as compared to NPK [6] . Soil Potential of Hydrogen (pH) also affects soil chemical properties and thus fertility. All plants have a preferred for pH level and knowing the pH for the soil helps farmers to determine what plants will thrive most or help to fine tune it to accommodate the desired plants [6].

The convergence of precision farming with artificial intelligence (AI) can be a great solution for sustainable food production and soil management [6]. Studies and commercial precision farming solutions have considered different parameters in an attempt to determine soil fertility. In a survey [7] of IoT technologies used in Agricultural environment, different studies emphasize the need to measure soil NPK and soil pH in ensuring a reliable solution to soil fertility management. In addition, as–discussed [7], some studies also include soil moisture and soil temperature but these do not exactly show how fertile a given soil sample is. This narrows down the parameters to be considered for a concrete soil fertility survey to soil pH, soil NPK and weather conditions.

Soil being complex and harboring living organisms constantly evolves, physically, chemically and biologically. Standard laboratory testing of soil to determine the levels of nutrient content is infrequent as it is expensive and slow yet levels of nutrients vary on short timescales [8]. Existing solutions are either based on offline expensive lab process or use of cloud-based architecture in which sensing devices have to collect data and send to the cloud so as to enjoy machine learning driven intelligence. Due to cost, connectivity and the need for real-time intelligence, there is a need for a solution that can enable machine learning at the edge to overcome the challenges. Therefore, this research work presents an embedded machine learning solution that will also ensure a real-time soil fertility management and prediction of crop to be grown thus leading to increased yields while at the same time conserving the environment.

II. LITERATURE REVIEW

A. Digitizing soil nutrients data

There exist different techniques used to evaluate the soil fertility of a particular field. To begin with, the basic method for measuring soil fertility consists of mixing a soil sample with water and chemically extracting the N, P, and K as nitrate, phosphate, and potassium. The N, P, and K amounts in the sample are determined by comparing the solution to a color chart [9]. The use of commercial soil NPK and Soil PH sensors has also been proposed in recent studies and solutions. A system is proposed that measures soil nutrients (N, P, K) for rice crop using color sensor TCS3200 [10]. The use of customized in-house sensors that measure soil chemical properties are proposed [11]. An optical transducer is developed and used to measure and to detect the presence of Nitrogen (N), Phosphorus (P) and Potassium (K) of that soil [12]. This sensor helps in deciding how much extra content of these nutrients are to be added to the soil to increase soil fertility to the desirable value. The N, P, and K value of the sample are determined by light absorption of each nutrient.

B. Precision farming solution based on soil fertility

A system that measures the soil nutrients, i.e. NPK, for rice crop using a color sensor is proposed [13]. It allows the farmer to view the soil fertility status at their convenience on a web application and also suggests which fertilizer they can add to get better yield. A system is proposed that uses pH value, Moisture value, Temperature and Humidity value from the soil and analyzes its status [14]. It thereafter helps the farmer to analyze the fertility of their field and plant the better crop to increase their productivity and profit. This system uses a code algorithm (data driven approach) to analyze and predict the soil fertility and suitable crop. Such studies and other related studies show that monitoring the soil NPK and PH are essential when developing solutions that monitor soil fertility. They also support the argument that the fertility of the soil change overtime. However, monitoring this constant change with the cloud is expensive in terms of devices and connectivity.

C. Artificial Intelligence in Soil fertility management

Artificial intelligence centered with deep learning provides a number of algorithms that can help in monitoring the health of the soil before planting and during the growth process also. Soil deficiencies can be analyzed so as to ensure smooth crop growth [15]. With soil weakness comes a number of crop defects and low production so continuous assessment of nutrient levels in the soil is relevant

Coupling existing models for nutrient cycling and crop productivity with embedded AI approaches can help optimize targeting, uptake, delivery, nutrient capture and long-term impacts on soil microbial communities that combine optimal safety and functionality profiles [15]. This can as well help farmers to respond in real time to changes in plant growth based on the soil nutrient states.

A system that uses predictive analysis to suggest the fertilizer which has to be added to the soil in order to increase the crop productivity is presented [16]. The prediction is done based on a Bayesian algorithm at the cloud to give farmers information after a certain period of time.

A logistic regression ML algorithm is used at the cloud [17] to analyze data that is being sent from the field. The collected data is based on NPK sensors and after analysis, information is sent to the farmers to know the status of their farms. A web portal is also created which gives information about the fertilizer(s) required for their crops [18]. Milija Bajčeta et al. [19] developed an IoT-based private cloud platform that is used in ecological monitoring and agriculture. In this paper, IoT nodes are used and they communicate to the server in a cloud gateway or directly. The server is used to host analysis for data integration, remote visualizations and smart application development and deployment.

An application of IoT for soil quality is proposed by Gunjan et al. [20]. In the solution eight different sensors are used to analyze the soil type, soil moisture levels, and soil quality in relation to weather aspects including wind, temperature and humidity. A node MCU is used with data being sent to the cloud through Wi-Fi technology. A related commercial solution BAZAFARM [21] is used in Rwanda for irrigation decisions based on a virtual cloud.

In most of these systems, the need to reduce the application of external chemical fertilizers to the fields is not emphasized yet this has been proven to have a negative impact on the environment in the long run. Furthermore, some of the systems only present to the farmer the state of their field in terms of soil nutrient content and this leaves them to make uninformed decisions on what to do with the data. In addition, the solutions that recommend the use of predictive algorithms depend on a cloud based architecture that is not applicable to the African setting where connectivity is a challenge. Thus the need for an edge based solution.

III. DESIGN OF THE CROP PREDICTION SYSTEM

This is to design and simulate an Embedded AI based precision farming system that monitors the soil fertility (NPK) and soil PH over a period of time so as to recommend the best crop to be grown with the exiting conditions to limit the over-use of fertilizers thus conserve the environment.

A. *System Design*

Soil nutrient sensors and soil pH sensors integrated with communication modules and microcontrollers form part of the sensing unit of the system. Different sensor nodes are deployed in a farm. Each node collects data on a daily basis

and forwards it to the sink node via Bluetooth Low Energy (BLE). The collected data is then aggregated and integrated with forecast weather (rainfall, temperature and humidity) data at the sink node. An embedded AI model is then used to predict the best crop to grow based on the observed soil parameters with notifications being shown on the device and also sent by SMS to the farmer's mobile phone.
The data aggregated by the sink node and the prediction results are sent to the cloud through cellular networks. Data is stored on ThingSpeak cloud platform with the information being made available through a web and mobile based dashboards for storage and data sharing. Energy harvesting using solar radiation from the sun is used to power the system. Fig. 1 shows the system architecture.

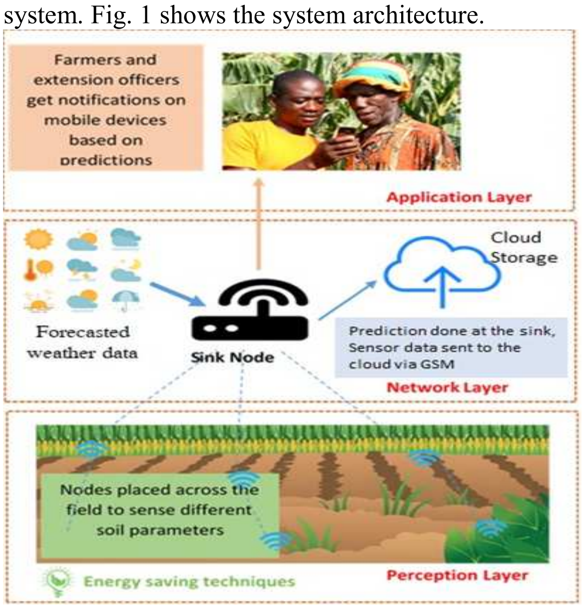

Fig. 1. System Architecture

B. Datasets

Sources of data include; actual data collection, open source datasets and synthetic data generation among others. Open datasets from various studies can easily be explored from readily online datasets which provide links to many different data sites. Due to issues of privacy and security concerns, identifying open datasets in some areas of study may be limited. Data collected from African settings are also limited. This pushes the need for exploration of synthetic data generation to complement the small datasets. There are AI-powered synthetic data solutions that take original data and transform it into privacy-compliant synthetic copies. Synthetic data comes as a solution to the lack of enough datasets that are needed to build strong and accurate machine learning models to aid in prediction systems [22]. Besides, Table 1 presents the crop suitability based on the quantity of N, P and K components [23].

TABLE I. N, P, K RANGE REQUIREMENTS OF EACH CROP

Crop	Beans	Maize	Lentil	Peas	watermelon
NPK (mg/kg)	20, 65, 25	74, 50, 18	20, 70, 19	40, 70, 77	99, 20, 50

C. Embedded ML Process flow

Our Embedded ML process is presented in Fig. 2. The process starts with datasets for training and generation of synthetic data. The dataset was collected with the same sensors as per the system design.

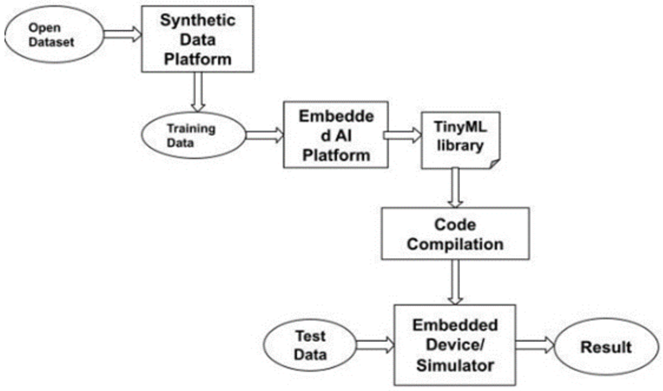

Fig. 2. The Embedded AI Process

The synthetic data forms input to the ML process and is used to train a model. An Embedded ML package is then generated for compilation and simulation or implementation on an embedded device. For our simulation context, test data is used to test the model in the cloud and results compared to when the same is used in the edge simulation environment.

D. Simulation design of Embedded Kit

A high-level simulation context of the proposed solution is shown in Fig. 3. The Embedded ML model executable is deployed in an STM32F401CC board on proteus design suit. Input data of readings from sensors and weather information is given in the form of a file from an sd card with the inference results being shown on the serial terminal.

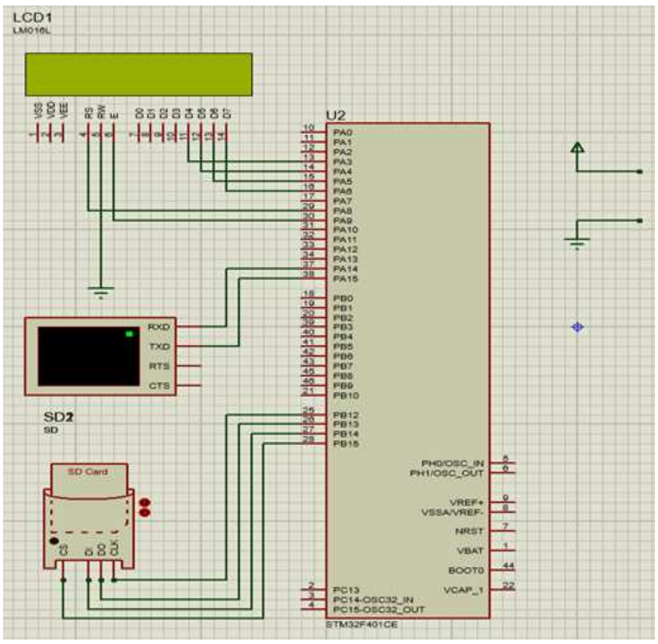

Fig. 3. The simulation layout

E. Hardware Components

1) STM32F401CC

The STM32F401xC devices are based on the high-performance Arm® Cortex® -M4 32-bit RISC core operating at a frequency of up to 84 MHz [24].

2) Sensors

Data used for the simulation was collected by the following sensors;

a) *Soil NPK Sensor* - the RS485 soil nutrient fertilizer detector meter which is suitable for detecting the content of nitrogen, phosphorus, and potassium in the soil.

b) *Soil PH Sensor*- the RS485 Arduino Soil pH Sensor for Agriculture was used. The sensor is widely used and reliable in soil PH testing and other occasions that need pH monitoring.

c) *Weather data sensors include; rainfall sensor, temperature sensor and humidity sensor*

F. *Software Tools*

1) *Embedded ML*

Embedded ML allows use of AI in resource constrained smart devices. It is a type of machine learning that enables the shrinking of deep learning networks so as to fit tiny hardware. Tensor Flow Lite, a machine learning framework for embedded devices created by Google is used in Embedded ML. The framework makes deep learning smaller and faster for implementation in embedded devices.

2) *STM32CubeIDE*

STM32CubeIDE is an advanced C/C++ development platform with peripheral configuration, code generation, code compilation, and debug features for STM32 microcontrollers and microprocessors [24].

3) *Proteus Design Suite*

The Proteus Design Suite combines ease of use with a powerful feature set to enable the rapid design, test and layout of professional printed circuit boards [25].

IV. EVALUATION OF EMBEDDED ML FOR PREDICTING BEST CROP

A. *Input: Synthetic Dataset*

In this work, an open data set collected from a farm [23] was used as input to the synthetic data generation platform. The reason for using synthetic data is to increase the volume of data so as to enable a better deep learning model. The free version of a commercial synthetic data platform, Mostly.AI, was used to generate more data [22]. The dataset includes information on N, P, K, pH, temperature, humidity and rainfall collected everyday over a period of time with labels of the best crops that did well under the specified conditions. Data relating to five food crops were selected for the purpose of our study. Before use, the generated synthetic data was tested and the performance compared to using the original data set and was 99% accurate. Synthetic data generation reports also show that all the required thresholds including privacy tests were met.

B. *Embedded AI model generation*

The training model was developed using an open source embedded ML platform called edge impulse. The data was preformatted and JSON files created for upload into the platform. Five files each with data about the five selected crops were uploaded and data automatically separated into the training, validation and test sets using the holdout method. The raw data was classified using a Neural Network classifier. The model had 7 inputs, from sensor and weather data and 5 outputs being the selected crops which were Maize, Beans, Lentil, Peas and watermelon. The window size used was 1000ms with a sampling rate of 1000ms for the data.

With use of synthetic data, a model accuracy of 92.2% was achieved with a loss of 0.24% from the validation set. Fig. 4 shows the confusion matrix for the validation set with synthetic data


ACCURACY 92.2%

LOSS 0.24

Confusion matrix (validation set)

	BEANS	LENTIL	MAIZE	PEAS	WATERMELOI
BEANS	89.6%	5.3%	3.1%	2.1%	0%
LENTIL	4.0%	90.8%	3.5%	1.6%	0.1%
MAIZE	6.7%	2.6%	89.4%	0.6%	0.7%
PEAS	2.9%	2.9%	0.9%	93.3%	0.1%
WATERMELON	0.4%	0.1%	1.5%	0%	98.0%
F1 SCORE	0.88	0.90	0.90	0.94	0.99

Fig. 4: Model confusion matrix with synthetic data

With the non-synthetic data, the accuracy was 78.8% and a loss of 0.32. Fig. 5 shows the confusion matrix with non-synthetic low small datasets.


ACCURACY 78.8%

LOSS 0.32

Confusion matrix (validation set)

	LENTIL	BEANS	MAIZE	PEAS	WATERMEL
LENTIL	93.3%	0%	6.7%	0%	0%
BEANS	0%	92.9%	7.1%	0%	0%
MAIZE	0%	0%	100%	0%	0%
PEAS	0%	0%	0%	100%	0%
WATERMELOI	0%	0%	6.7%	93.3%	0%
F1 SCORE	0.97	0.96	0.89	0.77	0.00

Fig. 5. Model confusion matrix with non-synthetic data.

This comparison justifies the importance and relevance of generating big volumes of data from the available small volumes through synthetic data generation. With big volumes of data, the accuracy is seen to improve to 92% from 78% for embedded ML.

C. *Model Validation*

So as to validate the model, test data from the real open datasets was used to find out how accurately the best crop to be grown can be predicted. When the test data was applied on both the cloud and embedded device, the model predicted the crop to be grown with 99.9% accuracy. This shows that the model is effective in predicting the best crop to be grown considering the real time condition of the soil. In addition, this confirms that synthetically enhanced data has minimal effects on the performance of the resulting models.

D. Inference Simulation

A C++ project was created in STM32CubeIDE and the CMSIS-PACK integrated into the project. The project was then compiled and debugged and an executable HEX file was created for simulation on proteus. Fig. 6 gives a sample output from the simulation on proteus design suite. This is the same result as when compared to classification in the cloud using the same data as shown in Fig. 7.

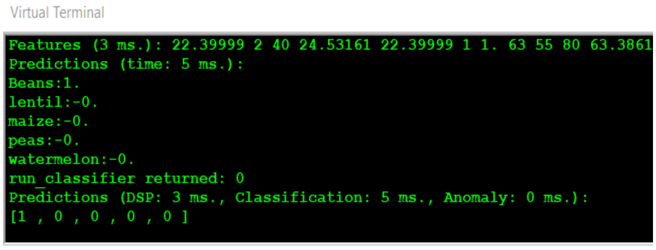

Fig. 6. Inference result on a serial monitor

From the result, the crop with value 1 indicates the predicted crop to be planted based on the real time condition of the soil, then value 0 shows the crops not suitable for the soil in that state. The classification of the data took 5ms and the digital signal processing (DSP) of the data took 3ms


Detailed result

Show only unknowns

TIMESTAMP	BEANS	LENTIL	MAIZE	PEAS	WATERMELON
0	1.00	0	0	0	0

Fig. 7. Cloud inference output

The results give a prediction of the best crop to be grown without using fertilizers as the conditions on the validation dataset are appropriate for the recommend crop. This supports the objectives of the study on limiting the use of fertilizers and thus environmental conservation.

V. ANALYSIS AND DISCUSION

A. Embedded ML

The training of an Embedded ML model still requires cloud based resources and the after packaged for deployment on embedded devices. The model was trained using a similar dataset and deployed at the cloud to test if the inference would be the same as the inference at the edge device, the result was satisfactory that the embedded AI result is still accurate. It implies that the embedded Machine Learning model is perfect and accurate and gives the same result as would be done in the cloud

The required on device resources by the model were analyzed so as to determine if the model could run on an embedded device as was intended. The estimated on-device performance by the model on an embedded device from the cloud training platform was 1.7 Kb peak RAM usage, 17.4Kb ROM usage and an inference time of 1ms as shown in Fig. 8. The results show that the required resources are still minimal and thus the model can be used on many commercially available embedded devices that have the required ARM cortex M4 core.

Fig 8: On device performance

B. Sensor Significance

Different parameters were omitted during the model training so as to verify the significance of each parameter in predicting the best crop to be grown. Fig. 9 gives the performance of each of the three classes of parameters used namely soil nutrient, Soil PH and weather. This was done using the same settings for the neural network.

The result shows that weather (humidity) with 68% and soil nutrients (NPK) with 78% are the major considerations that are mandatory for predicting the best crop to grow as compared to pH which is 50%. The soil pH is dependent on the soil nutrient content hence the low performance when tested individually.

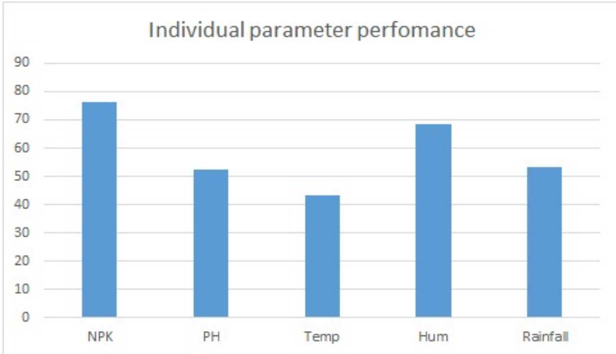

Fig. 9. Individual sensor performance

C. Effect of Soil Moisture on soil NPK and PH

During the testing of the working of the prototype it was noted that soil moisture affects the values for both NPK and pH. When soils were dry, the pH values tended to hike beyond 7 and the NPK values also tended to lower down. This is one of the reasons why rainfall is very key in crop growth. It moisturizes the soil and helps the NPK values to increase and stabilize. When the soil is too acidic, lower than the recommended level of 5.5 for good crop yield, there will be a decrease in the crop yield instead.

VI. PERSPECTIVE AND FUTURE WORKS

This work introduces the use of embedded ML in Agriculture. It proposes and evaluates an AI model for the prediction of the best crop to grow under the existing conditions so as to minimize the use of fertilizers. With the embedded ML, the farmer can daily monitor the state of their field soil to take timely actions in form of a sustainable soil management. In addition, the use of open dataset and synthetic data generation is also demonstrated. In future works we will prototype on a real embedded development board and conduct tests with soil from different farms to further evaluate the performance of the proposed solution.

VII. CONCLUSIONS

This research proposes the use of Embedded AI in precision crop farming for the prediction of the best crop to grow with the existing soil conditions with the aim of conserving the environment. This is a move from the existing solutions that mostly use cloud based solutions. The use of Embedded AI helps overcome connectivity challenges in Africa and ensure real time responses for precision solutions.

The environment is thus conserved in a way that the crop prediction is made on a fertilizer free based decision considering the real time soil nutrient state. The system is able to do a day to day monitoring of the soil nutrient evolution so that the farmer can take timely actions about the soil fertility.

Our model was tested in both the cloud and embedded device with the results giving the same accuracy. This supports the use of Embedded ML for precision farming solutions and is scalable to other use cases so long as the data for model training is available. The study also shows that synthetic data can also be applied in smart agriculture in cases of limited data for machine learning. Our experiment shows that use of synthetic data does not degrade the performance of an AI model so long as the right methods are applied. From the evaluation of the sensors we note that soil nutrient and weather information are vital when making a decision on which crop to best plant. Since pH is related to the underlying soil nutrient levels its effect on the model performance is minimal.

Considering that this is an ongoing research, the next step is to implement this solution, which will lead to conservation of the environment by ensuring that farmers minimize the use of fertilizers that have a lasting effect on the environment. The use of embedded ML will also ensure that costs are reduced and real time actions are taken to enhance productivity.

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